Conference Proceedings

2nd Edition

INTERNATIONAL JOURNAL OF ACCOUNTING, FINANCE AND INFORMATION SYSTEM (I-JAFIS)

Published by:
Association of Chartered Certified System Accountants (ACCSA) Global

3535 S. Sherwood Forest Blvd,
Suite 201, #7, Baton Rouge,
LA, 70816, USA

In Conjuction with

Southern University,
Baton Rouge,
Louisiana, USA.

Theme: Emerging Technologies as Enablers of National Economic Modernization: Strategic Architecture for Sustainable Growth and Global Competitiveness.

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Volume 1, Number 2, November 2026

ISSN: 3027-1231

PUBLISHED BY:
Association of Chartered Certified System Accountants (ACCSA), USA

In Conjunction with

Southern University - USA,
3535 S. Sherwood Forest Blvd,
Suite 201, #7, Baton Rouge,
LA, 70816, USA

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KEYNOTE

Distinguished scholars, esteemed colleagues, industry leaders, policymakers, researchers, and participants from across the globe, it is both an honour and a privilege to deliver this keynote address at the ACCSA Global Academic Conference. I extend my warmest greetings to all participants whose scholarly contributions have enriched this important intellectual gathering. The diversity of perspectives represented in this conference demonstrates the growing importance of interdisciplinary and international collaboration in addressing the technological, economic, institutional, and societal challenges of our time.

This year's theme - "*Emerging Technologies as Enablers of National Economic Modernization: Strategic Architecture for Sustainable Growth and Global Competitiveness"* - captures one of the defining transformations of the 21st-century global economy. The convergence of artificial intelligence, advanced communications, real-time data analytics, predictive modelling, digital governance, interoperable information systems, and intelligent automation is fundamentally reshaping the way governments, businesses, institutions, and societies operate. Emerging technologies are no longer simply tools for improving efficiency; they are increasingly becoming strategic instruments for economic modernization, national resilience, sustainable development, and global competitiveness.

The scholarly contributions presented at this conference demonstrate the breadth of this transformation. The research on a scalable zero-trust AI security methodology for Criminal Justice Information Services highlights the critical importance of cybersecurity, data protection, adversarial defence, and compliance assurance. As government and institutional systems become increasingly digital, trust and security must constitute foundational elements of technological modernization. Similarly, the work on secure and resilient advanced communications infrastructure and the economic resilience implications of 5G and 6G emphasizes that telecommunications networks, fibre infrastructure, and next-generation connectivity have become critical economic infrastructure. Their reliability directly affects financial services, manufacturing, healthcare, logistics, public administration, and national security.

A major theme emerging from the conference is the transition from traditional, largely reactive decision-making to predictive and intelligence-driven economic management. The contributions on predictive economic decision-support frameworks, real-time economic intelligence, trade policy, industrial policy, manufacturing competitiveness, and energy security demonstrate how real-time data analytics and predictive modelling can strengthen policy responsiveness. Governments and institutions can increasingly identify emerging risks, model possible scenarios, anticipate supply-chain disruptions, and develop interventions before economic challenges become systemic.

This capability is particularly important for manufacturing and supply-chain resilience. The research on risk-informed capital deployment in U.S. manufacturing and the economic impact of real-time analytics on critical industrial and medical-product supply chains highlights the growing importance of data-driven resource allocation. Working capital, production capacity, inventories, logistics, and supply-chain decisions can increasingly be informed by real-time information and predictive intelligence. The implication is that modern economic competitiveness will depend significantly on the ability to transform data into timely and actionable decisions.

Healthcare is another important area of technological transformation. The contributions addressing AI-enabled health information interoperability, secure health information exchange, Medicaid transformation, predictive modelling, and healthcare productivity demonstrate how interoperable information systems can reduce administrative burdens, improve data efficiency, strengthen decision-making, and enhance healthcare-system resilience. The economic significance of these

developments extends beyond improved healthcare outcomes, as more efficient information systems can reduce institutional costs and contribute to wider productivity.

The conference also draws attention to the governance dimensions of emerging technologies. The studies addressing risk-based AI governance in the financial sector, data-driven governance of the digital economy, and risk-based trust and safety on online platforms demonstrate that technological innovation must be accompanied by effective governance. AI can improve efficiency, risk assessment, compliance, fraud detection, and decision-making, but inadequate governance can create new cybersecurity, ethical, regulatory, privacy, and systemic risks. The objective should therefore be to develop governance frameworks that encourage innovation while ensuring accountability, transparency, security, responsible use, and public trust.

The importance of infrastructure and project delivery is similarly reflected in the proposed AI-enabled strategic project management framework for resilient fibre and substation infrastructure. Infrastructure modernization requires not only financial investment but also intelligent planning, risk management, monitoring, resource optimization, and timely implementation. AI-enabled project management can enhance the delivery and resilience of critical infrastructure and contribute to the continuity of essential economic services.

The conference contributions further demonstrate that technological modernization extends beyond finance, industry, and infrastructure. Precision agriculture and data-driven nutrient management illustrate the potential of emerging technologies to improve agricultural productivity, resource efficiency, food security, and competitiveness. Cultural heritage digitization demonstrates how technology can strengthen institutional efficiency, preservation, public access, research, education, tourism, and the wider cultural economy. The contribution addressing Bloom's Two-Sigma Problem through the DARTS approach highlights another transformative possibility: the use of AI to provide personalized mentoring and adaptive learning support to students. This illustrates the potential of emerging technologies to democratize access to high-quality education and strengthen human capital development.

Taken together, these contributions reveal a unifying principle: the future of national economic modernization lies not in isolated technological adoption, but in the strategic integration of emerging technologies across the major systems that sustain national development. Secure digital infrastructure, trustworthy AI governance, real-time economic intelligence, resilient productive systems, and human capital must function as interconnected components of a coherent national strategy.

A strategic architecture for sustainable growth should therefore address five fundamental dimensions. First, nations require secure and resilient digital and physical infrastructure capable of supporting increasingly interconnected economic systems. Second, AI and data must be governed through appropriate frameworks that protect security, privacy, accountability, transparency, and public trust. Third, governments and businesses must develop real-time analytical and predictive capabilities to improve economic and strategic decision-making. Fourth, critical sectors such as manufacturing, healthcare, agriculture, finance, energy, communications, and supply chains must be strengthened against disruption. Fifth, sustained investment in education, research, professional development, and human capital must accompany technological investment.

The global and interdisciplinary nature of this conference is itself an important reflection of the changing knowledge economy. The complex challenges associated with AI, digital infrastructure, economic resilience, supply chains, healthcare, finance, agriculture, education, and governance cannot be effectively addressed within disciplinary or national boundaries alone. Stronger

collaboration among universities, professional institutions, governments, industry, researchers, and technology developers is therefore essential for translating technological possibilities into sustainable economic value.

The central message emerging from the conference is clear: emerging technologies provide extraordinary opportunities for transforming economies, but technology alone does not guarantee modernization. The benefits of innovation depend upon the quality of governance, infrastructure, institutions, human capital, and strategic leadership within which technology is deployed. The objective must therefore be to build economies that are intelligent enough to anticipate emerging challenges, resilient enough to withstand disruption, secure enough to command trust, innovative enough to compete globally, and inclusive enough to ensure that the benefits of modernization are broadly shared.

In conclusion, the scholarly contributions contained in these proceedings provide valuable perspectives on how emerging technologies can support national economic modernization and global competitiveness. They demonstrate that artificial intelligence, predictive analytics, advanced communications, interoperable information systems, precision technologies, and digital governance are already reshaping the foundations of economic activity.

The strategic imperative is to move beyond technology adoption towards technology integration - transforming data into intelligence, intelligence into informed decisions, decisions into productive action, and innovation into sustainable economic value. Achieving this requires strategic vision, responsible governance, resilient institutions, interdisciplinary collaboration, and continuous investment in human capability.

The future of national competitiveness will increasingly depend not simply on the technologies a country possesses, but on its capacity to integrate technology, governance, infrastructure, finance, knowledge, security, and human capital into a coherent architecture for sustainable development. This conference represents an important contribution to that agenda and provides a valuable platform for advancing the research, dialogue, and innovation required to shape a more resilient, productive, sustainable, and globally competitive future.

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FOREWARD

The publication of these Conference Proceedings marks an important contribution to the continuing global discourse on technological transformation, economic modernization, institutional resilience, and sustainable development. The proceedings bring together a rich collection of scholarly perspectives examining the rapidly evolving relationship between emerging technologies and the capacity of nations, institutions, industries, and communities to respond effectively to the challenges and opportunities of the contemporary global economy.

The theme of this conference, *"Emerging Technologies as Enablers of National Economic Modernization: Strategic Architecture for Sustainable Growth and Global Competitiveness,"* is both timely and significant. The world is experiencing a period of unprecedented technological change characterized by rapid advances in artificial intelligence, real-time data analytics, predictive modelling, advanced communications, digital platforms, interoperable information systems, intelligent automation, and precision technologies. These developments are fundamentally changing the architecture of economic activity and creating new possibilities for improving productivity, resilience, governance, public services, and global competitiveness.

The significance of these developments extends well beyond the traditional boundaries of the technology sector. Emerging technologies are increasingly embedded in the systems through which nations produce goods and services, manage public resources, protect critical infrastructure, deliver healthcare, educate citizens, conduct international trade, administer financial systems, manage supply chains, and preserve cultural assets. Consequently, technological modernization has become an integral component of national economic strategy.

The contributions contained in these proceedings provide valuable evidence of this transformation. Collectively, they demonstrate that artificial intelligence and related technologies are not simply instruments for automation, but increasingly constitute strategic resources for anticipating risks, improving decision-making, optimizing resources, strengthening institutional performance, and creating new pathways for sustainable economic development.

A particularly important dimension of the conference is the emphasis on cybersecurity, trust, and responsible technological governance. The contribution on a scalable zero-trust AI security methodology for Criminal Justice Information Services demonstrates the growing need to protect sensitive information and critical institutional systems in an increasingly interconnected environment. Similarly, the contributions addressing risk-based AI governance in the financial sector, the digital economy, and online platforms emphasize that technological innovation must be accompanied by appropriate mechanisms for accountability, security, transparency, privacy, compliance, and risk management.

These perspectives are particularly relevant because the rapid expansion of AI creates both opportunities and vulnerabilities. The economic benefits of intelligent systems cannot be fully realized where citizens, businesses, governments, and institutions lack confidence in the security and integrity of the systems upon which they increasingly depend. Trust must therefore be regarded as an essential component of the digital economy and a fundamental prerequisite for sustainable technological adoption.

The proceedings also demonstrate the strategic importance of advanced communications infrastructure. The contributions on secure and resilient communications, fibre and substation infrastructure, and economic resilience in the 5G/6G era reinforce the recognition that connectivity has become critical economic infrastructure. Modern financial systems, manufacturing networks, healthcare services, logistics, government operations, education, and commerce all depend

increasingly upon reliable digital connectivity. Investment in advanced communications must therefore be regarded as an investment in national productivity, economic continuity, and competitiveness.

Another significant contribution of the proceedings lies in the examination of predictive economic intelligence and real-time decision-support systems. The research addressing trade policy, industrial policy, manufacturing competitiveness, energy security, and supply-chain resilience reflects a fundamental shift from retrospective to predictive approaches to economic management. Real-time data analytics and predictive modelling provide governments and organizations with opportunities to identify emerging risks, assess alternative scenarios, anticipate disruptions, and make more timely and evidence-based decisions.

This shift has profound implications for economic policy and institutional leadership. In an increasingly interconnected global economy, the ability to anticipate change is becoming as important as the ability to respond to change. Nations and organizations that can effectively transform data into intelligence and intelligence into timely action will be better positioned to manage uncertainty, optimize resources, and maintain competitive advantage.

The proceedings further highlight the importance of technology in strengthening productive and social systems. Contributions on AI-enabled health information interoperability and predictive health systems demonstrate how digital technologies can reduce administrative burdens, improve information efficiency, strengthen healthcare decision-making, and enhance system resilience. Similarly, research on risk-informed capital deployment and manufacturing resilience demonstrates the importance of integrating financial intelligence, technology, and supply-chain considerations into industrial decision-making.

Agriculture, too, is increasingly becoming a data-driven sector. The contribution on precision agriculture and data-driven nutrient management demonstrates the potential for emerging technologies to improve productivity, resource utilization, food security, and agricultural competitiveness. Such innovations are particularly significant in an era of changing climate conditions, resource constraints, population growth, and increasing pressure on food systems.

The proceedings appropriately extend the modernization conversation to cultural heritage and education. The research on scalable cultural heritage digitization illustrates how technology can improve collections management, preservation, public access, research, education, and the broader cultural economy. Meanwhile, the contribution examining Bloom's Two-Sigma Problem and the DARTS approach raises an important question concerning the potential of AI to provide personalized mentoring and learning support to students. These contributions reinforce the understanding that technological modernization must ultimately serve people and strengthen the institutions through which knowledge, culture, and human capability are developed.

A major strength of these proceedings is therefore their multidisciplinary character. The contributions collectively bring together perspectives from technology, economics, finance, governance, healthcare, infrastructure, manufacturing, agriculture, education, culture, cybersecurity, and public policy. This breadth is particularly valuable because the challenges associated with technological transformation are interconnected. Cybersecurity affects financial stability; communications infrastructure affects healthcare and manufacturing; supply-chain resilience affects national economic security; AI governance affects public trust; and human capital determines the capacity of institutions to adopt and effectively utilize emerging technologies.

The proceedings consequently support a central proposition: successful national economic modernization requires a strategic architecture in which technology, infrastructure, governance, finance, human capital, and institutional resilience operate as mutually reinforcing components.

Technology acquisition alone cannot guarantee modernization. Sophisticated AI systems require reliable infrastructure, quality data, appropriate governance, cybersecurity, skilled personnel, institutional capacity, and sustainable investment. Likewise, infrastructure investment produces greater value when supported by intelligent planning, predictive analytics, effective governance, and competent human resources.

This integrated perspective is particularly important for developing and emerging economies. Technological transformation provides opportunities for countries to overcome traditional development constraints through digital platforms, intelligent public services, precision agriculture, digital education, modern financial systems, and technology-enabled industrialization. However, realizing these opportunities requires deliberate policy, strategic investment, strong institutions, research capacity, and continuous development of human capital.

The publication of these proceedings is therefore not intended merely to document papers presented at a conference. It represents an effort to preserve, disseminate, and extend the intellectual contributions of researchers and professionals whose work addresses some of the most important questions confronting the global economy. It is hoped that the ideas contained herein will stimulate further research, inform policy development, encourage innovation, and promote practical collaboration among academia, industry, government, professional institutions, and technology communities.

The ACCSA Global Academic Conference provides an important platform for this type of engagement. Through interdisciplinary scholarship and international participation, the conference contributes to the development of a community of researchers and practitioners committed to understanding and shaping the future of economic and technological transformation.

As Managing Editor, I acknowledge with profound appreciation the intellectual contributions of all authors, researchers, delegates, reviewers, technical contributors, and members of the organizing team whose efforts have made these proceedings possible. Their collective commitment to scholarship, innovation, professional excellence, and knowledge dissemination is reflected throughout this volume.

The central message emerging from these proceedings is both clear and compelling: the future competitiveness of nations will depend increasingly on their ability to integrate emerging technologies into coherent systems of economic production, governance, infrastructure, finance, knowledge, security, and human development. Artificial intelligence, advanced communications, predictive analytics, digital governance, precision technologies, and interoperable information systems offer enormous opportunities, but their value will ultimately depend upon the strategic choices made by institutions and societies.

The task before policymakers, scholars, professionals, and institutional leaders is therefore not merely to adapt to technological change, but to shape that change responsibly and strategically. The objective should be to build economies that are innovative yet secure, productive yet sustainable, digitally advanced yet inclusive, and globally competitive while remaining firmly grounded in sound governance and human development.

It is my sincere hope that these Conference Proceedings will serve as a valuable reference for researchers, policymakers, professionals, educators, students, technology practitioners, and other

stakeholders interested in the future of economic modernization. May the ideas presented in this volume stimulate further inquiry and contribute to the development of practical strategies capable of transforming technological innovation into sustainable economic and societal value.

The future will belong to those economies and institutions that can successfully transform data into intelligence, intelligence into informed decisions, decisions into productive action, and innovation into sustainable value. These proceedings constitute one contribution towards advancing that important agenda.

Lambe K. Isaac, Ph.D., FCCSA
Associate Professor of Accounting & Finance
Managing Editor
(Regional Representative for Africa - ACCSA Global)

WELCOME ADDRESS

Distinguished scholars, esteemed colleagues, industry leaders, policymakers, researchers, professional practitioners, and participants from across the globe, it is my great pleasure to warmly welcome you to the Proceedings of the ACCSA Global Academic Conference on *"Emerging Technologies as Enablers of National Economic Modernization: Strategic Architecture for Sustainable Growth and Global Competitiveness."*

This Conference comes at a critical moment when emerging technologies are rapidly transforming the foundations of economic activity, institutional governance, professional practice, and national competitiveness. Artificial intelligence, advanced communications, real-time data analytics, predictive modelling, digital platforms, intelligent automation, and interoperable information systems are no longer simply technological innovations; they are increasingly becoming strategic instruments for economic modernization and sustainable development.

The papers presented at this Conference demonstrate the breadth and depth of this transformation. From zero-trust AI security and resilient communications infrastructure to predictive economic intelligence, manufacturing competitiveness, healthcare interoperability, financial-sector governance, supply-chain resilience, 5G/6G infrastructure, precision agriculture, cultural heritage digitization, and AI-enabled education, the contributions collectively demonstrate how technology can be strategically deployed to address complex national and global challenges.

A particularly important message emerging from these contributions is that technology alone does not guarantee economic transformation. Sustainable value is created when technological capabilities are supported by appropriate governance frameworks, resilient infrastructure, sound financial systems, effective institutions, skilled human capital, responsible leadership, and evidence-based decision-making. The future therefore requires not merely the adoption of emerging technologies, but their thoughtful integration into national economic and institutional architectures.

This Conference also reinforces the importance of collaboration. The complexity of contemporary economic and technological challenges requires universities, governments, professional bodies, industries, technology developers, researchers, and other stakeholders to work together in developing solutions that are innovative, secure, inclusive, and sustainable. Academic conferences such as this provide an important platform for such intellectual exchange and professional engagement.

On behalf of ACCSA Global, I commend all the authors, presenters, researchers, delegates, reviewers, organizers, and technical contributors whose commitment has made this Conference and its Proceedings possible. Your contributions enrich the global conversation on how emerging technologies can be harnessed to strengthen economic resilience, institutional effectiveness, human development, and international competitiveness.

As you engage with the papers contained in these Proceedings, I encourage readers to look beyond the technologies themselves and consider the broader strategic questions they raise: How can innovation create sustainable economic value? How can technology strengthen institutional resilience? How can data be transformed into actionable intelligence? And how can emerging technologies be governed in ways that promote trust, inclusion, security, and long-term prosperity?

It is my sincere hope that these Proceedings will serve not only as a record of this important academic gathering, but also as a valuable resource for researchers, policymakers, professionals, institutions, and decision-makers seeking practical and innovative pathways toward national economic modernization.

Once again, I warmly welcome you to this Conference and to the intellectual contributions contained in these Proceedings. May the ideas presented here stimulate further research, inspire meaningful collaboration, and contribute to building a more resilient, innovative, competitive, and sustainable global economy.

Jose Naogera, Ph.D., FCCSA
Research Director – ACCSA Global

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Abstract

Advanced communications infrastructure has become an enabling system for U.S. economic production, financial transactions, logistics, public safety, health care, energy control, water operations, cloud computing, and government services. CISA identifies communications as a foundational dependency for virtually all modern infrastructure systems, while communications itself depend on electricity, information technology, transportation, and fuel supply chains [1]. Yet U.S. broadband policy and economic-impact analysis have historically emphasized availability, adoption, and speed more than economically weighted reliability, cyber-physical survivability, recovery time, path diversity, and cross-sector cascading failure. Recent empirical evidence reinforces the distinction: broadband benefits arise principally when infrastructure is actually adopted and productively used, while reliability research finds that conventional speed-based measures omit important service-quality and outage dimensions [16]– [19], [21]. [1]. This paper develops an integrated framework for quantifying how secure and resilient fiber, mobile, satellite, cloud-edge, public-safety, and supporting power infrastructure can reduce state and regional economic losses from natural hazards, cyberattacks, equipment failures, power interruptions, and common-mode network failures. It addresses an unresolved research problem: the absence of a standardized U.S. framework linking communications-network engineering indicators to business-continuity performance, critical-infrastructure interoperability, state and regional value added, and investment benefit-cost metrics. This characterization is an inference from the fragmented state of the literature, including recent work identifying unpriced internet-resilience externalities and reliability-measurement gaps [21], [22]. [2]. The proposed Regional Communications Economic Resilience Framework (RCERF) integrates FCC Broadband Data Collection and disaster-outage information, BEA state/county/industry accounts, NOAA hazard losses, CISA dependency structures, and operator-level engineering metrics with graph-theoretic network analysis, stochastic hazard simulation, dynamic interoperability input-output modeling, econometric estimation, and robust infrastructure optimization. The method converts network degradation into time-dependent sector inoperability, regional value-added loss, business-continuity loss, and expected annual loss. FCC, BEA, and other public datasets make substantial portions of such a framework technically feasible, although operator-specific topology and restoration data remain an important data-access constraint [3], [5]–[7], [24]. [3]. Public evidence indicates material economic exposure. BEA estimated the U.S. digital economy at approximately $2.6 trillion, or 10.0% of U.S. GDP, in 2022, supporting approximately 8.9 million jobs and $1.3 trillion in employee compensation [2]. Hurricane Helene's October 1, 2024 FCC status report showed 707 of 1,452 reported cell sites, 48.69%, out of service in affected North Carolina counties, while Hurricane Milton's October 10 report showed 1,953 of 15,877 reported Florida cell sites, 12.3%, out in the disaster area [5], [6]. These figures do not equal percentages of customers without service because overlapping coverage, roaming, temporary facilities, and other engineering factors can preserve service despite individual site outages. NOAA recorded 27 U.S. billion-dollar weather and climate disasters in 2024 costing approximately $182.7 billion, illustrating the hazard environment in which communications resilience must operate [4]. [4]. Public investment should move from a predominantly coverage-oriented concept of digital infrastructure toward resilience-adjusted connectivity, in which funding and regulation recognize uptime, recovery speed, cyber integrity, route and provider diversity, backup-power endurance, satellite or deployable fallback, and economic criticality. The $42.45 billion BEAD program provides a major deployment platform, and by July 17, 2026, NTIA reported that 55 states and territories had Final Proposals approved, with NIST approval making funds available for

54 [15]. The framework proposed here would complement deployment metrics with auditable resilience KPIs rather than treating nominal availability as equivalent to continuity [15], [21]. [5]

Keywords: Communications Resilience; Economic Resilience; Critical Infrastructure; Business Continuity; Regional Economics

INTRODUCTION

Research Context, Problem Definition, and Contribution

Communications infrastructure is not only an asset of the telecommunications industry. It is a general-purpose economic continuity infrastructure. CISA describes communications networks as supporting energy-system monitoring and control, transportation management, water and wastewater operations, emergency response, information technology, and financial transactions. The relationship is bidirectional: communications facilities depend on electricity, IT infrastructure, transportation access, and fuel delivery for generators. A disruption can feed back on itself instead of failing in one direction [1]. [6]

That dependence has grown large. BEA's most recent dedicated Digital Economy Satellite Account estimated 2022 digital-economy value added at $2.6 trillion, representing 10.0% of U.S. GDP. Real digital-economy value added increased 6.3% in 2022, versus 1.9% for aggregate real U.S. GDP. Software represented approximately 24% of digital-economy value added, telecommunications services approximately 18%, and business-to-business e-commerce approximately 16% [2]. BEA subsequently discontinued production of the dedicated account because of budget constraints, meaning the 2022 figures should be treated as the latest estimates from that specific satellite-account series and not as current 2026 digital-economy GDP [2]. [7]

Approximate composition of U.S. digital-economy value added, 2022 [2]

Software	24%
Telecommunications	18%
B2B e-commerce	16%
Other digital activities	42%

The economic case is messier than “more bandwidth produces more GDP.” Briglauer, Krämer, and Palan's 2024 review finds broad positive evidence for growth, productivity, and resilience, but also diminishing benefits beyond some quality levels, heterogeneous urban-rural effects, ambiguous employment effects, and, crucially, stronger benefits from actual adoption than from infrastructure availability alone [18]. Koutroumpis and Sarri similarly find that higher broadband speeds were associated with stronger sales, profits, and labor productivity among adopting small firms in their microdata, whereas simple availability produced much weaker results [19]. U.S. evidence from USDA's Broadband Initiatives Program also indicates effects on employment and establishment survival that differ geographically and by sector [16], [17]. [8]

A policy gap follows from this. Availability, speed, adoption, security, resilience, and economic continuity are distinct variables**.** A census block may be classified as served while its only backhaul routes share the same conduit. Two providers may exist while depending on the same long-haul fiber, electric substation, Internet exchange, cloud region, or pole corridor. A cellular network may exhibit extensive physical site damage without corresponding one-for-one service loss because surviving sites, temporary cells, roaming, and power adjustments compensate. Conversely, apparently operational radio equipment may become economically unusable because backhaul, authentication, DNS, cloud control planes, payment networks, or power have failed. FCC disaster reports caution that reported cell-site outages cannot be read as the percentage of consumers without service [5], [6]. [9]

Reliability research arrives at the same point. Grindal and Meinrath's 2025 analysis of two years of Alaskan network data argues that speed-based definitions fail to capture important dimensions such as latency and outage reliability [21]. Howell's 2025 analysis goes further, arguing that resilience across the internet ecosystem creates benefits not fully internalized by individual infrastructure operators, creating a coordination and public-good problem [22]. These findings imply that a socially optimal state or federal investment portfolio may differ from one selected on household coverage, peak throughput, or private carrier return alone. [10]

This paper therefore formulates the unresolved question as:

How can the United States quantify, compare, and optimize communications-resilience investments according to the regional economic activity and critical functions they preserve under correlated cyber-physical disruptions?

The contribution is the proposed Regional Communications Economic Resilience Framework, RCERF, which joins five analytical domains that are usually kept apart: telecommunications network reliability; cybersecurity; business continuity; critical-infrastructure interdependency; and regional economic modeling. Its output is not merely “percent coverage” or “expected network downtime,” but dollars of regional value added protected, critical-function-hours preserved, recovery time reduced, and expected annual economic loss avoided per dollar invested.

The distinction matters because U.S. regional economies are not alike. In the first quarter of 2026, BEA reported that real GDP increased in 46 states and the District of Columbia, with annualized state changes ranging from +4.5% in Washington to -1.6% in South Dakota; the information industry was the leading contributor to Washington's growth [3]. County data also reveal substantial geographic dispersion in economic performance. Resilience investments should reflect local industry composition and dependencies, not assume that an hour of communications disruption carries the same economic value everywhere [3], [25]. [11]

Economic Exposure, Threat Environment, and Infrastructure Dependencies

Communication resilience must address multiple hazards simultaneously. Natural disasters can destroy sites and fiber, interrupt utility electricity, prevent fuel deliveries, inundate central offices, and constrain workforce access. Cyberattacks can compromise management planes, routers, authentication systems, signaling environments, or administrative networks without visibly damaging physical assets. Equipment and software failures can propagate through homogeneous architectures. Supply-chain problems can delay restoration. These failure modes can also occur concurrently, making independent-component reliability assumptions inappropriate for systemic resilience modeling [1], [8]–[10]. [12]

The recent U.S. hazard record shows the scale of that exposure. NOAA reports that 2024 experienced 27 billion-dollar weather and climate disasters, with estimated aggregate costs of $182.7 billion and 568 fatalities. Hurricane Helene accounted for approximately $78.7 billion of those losses and Hurricane Milton approximately $34.3 billion. Across 2015–2024, NOAA counted 190 separate billion-dollar events costing approximately $1.4 trillion in aggregate [4]. These totals are economy-wide disaster losses rather than communications-only losses, but they establish the scale of hazards against which communications systems must be engineered. [13]

Disaster Report	Geography / Date	Reported Cell Sites Out	Share Out	Reported Cable/Wireline Subscribers Out
Hurricane Helene [5]	North Carolina affected area, Oct. 1, 2024	707 / 1,452	**48.69%**	796,999
Hurricane Milton [6]	Florida affected area, Oct. 10, 2024	1,953 / 15,877	**12.3%**	1,273,354

FCC operational data show how those hazards translate into telecommunications stress.

The FCC reports attributed large numbers of outages to commercial power and transport failures in addition to physical site damage. Again, these counts are infrastructure-status observations and should not be converted directly into consumer-outage percentages [5], [6]. [9]

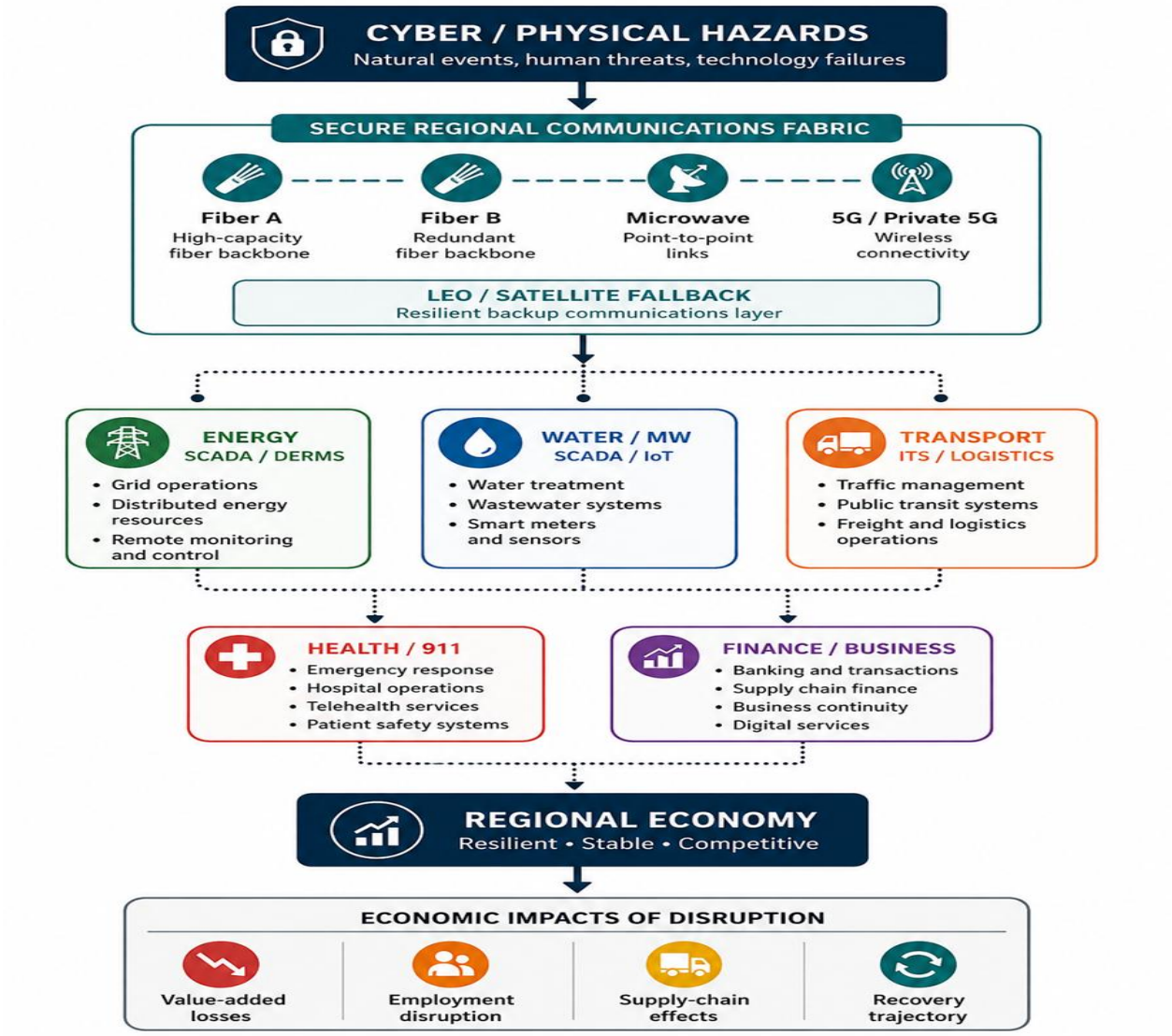
Disaster / Location	**Reported Cell-Site Outage Rate**
Hurricane Helene, NC	48.69%
Hurricane Milton, FL	12.30%

The comparison carries an engineering-economic implication: communications resilience is frequently a systems problem rather than a tower-hardening problem. A radio access node can be structurally intact yet unavailable because of backhaul or power. Hardening a data center while leaving its fiber paths geographically correlated may likewise produce far less systemic resilience than its asset-level reliability suggests. CISA explicitly identifies power and communications as mutually dependent systems and notes that transportation access can be required to deliver diesel for communications backup generation [1]. [6]

The cyber dimension carries similar weight. In late 2024 and during 2025, U.S. agencies publicly documented compromises of telecommunications infrastructure associated with People's Republic of China state-sponsored actors, commonly discussed under the Salt Typhoon designation. CISA and partners subsequently issued network-visibility and hardening guidance emphasizing stronger monitoring and defensive practices for communications infrastructure [8], [9]. These incidents demonstrate why economic-resilience planning cannot assume that redundant physical routes are independent if common administrative, control, authentication, or software systems can be compromised simultaneously. [14]

Security architecture belongs inside resilience analysis, not beside it. NIST's March 2026 final 5G cybersecurity publications emphasize that 5G's cloud-based complexity creates cybersecurity and privacy risks and that 3GPP-defined security capabilities must still be correctly implemented and configured by operators and users. NIST also highlights hardware roots of trust and remote attestation as mechanisms for strengthening platform integrity [10], [11]. Zero-trust principles provide an additional architectural basis for limiting implicit trust and lateral compromise [12]. [15]. A resilient regional architecture should consequently

be heterogeneous and layered, rather than dependent on a single failure domain:



Public-safety and satellite systems illustrate heterogeneous fallback. FirstNet deployable assets can provide temporary cellular coverage and use satellite connectivity when terrestrial infrastructure or commercial power is unavailable, while the FCC's Supplemental Coverage from Space framework is designed to permit satellite systems to supplement terrestrial mobile coverage in otherwise uncovered locations [13], [14]. These mechanisms do not eliminate the need for hardened terrestrial infrastructure, but they reduce reliance on a single restoration pathway [13], [14]. [16]

Proposed Regional Communications Economic Resilience Framework

RCERF treats communications disruption as a time-dependent shock to a coupled network-economy system. The unit of analysis can be a county, metropolitan statistical area, state, multistate corridor, Tribal area, utility service territory, port region, or other economically coherent geography. The design separates *exposure*, *network vulnerability*, *service degradation*, *economic dependency*, and *adaptive capacity*.

Let VA_{ri} denote annual value added for industry i in region r, and let $d_{ri} \in [0,1]$ represent that industry's estimated dependence on communications-enabled operations. Define communications-weighted economic exposure as

$$E_r = \sum_{i=1}^{n} VA_{ri} d_{ri}.$$

The dependency coefficient should not be interpreted as "the share of a sector that uses the internet." It represents the fraction of normal economic functionality that becomes unavailable, after available workarounds, as required communications services deteriorate. It can be estimated using outage data, firm surveys, production-function econometrics, business-continuity exercises, or sector experts.

A more complete criticality-adjusted version is

$$E_r^* = \sum_{i} VA_{ri} d_{ri} c_i, \qquad c_i \geq 1,$$

where c_i increases the policy weight of industries or functions with disproportionate safety, security, or cascading importance. A hospital's communications dependency, for example, cannot be valued solely by its direct short-run contribution to GDP because loss of emergency communications can create nonmarket health and safety consequences.

Network-to-economy transmission

Define communications service availability $a_r(t) \in [0,1]$, where 1 represents normal economically usable communications service, not merely powered equipment. Communications inoperability is

$$q_c(t) = 1 - a_r(t).$$

The term can be multidimensional:

$$q_c(t) = [q_{fixed}, q_{mobile}, q_{cloud}, q_{voice}, q_{911}, q_{OT}, q_{sat}]^{\top}.$$

A binary outage definition would miss this. Firms may retain email while losing cloud ERP access, or maintain ordinary mobile data while losing low-latency operational-technology connectivity.

RCERF then extends the dynamic inoperability input-output approach used in infrastructure and cyber-risk research. Let $q_r(t)$ contain sector inoperability values and $A_r^* represent normalized economic interdependencies. A communications-dependency matrix B_r maps network degradation onto industrial functionality:

Economic loss is then obtained by integrating inoperability against baseline daily value added:

$$L_r(T) = \int_0^T v_r^{\top} q_r(t)\, dt + L_{direct} + L_{response} + L_{welfare},$$

where v_r is sector daily value added. The additional terms capture direct asset damage, extraordinary response expense, and welfare costs that national accounts may not value.

Hazard and common-mode modeling

For hazard h, with annual occurrence rate λ_h, expected annual loss is

$$EAL_r = \sum_h \quad \lambda_h E[L_r \mid h].$$

The hazard library should include severe weather, flood, wildfire, earthquake where applicable, extended power outage, fiber cut, route vandalism, cloud-region outage, software/common-control failure, ransomware, distributed denial of service, routing incidents, and sophisticated state-sponsored compromise. Correlation must be modeled. Two physically different connections that traverse one bridge, conduit, utility substation, Internet exchange, or administrative domain are not independent.

Graph $G = (V, E)$ represents communications assets and dependency relationships. Each edge e carries capacity C_e, latency l_e, conditional failure probability $p_e(h)$, restoration distribution T_e, ownership domain, power source, geographic risk zone, and cyber trust domain.

For critical facility j, define route-diversity quality as

$$D_j = \frac{number\ of\ physically\ and\ logically\ independent\ viable\ paths}{required\ independent\ paths}, \quad D_j \leq 1.$$

Different carrier names are not enough. Paths must be checked for shared fiber, ducts, towers, exchanges, electric feeds, cloud dependencies, software controllers, and geographic hazards.

A Monte Carlo implementation can estimate the distribution rather than merely the mean of regional economic loss:

RCERF Stochastic Resilience Simulation

Stage	Description
Inputs	Regional value added, communications network, critical-facility demand, hazard scenarios, interindustry dependencies, communications dependencies, restoration models, and candidate investments
1. Apply Investment	Modify the communications network according to each candidate resilience investment portfolio
2. Simulate Hazard	Draw a hazard scenario and correlated infrastructure/network failures
3. Assess Communications	Determine surviving network capacity, viable paths, and communications service availability over time
4. Estimate Economic Effects	Propagate communications disruption through critical facilities and regional industry dependencies
5. Model Recovery	Simulate infrastructure restoration and business adaptation
6. Calculate Losses	Estimate regional economic losses for each simulation
7. Evaluate Portfolio	Compare expected losses, tail risk, resilience benefits, cost, equity, and critical-facility protection
Decision	Select the investment portfolio that provides the greatest resilience benefit while satisfying budget and minimum-resilience constraints

Simplified flow:

Inputs → Hazard Simulation → Communications Disruption → Economic Loss → Recovery → Portfolio Selection

Purpose**:** RCERF identifies which communications resilience investments provide the greatest reduction in expected and extreme regional economic losses

Quantitative KPIs, Engineering Metrics, and Analytical Toolchain

The principal policy innovation should be a shift from connectivity KPIs toward continuity KPIs. FCC Broadband Data Collection information remains essential for establishing where fixed and mobile services are reported as available, and the latest FCC availability dataset listed by the Commission is as of December 31, 2025 [24]. Availability mapping should be the first layer of resilience analysis, not the final outcome variable [21], [24]. [19]

A proposed Secure and Resilient Communications Index, SRCI, is

$$SRCI_r = 100 \prod_{k=1}^{K} z_{rk}^{w_k}, \qquad \sum_{k} w_k = 1, \quad 0 \le z_{rk} \le 1.$$

A geometric rather than arithmetic aggregation is intentionally used because severe weakness in one dimension should not be completely offset by excellence in another. A region with excellent broadband speeds but essentially no route diversity should not receive the same score as a genuinely fault-tolerant region.

KPI	Definition	Economic interpretation
Service availability	Economically usable service time / required service time	Frequency of interrupted production
MTTR	Mean time to restore required service	Duration-driven business losses
MTTD / MTTC	Mean time to detect / contain cyber compromise	Limits cyber propagation
Route diversity	Independently survivable paths per critical node	Resistance to common fiber cuts
Provider diversity	Independent service domains after shared-risk correction	Substitutability
Power autonomy	Hours at required load without grid power	Survivability during grid outage
Failover success rate	Successful automated/operational failovers / tests	Whether redundancy works in practice
Critical-facility coverage	Facilities meeting minimum resilient service standard	Public-safety continuity
Recovery time objective compliance	Share restored within sector-specific RTO	Business continuity

KPI	Definition	Economic interpretation
Cyber trust integrity	Verified identity, segmentation, attestation, key-control metrics	Compromise resistance
Economic loss per outage hour	Modeled regional loss / service-degradation hour	Prioritization
Expected annual loss	Probability-weighted annual disruption loss	Risk monetization
Resilience ROI	Expected discounted loss avoided / lifecycle cost	Capital allocation
Critical-function-hours preserved	Functional hours retained relative to baseline	Non-GDP resilience benefit

Availability percentages are particularly easy to misinterpret because apparently small differences correspond to large differences in annual disruption time:

Availability	Maximum equivalent downtime/year
99.0%	87.6 hours
99.9%	8.76 hours
99.99%	52.6 minutes
99.999%	5.26 minutes

These values follow directly from $365 \times 24 \times (1 - A)$. The relevant target should be end-to-end service availability for the critical function, not merely a component SLA.

Business-continuity metrics should be directly linked to the network model. Let RTO_f denote the recovery-time objective of business function f, $MTPD_f$ its maximum tolerable period of disruption, and T_f modeled restoration time. Define continuity compliance as

$$BCC_f = \{1, T_f \leq RTO_f \; exp[-\gamma_f(T_f - RTO_f)], T_f > RTO_f.$$

This approach distinguishes two regions with identical total outage minutes when one suffers several short interruptions and the other experiences a multiday outage that exceeds firms' inventory, generator, or manual-workaround endurance.

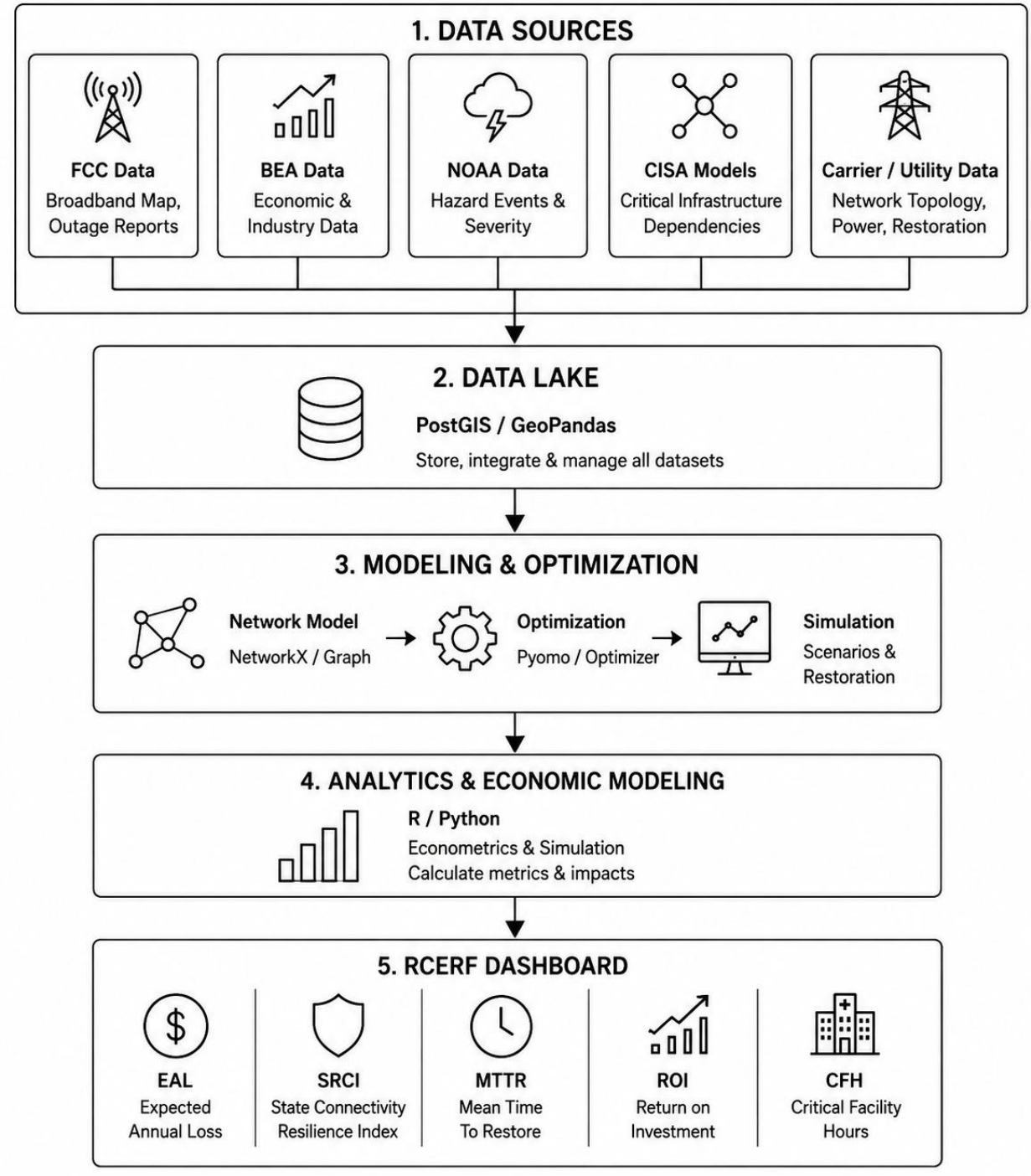
The classic resilience-triangle concept can also be operationalized. If $P(t)$ denotes normalized service performance,

$$R_T = \frac{1}{T}\int_0^T \quad P(t)\, dt.$$

For example, suppose service drops to 50% for 0.5 day, 80% for 1.5 days, 95% for 2 days, and is otherwise recovered over a four-day assessment interval. The integral formulation captures both the depth and duration of degradation, unlike peak outage percentage alone.

Data architecture

A reproducible U.S. implementation can combine:



FCC's Disaster Information Reporting System is specifically intended to collect operational-status and restoration information during disasters, and FCC rules have expanded mandatory disaster reporting for covered communications providers [7]. Such information, appropriately protected and aggregated, is valuable for calibrating recovery curves instead of relying on engineering assumptions alone [7]. [20]

Preliminary Scenario Analysis and State or Regional Applications

Because a unified national RCERF dataset does not yet exist publicly, the following calculations are illustrative scenario results, not estimates of an actual state outage. Their purpose is to demonstrate how network engineering assumptions become economic quantities.

Consider a hypothetical state with annual GDP of $500 billion. Assume that, after sector weighting and substitution, 35% of value added is operationally communications-dependent for the scenario under consideration. Suppose a disruption reduces effective communications functionality by 20% for two days.

First-order exposed value-added loss is

$$L_D = \frac{\$500\ B}{365}(0.35)(0.20)(2) \approx \$191.8\ million.$$

If cross-industry effects, delayed transactions, supply-chain disruption, and recovery effects produce an illustrative total multiplier of 1.6, system-wide loss becomes

$$L_T \approx 1.6(\$191.8\ M) = \$306.8\ million.$$

If a $40 million resilience portfolio cuts average service degradation from 20% to 8% and recovery from two days to one day, the same first-order framework gives

$$L_D^R = \frac{\$500\ B}{365}(0.35)(0.08)(1) \approx \$38.4\ million.$$

The avoided direct exposure in that event would be approximately $153.4 million before modeling indirect effects. The example shows why the relevant economic question is not “How much does a backup link cost?” but “How much expected regional value added and critical-function capacity does the backup link preserve across the probability distribution of outages?”

A state-level deployment model should differentiate at least four regional archetypes.

Dense technology and financial metros typically have high output per square mile, substantial cloud dependence, and extensive fiber. Their primary risks may be concentrated conduit routes, data-center and electric dependencies, cyber common-mode failures, exchange-point congestion, and correlated cloud or software outages. Because economic output per minute may be high, even short interruptions can justify expensive redundancy.

Industrial and logistics corridors may have somewhat lower communications revenue intensity but very high operational dependencies through ports, warehouse-management systems, railroad control, precision manufacturing, automated inventory systems, customs processing, payment networks, and fleet dispatch. Here, low-latency industrial connectivity, route diversity along transportation corridors, and rapid restoration may dominate household peak-throughput considerations.

Rural and agricultural regions face a different optimization problem. Long loops and sparse populations can make terrestrial redundancy expensive, while farms, telehealth, distance education, emergency response, precision agriculture, and small businesses can depend heavily on connectivity. Empirical U.S. studies of broadband subsidies find geographically heterogeneous employment and establishment effects, while broader broadband research finds benefits depend on adoption and complementary capabilities [16]–[18]. Satellite fallback, fixed wireless, regional fiber rings, and hardened community anchor institutions may therefore have unusually high resilience value even when private revenues alone do not justify duplicate routes. [21]

Disaster-exposed coastal, wildfire, tornado, and flood regions require explicit hazard-conditioned route engineering. Hurricane data demonstrate that power and transport failures can remove many sites without direct structural destruction [5], [6]. For these regions, fuel logistics, elevated or buried plant where appropriate, geographically separated backhaul, renewable-plus-storage microgrids, deployable wireless assets, satellite backhaul, pre-negotiated roaming, and cross-jurisdiction restoration agreements should be tested jointly rather than funded as isolated programs. [22]

Econometric validation strategy

Once sufficient panel data are assembled, the causal economic effect of resilience improvements can be estimated rather than assumed. A state/county panel could use staggered infrastructure upgrades, disaster exposure, and pre/post restoration outcomes:

$$Y_{rt} = \alpha_r + \delta_t + \beta_1 Resilience_{rt} + \beta_2 Shock_{rt} + \beta_3 (Resilience_{rt} \times Shock_{rt}) + \Gamma X_{rt} + \epsilon_{rt}.$$

Here Y_{rt} can be establishment employment, payroll, sales proxies, sector value added, business openings/closures, or recovery time. The parameter of greatest interest is β_3: whether areas with stronger communications resilience suffer smaller economic contractions or faster recovery conditional on comparable shocks.

A modern staggered difference-in-differences or event-study design should be preferred over simple two-way fixed-effects specifications when infrastructure adoption timing varies across regions. Broadband studies already demonstrate the importance of distinguishing supply availability from actual adoption and use [16], [19]. RCERF extends this distinction by treating tested failover and outage survival as the relevant treatment rather than advertised broadband availability [16], [19], [21]. [23]

Outcome metrics should be observed across multiple horizons. During the first hours, the dominant variables may be 911 availability, payment processing, industrial control, emergency coordination, and cloud access. Over days, supply chains, labor productivity, telework, health care, fuel logistics, and retail operations become important. Over weeks, firm relocation, inventory replacement, insurance effects, missed exports, and business survival may emerge. Decomposing by horizon keeps an economically important resilience benefit from disappearing inside an annual GDP aggregate.

Business Continuity as a National Economic Transmission Channel

Communications resilience has national importance and impact because network outages can quickly spread beyond the telecommunications industry, disrupting production, payments, logistics, healthcare, public services, remote work, and supply-chain coordination. These disruptions can reduce firm output, employment stability, regional productivity, and recovery capacity.

At the firm level, communications failures create losses through operational interruption, transaction delays, reduced access to digital platforms, and production constraints. For highly complementary production systems, even full worker availability cannot sustain output when critical communications, payment, cloud, or control systems are unavailable. More adaptable service industries may partially offset losses through cellular backup, offline processing, alternate cloud regions, telework, manual operations, or deferred transactions.

The effects may be especially significant for small and medium-sized enterprises, which often cannot independently finance redundant carriers, private fiber, backup power, cybersecurity capabilities, or geographically distributed systems. Shared regional resilience investments can therefore deliver broad economic benefits across many firms simultaneously.

Strengthening communications continuity can reduce cascading economic losses, protect employment and revenues, preserve critical services, support supply-chain stability, and accelerate post-disaster recovery. Accordingly, communications resilience should be treated as a national economic resilience strategy, not solely as a telecommunications objective.

[19]. [24]

Policy Architecture, Investment Strategy, and Conclusion

The analysis points U.S. communications policy toward a resilience-adjusted infrastructure standard. The objective is not to replace coverage, affordability, or speed targets but to add the missing question: *Will economically essential service remain usable when the system is stressed?*

The timing is favorable. The United States is already undertaking large-scale broadband investment. BEAD is a $42.45 billion federal grant program, and NTIA reported on July 17, 2026 that 55 states and territories had obtained Final Proposal approval and 54 had progressed through NIST approval to make grant funds available [15]. With deployment decisions moving toward implementation, incorporating measurable resilience properties into state infrastructure planning can influence assets expected to remain in service for decades [15]. [25]

The first policy recommendation is to establish regional resilience baselines. Every state should map critical communications dependencies at the facility and economic-corridor level, including hospitals, 911 centers, electric substations, water plants, fuel terminals, ports, major logistics facilities, government operations, financial nodes, and major employment clusters. The map should identify shared-risk link groups, power dependencies, restoration constraints, and alternate pathways. CISA's infrastructure-dependency framework already establishes the importance of bidirectional and cascading dependencies, providing a conceptual basis for this work [1]. [26]

Second, grant and regulatory programs should distinguish nominal provider diversity from fault-domain diversity. Two retail carriers should not be treated as two fully independent connections when both ultimately use the same conduit, pole corridor, aggregation facility, utility feed, cloud control plane, or vulnerable long-haul route. Procurement standards for high-criticality sites should specify physically and administratively diverse connectivity and require periodic failover tests.

Third, resilience programs should combine communications and energy planning. FCC disaster reports from Helene and Milton demonstrate the importance of commercial power and transport failures to cellular outages [5], [6]. A policy that funds additional radio sites without examining electric-feed diversity, batteries, generators, renewable-plus-storage systems, fuel contracts, and backhaul can create nominal capacity without proportional outage resilience. [9]

Fourth, cybersecurity investments should be treated as economic-resilience capital. Modern 5G and cloud-native communications systems contain complex software and virtualized control layers, and recent U.S. government advisories concerning sophisticated telecommunications compromises show that cyber common-mode risk is not hypothetical [8]–[10]. NIST's 2026 5G guidance, hardware-enabled roots of trust, remote attestation, strong identity, segmentation, logging, and zero-trust architectures should therefore enter resilience scoring alongside physical redundancy [8]–[12]. [27]

Fifth, resilience planning should explicitly value technological heterogeneity. Fiber should remain the high-capacity backbone in many environments, but resilient architectures can combine geographically diverse fiber, mobile networks, microwave, private wireless, deployable public-safety systems, and satellite links. FCC

Supplemental Coverage from Space and FirstNet deployables demonstrate institutional pathways for terrestrial-space and temporary-cellular fallback [13], [14]. The objective is not indiscriminate duplication but reduction of correlated failure probability for high-value functions. [28]

Sixth, governments should procure resilience using outcomes. A performance-based contract could specify, for example:

$$\text{Payment} = P_0 + \theta_1(\text{RTO compliance}) + \theta_2(\text{tested failover}) + \theta_3(\text{critical availability}) - \theta_4(\text{unplanned critical downtime}).$$

This would create incentives to design maintainable systems, not just install infrastructure.

A state infrastructure board could rank candidate projects using a transparent Resilience Benefit-Cost Ratio:

$$RBCR_j = \frac{PV\left[\Delta EAL_j + \Delta W_j + V_{CFH}\Delta CFH_j\right]}{PV(CAPEX_j + OPEX_j)}.$$

Projects with a high private return may proceed without subsidy. Public funding becomes most defensible where $RBCR$ is high but private monetizable return is low because resilience benefits spill across firms, sectors, jurisdictions, or populations. Howell's public-good analysis provides a theoretical foundation for precisely this type of divergence between individual-operator incentives and ecosystem-level resilience value [22]. [29]

A related Resilience Value at Risk measure could be reported for every state:

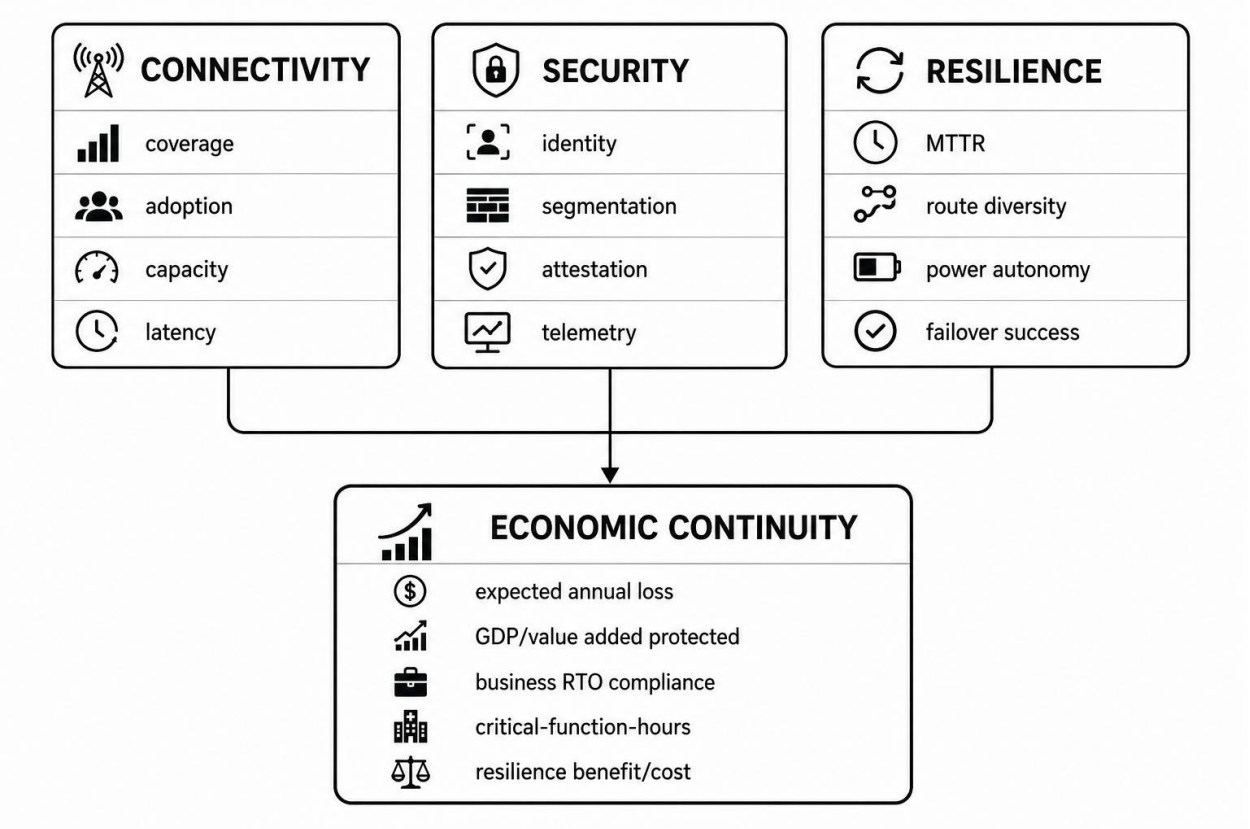
$$RVaR_{95,r} = Q_{0.95}(L_r),$$

with conditional tail loss

$$RCVaR_{95,r} = E[L_r \mid L_r \geq RVaR_{95,r}].$$

This is particularly important because expected annual loss can hide low-frequency, extremely consequential events. A portfolio that performs well against routine fiber cuts but collapses under a regional power-plus-cyber event should not be rated highly merely because its mean annual outage count is low.

The proposed federal-state dashboard would therefore report four categories together:



The principal research limitation is data granularity. Public FCC availability maps can establish service footprints, and public disaster reporting offers important outage observations, but rigorous common-mode analysis requires topology, shared conduits, upstream carriers, power dependencies, restoration sequencing, cybersecurity architecture, and firm-level continuity data that are often proprietary or security-sensitive [7], [24]. The solution should not be unrestricted public disclosure. Better architecture would establish protected analytical environments in which regulators, state agencies, infrastructure operators, and researchers can calculate aggregated resilience indicators without exposing exploitable network details.

A second limitation is causal identification. Regions that receive resilient infrastructure may differ systematically from those that do not. Infrastructure can also be built in response to previous disasters, producing reverse causality. Future empirical work should therefore exploit phased deployments, quasi-experimental funding rules, exogenous hazard realizations, route upgrades, and event-study designs, while controlling for power restoration, physical damage, industrial structure, income, urbanization, and baseline network quality.

A third limitation is that GDP captures only part of resilience value. Communications supporting emergency medicine, 911, public warning, national defense, water safety, and grid stability can prevent harm that does not appear fully in measured market output. Consequently, investment appraisal should report economic-loss avoidance and critical-function preservation separately, rather than forcing every public-safety benefit into an uncertain GDP conversion.

The core policy conclusion is therefore broader than "build more broadband." U.S. economic resilience increasingly depends on communications systems that continue functioning, degrade gracefully, resist compromise, fail over across genuinely independent technologies, and recover rapidly when failure is unavoidable. Existing evidence demonstrates substantial digital-economic exposure, major disaster-driven communications disruptions, increasingly sophisticated cyber threats, and strong cross-sector dependencies

[1]–[10]. At the same time, economic research shows that productive adoption and actual reliability matter more than nominal infrastructure presence alone [16]–[22]. [30]

The unresolved analytical gap is the absence of a common metric connecting those engineering and cybersecurity characteristics to the economic activity they preserve. RCERF addresses that gap by converting communications failure into dynamic sector inoperability, regional loss distributions, business-continuity outcomes, critical-function-hours, and investment benefit-cost ratios. The framework changes the policy question from **"**Where is advanced communications infrastructure available?" to the economically more consequential question: "Which combination of secure communications investments minimizes the expected social and economic consequences of failure in each U.S. region?"

That is the basis on which communications infrastructure can be treated not simply as a digital-development asset, but as a measurable component of U.S. economic security.

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PREDICTIVE ECONOMIC DECISION-SUPPORT FRAMEWORKS FOR MODERNIZING U.S. TRADE AND INDUSTRIAL POLICY: A REAL-TIME DATA ANALYTICS APPROACH TO STRENGTHENING MANUFACTURING COMPETITIVENESS AND ENERGY SECURITY

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Abstract

This study develops a predictive economic decision-support framework for modernizing U.S. trade and industrial policy. It combines official statistics with validated high-frequency indicators from trade, labor markets, manufacturing, supply chains, logistics, and energy systems to address limitations in the timeliness, granularity, and integration of conventional economic monitoring. Using a design-science and scenario-based approach, the framework incorporates mixed-frequency analysis, structural-change detection, natural language processing, input-output analysis, production-network mapping, policy simulation, and robustness testing. The analysis shows that industrial vulnerabilities are often interconnected, with trade disruptions, workforce shortages, supplier concentration, manufacturing constraints, and energy limitations capable of generating wider economic effects. The framework supports earlier risk identification, more targeted policy evaluation, and coordinated assessment of trade, workforce, industrial, infrastructure, and energy interventions. Its principal contribution is the integration of trade exposure, workforce readiness, manufacturing capacity, supply-chain dependency, and energy security within a transparent, human-governed policy process. As a conceptual and scenario-based framework, it requires future sector-specific and regional validation before broader empirical application.

Keywords: Predictive Economic Decision Support, Industrial Policy, Trade Policy, Manufacturing Competitiveness, Supply-Chain Resilience, Workforce Intelligence, Energy Security, Real-Time Analytics

INTRODUCTION

I. INTRODUCTION

1.1 Background of the Study

The United States is navigating sustained economic and industrial uncertainty shaped by changing trade relationships, geopolitical competition, supply-chain disruptions, technological change, workforce constraints, and pressure on domestic energy infrastructure. These conditions have renewed interest in trade and industrial policy as instruments for strengthening domestic production, protecting critical supply chains, and sustaining manufacturing competitiveness. Recent research also emphasizes that industrial policy should be evaluated through evidence concerning productive capabilities, market constraints, and the wider effects of public intervention across industries (Bartelme et al. (2025). Industrial policy works not just thru incentives, tariffs, or public investment, but also thru the quality and timeliness of the information accessible to those who decide policy. Modern production systems link enterprises thru intermediate inputs, labor, transport, finance, digital infrastructure and energy. Therefore, an upset in a sector might spill over other industries and locations not directly involved in the original occurrence. These linkages can transmit and amplify sectoral shocks, with

implications for aggregate economic outcomes, as shown by production network research (Acemoglu et al., 2016; Baqaee & Farhi, 2022).

Official statistics are still crucial for monitoring employment, trade, production, pricing, investment and industrial activity. However, their reporting dates and levels of aggregation may restrict their capacity to highlight limits that are growing fast. Shortage of workers, disruption of suppliers, rise in costs due to tariffs or a regional energy bottleneck may start to impact production before this is reflected in monthly or quarterly indications. Trade shocks also produce unequal effects across industries and locations because worker mobility, industrial structure, and access to substitute inputs differ across regions (Caliendo et al., 2019). There is an extra measuring challenge with global value chains . Bilateral trade numbers can only indicate the immediate origin and destination of products, but not necessarily the upstream and downstream production links involved in those flows. Hence, effective analysis should account imported intermediate inputs, domestic value added, supplier concentration and indirect production interdependence (Borin et al., 2025). A tiny, but well linked supplier may be more economically important than it looks at first glance in terms of its direct employment or production.

Workforce readiness and energy security are equally important to manufacturing performance. Technological change can reorganize workplace tasks and create combinations of technical, digital, analytical, and operational skills that are not visible in broad occupational categories (Alabdulkareem et al., 2018). Skills are also shaped by production technologies and workplace organization rather than supplied independently of industrial demand (Allais, 2022). Similarly, manufacturing expansion depends on reliable and affordable energy, while changes in the power sector can alter regional employment and industrial capacity (Bücker et al., 2025). These links imply that manufacturing competitiveness cannot be explained by capital investment alone. This depends on the coordinated availability of labor, suppliers, infrastructure, technology, logistics and energy. Thus, interindustry resilience is the ability of interconnected industries to absorb and adapt to shocks without producing excessive losses in the total economy (Agnani et al., 2024).

This research proposes a predictive economic decision support system based on official information and validated high frequency indicators. This technique is designed to be able to detect new dangers, to follow their propagation across sectors and regions and to assess different policy remedies. It considers trade exposure, workforce preparation, manufacturing capacity, supply chain dependence and energy security as aspects of a single economic system. This corresponds to the economic-complexity literature, which links competitiveness to the interaction of productive capabilities, knowledge, institutions and industry connections (Balland et al., 2022). The framework does not replace official statistics or transfer policy authority to automated systems. Economic nowcasting, structural-break detection, input-output analysis, production-network mapping, and scenario modeling are used to improve the evidence available to decision-makers. Artificial intelligence and machine learning are limited to defined functions such as processing job-posting data, detecting anomalies, identifying non-linear relationships, and improving short-term forecasts. Final decisions remain subject to economic interpretation, legal authority, institutional accountability, and human review.

1.2 Objectives of the Study

The general objective of this study is to develop an integrated predictive economic decision-support framework for modernizing U.S. trade and industrial policy. Specifically, the study examines the limitations of conventional monitoring systems, integrates official and high-frequency data, identifies labor, trade, supply-chain, manufacturing, and energy risks, models the transmission of disruptions across sectors and

regions, and establishes a process for comparing policy interventions under uncertainty. It also proposes evaluation indicators and governance requirements for future sector-specific and regional validation.

1.3 Problem Statement

U.S. trade and industrial-policy decisions increasingly must respond to economic changes that develop faster than conventional reporting and planning systems can capture. Although official datasets provide credible national and regional measures, publication delays and broad classifications may obscure emerging skill shortages, production constraints, supplier dependencies, and infrastructure limitations.

The problem is intensified by institutional fragmentation. Trade exposure may be evaluated separately from labor availability; manufacturing incentives may be designed without sufficient consideration of regional energy capacity; and workforce programs may not reflect supplier concentration, import dependence, or changing technological requirements. This separation is inconsistent with an economy in which sector-specific disturbances can create broader effects through production networks (Acemoglu et al., 2016; Baqaee & Farhi, 2022).

The central problem is therefore the absence of a unified and policy-oriented framework that connects timely trade, labor, manufacturing, supply-chain, and energy intelligence. Without such integration, public intervention may be delayed, poorly targeted, or beneficial to one sector while creating unintended constraints elsewhere. The proposed framework addresses this gap by supplementing official statistics with validated high-frequency indicators, mapping cross-sector dependencies, and comparing policy options together with their costs, uncertainties, and spillover effects.

1.4 Context and Motivation

The motivation for this study is the increasingly interconnected nature of U.S. economic security. Manufacturing expansion requires more than a new facility or financial incentive. It also requires workers, suppliers, transportation, technology, and sufficient energy capacity. Trade restrictions may support one industry while increasing costs for downstream producers, and reshoring may create new regional demand for labor and infrastructure. These effects cannot be evaluated adequately through isolated policy systems.

A more integrated analytical process may improve the timing and targeting of public intervention. It can help decision-makers determine what risk is emerging, which sectors and regions are exposed, how the risk may spread, which policy tools are available, and what trade-offs accompany each option. The study is therefore motivated by the need for better economic visibility and coordination rather than technological novelty.

1.5 Research Questions

The study addresses five questions:

1. What limitations prevent conventional economic and industrial indicators from supporting timely trade and industrial-policy decisions?
2. How can official statistics and high-frequency data be integrated without compromising data quality, transparency, or accountability?
3. How can trade, labor, supply-chain, manufacturing, and energy shocks be identified and traced across sectors and regions?
4. How can alternative policy interventions be compared under conditions of uncertainty?
5. What governance and evaluation requirements are necessary for responsible implementation?

1.6 Scope and Delimitations

The study focuses on the design and policy application of a predictive decision-support framework for U.S. trade and industrial policy. Its scope covers trade exposure and critical-input dependency, workforce readiness, manufacturing capacity, supply-chain resilience, and industrial energy security. The framework is intended for national, sectoral, regional, and industrial-cluster analysis using official and high-frequency secondary data.

Methodologically, the study is limited to a conceptual architecture and scenario-based evaluation process. It does not claim completed nationwide empirical results, guarantee the prediction of disruptions, replace official statistics, automate final policy decisions, or apply one model uniformly across all industries and regions. Any numerical outcomes must be identified as prior research findings, scenario assumptions, model estimates, illustrative outputs, or targets for future validation. The framework's relevance lies in its capacity to evaluate cross-sector and regional spillovers while preserving methodological transparency and human oversight.

II. LITERATURE REVIEW

2.1 Review of Related Literature

2.1.1 Trade, Industrial Policy, and Production-Network Vulnerability

The revived interest in industrial policy is a symptom of increasing concerns that market forces alone struggle to maintain strategic productive capacity, handle supply-chain dependencies and coordinate investments with spillover effects across enterprises and industries. Bartelme et al. (2025) suggest that the economic rationale for industrial policy should be judged by facts about production capacities, market distortions and the larger impacts of policy intervention. This approach is especially pertinent in the United States as recent trade and industrial policy actions have been directed toward expanding local manufacturing, reducing reliance on weak foreign supply chains, and strengthening strategically vital industries.

The efficacy of industrial strategy is partially determined by how well policy makers understand the linkages among industries. Production does not occur in separate sectors. Firms rely on intermediate inputs, transportation, professional services, energy, monetary systems, technology and skilled labor. Acemoğlu et al. (2016) show how the network structure of the economy affects the transmission of sector-specific shocks and their effect on aggregate performance. Similarly, Baqaee and Farhi (2022) show that disaggregated supply and demand shocks can have larger economic effects thru inter-sectoral linkages.

These findings suggest that the economic significance of a sector cannot be evaluated solely through its direct employment, revenue, or output. A relatively small supplier may occupy a central position within a production network, making its interruption economically important to several downstream industries. Conventional measures that examine sectors independently may therefore understate the potential consequences of disruption.

Trade exposure is another layer to this problem. Trade shocks can affect manufacturing prices, jobs, pay rates, investment and regional economies. Caliendo et al. (2019) show that the impact of trade shocks is uneven across sectors and locations, since people, firms and productive resources do not respond immediately and uniformly. So national averages can disguise significant deficits in specific industries or locations.

The integration of global value chains is also measured by looking at indirect manufacturing relationships. Borin et al. (2025) argue that trade statistics should separate overall trade flows, domestic value added,

imported intermediate inputs and the economic linkages included in global value chains. A business connection between two nations may not alone reveal the extent to which U.S. enterprises depend on foreign inputs or the indirect effects of a disruption many links down the chain.

This literature supports the need for a decision-support framework that maps trade exposure and production-network relationships together. Such a framework should identify not only where goods originate, but also how imported inputs, domestic suppliers, industrial clusters, and infrastructure systems contribute to final production. It should also permit policymakers to examine whether a proposed tariff, subsidy, sourcing requirement, or supplier-diversification measure could create unintended costs elsewhere in the economy.

2.1.2 Workforce Intelligence and Manufacturing Competitiveness

Manufacturing competitiveness depends on the availability of workers whose capabilities correspond to changing production technologies and industrial processes. However, workforce planning commonly relies on occupational classifications, educational credentials, and historical employment patterns that may not capture emerging combinations of technical and digital skills.

Alabdulkareem et al. (2018) show that workplace skills are rearranged and polarized when technology and occupational demands shift. This method can form new linkages among talents that are hidden under broad occupational designations. For example, a manufacturing technical worker could have skills in classical machining, industrial robots, process controls, predictive maintenance, data analysis or cybersecurity. These differences influence the ability of workers to maintain high level production systems and the ability of enterprises to grow without labor constraints.

Allais (2022) also argues that talents should not be seen just as an externally provided quantity to the economy. Skill formation is shaped by productive structures, technology, workplace organization and institutional contexts. This means that workforce strategy cannot be focused just on raising the number of graduates or certifications. It must recognize the skills required by current and new production systems.

High-frequency labor-market information can complement conventional employment statistics. Online job postings, employer descriptions, credential requirements, wage offers, and technology references may provide earlier evidence of changing demand. Bone et al., (2025) show that vacancy data can help distinguish between degree-based and skill-based hiring patterns in AI- and green-related occupations. Such information can assist policymakers in identifying whether employers increasingly require specific technical skills, certifications, or combinations of capabilities that conventional occupational classifications do not capture.

Predictive labor intelligence is particularly relevant to industrial investment. Public incentives may attract new manufacturing facilities, but the economic return on those investments may be limited where the surrounding workforce lacks the required skills. Delayed recognition of labor shortages can increase project costs, postpone production, and reduce the wider benefits expected from industrial development. Conversely, early identification of adjacent or transferable skills may support faster movement of workers from contracting industries into expanding sectors.

Workforce intelligence should therefore be connected to trade exposure, industrial investment, and regional productive capacity. Labor shortages are not only human-resource problems for individual employers. Where they affect major industrial clusters or strategically important sectors, they may constrain output, weaken supply-chain resilience, and reduce the effectiveness of public investment.

2.1.3 Manufacturing, Supply Chains, and Energy Security

Manufacturing resilience depends on the ability of production systems to continue operating under conditions of trade disruption, supplier failure, infrastructure stress, or energy volatility. Agnani et al. (2024) examine resilience through an interindustry perspective, reinforcing the importance of evaluating how sectoral relationships influence the ability of an economy to absorb disruptions.

Supply chain resilience is more than merely hoarding or having alternate sources. It also has to understand what the specific inputs mean, if there are local substitutes available, shipping obstacles, requirement for supplier checks and the time needed to scale up alternate production. But even if the provider is a small percentage of the national total, the interruption of an important component might cause losses in output in several areas. Part of the analysis is energy security. Manufacturing plants depend on reliable and affordable energy, fuels, transportation systems and other supporting infrastructure. Industry growth might serve regional need for generating and transmission capacity. The energy price fluctuations might impact industrial costs and investment decisions. Therefore, efforts to expand domestic manufacturing should consider whether the locations in question can provide new industrial energy demand.

The connection also works in the other direction. Energy transitions can alter the location and mix of employment, generate demand for new industrial capabilities, and lower demand for certain existing vocations. Bücker et al. (2025) indicate that fast decarbonization of the electricity industry in the U.S. can have different employment impacts across areas and vocations. These impacts imply that energy policy, workforce development, and industrial planning should be integrated, not viewed as independent policy realms.

Economic-complexity research explains these links more generally. Balland et al. (2022) suggest that productive development is based on combinations of knowledge, competences, institutions and industrial connections. Therefore, the competitiveness of an area is not deducible from the existence of a single facility or sector. It is contingent upon whether the surrounding economy has the complementing labor, suppliers, infrastructure, technology, and institutional support."

The literature consequently supports an integrated assessment of manufacturing capacity, supplier relationships, regional labor availability, and energy infrastructure. A policy that addresses only one constraint may fail where other complementary conditions remain unresolved.

2.1.4 Real-Time Analytics and Economic Decision Support

Traditional economic statistics provide authoritative and methodologically consistent information, but their publication frequency may limit their usefulness during periods of rapid disruption. Real-time and high-frequency indicators can provide additional evidence about current production, hiring, logistics, trade, and energy conditions before changes become fully visible in aggregate statistics.

The value of such indicators depends on their integration with established economic methods. High-frequency information may be noisy, incomplete, commercially generated, or unevenly representative across industries and regions. It should therefore supplement, rather than replace, official statistics. The analytical challenge is to distinguish temporary fluctuations from persistent structural change and to determine whether a detected signal has meaningful economic implications.

A modular analytical architecture can separate data ingestion, signal detection, economic interpretation, and policy evaluation. Putrama and Martinek (2023) emphasize the value of separating high-velocity signal

extraction from later analytical stages so that noise does not automatically determine final outputs. This distinction is important for public policy because a statistical anomaly should not be treated as evidence for intervention until it has been examined against economic relationships, institutional knowledge, and alternative explanations.

Artificial intelligence can support selected functions within this process. Natural language processing may extract skills and technologies from job postings. Machine-learning models may identify anomalies or non-linear patterns. Forecasting models may combine information reported at different frequencies. However, predictive accuracy alone is insufficient for public decision-making. Policy recommendations must also be explainable, economically plausible, and subject to institutional review.

Evidence on workplace AI further supports a restrained approach. Brynjolfsson et al. (2025) show that generative AI can improve productivity in particular work settings, but the magnitude and distribution of benefits depend on the task, worker, and organizational context. The findings do not justify treating AI as a universal substitute for human expertise. In economic decision support, AI is better understood as an analytical aid that expands the capacity to process information while leaving interpretation, trade-off assessment, and final authority with accountable decision-makers.

2.1.5 Synthesis and Research Gap

The reviewed literature establishes several relevant findings. Production networks can transmit local disturbances across sectors. Trade shocks can create unequal regional and labor-market effects. Workforce capabilities evolve more rapidly than some occupational classifications. Manufacturing expansion depends on complementary supplier, labor, infrastructure, and energy conditions. High-frequency information may improve the timeliness of economic analysis when it is validated and interpreted carefully.

However, these research streams are often examined separately. Trade studies may not incorporate real-time workforce and energy constraints. Labor-market studies may not connect changing skill demand to import dependency or production networks. Supply-chain research may identify supplier risks without evaluating the workforce and infrastructure needed to expand domestic alternatives. Energy planning may not fully model the industrial consequences of manufacturing relocation or reshoring.

The gap is therefore not the absence of economic models, labor data, supply-chain analysis, or energy forecasting. It is the absence of a unified and governed framework that integrates these sources into a single policy process. The present study addresses this gap by connecting trade exposure, workforce readiness, manufacturing capacity, supply-chain dependency, and energy security within a predictive decision-support architecture.

2.2 Theoretical and Conceptual Framework

The study draws on three complementary perspectives: production-network theory, complex adaptive systems and resilience, and decision-support theory.

2.2.1 Production-Network and Input-Output Perspective

Production-network theory explains how industries are connected through purchases, sales, services, labor, and infrastructure. A disturbance affecting one sector may reduce output elsewhere because downstream firms cannot obtain necessary inputs or because upstream suppliers lose demand. This perspective supports the use

of input-output relationships and network measures to identify economically central sectors and potential disruption pathways (Acemoğlu et al., 2016; Baqaee & Farhi, 2022).

2.2.2 Complex Adaptive Systems and Resilience

The economy is also treated as a complex adaptive system composed of firms, workers, governments, suppliers, regions, and infrastructure providers. These actors respond differently to price changes, regulations, technology, and disruption. Resilience therefore involves more than returning to a previous equilibrium. It includes the capacity to anticipate risks, absorb shocks, adapt productive relationships, and reorganize resources while preserving essential economic functions (Agnani et al., 2024).

2.2.3 Decision-Support Perspective

Decision-support theory provides the institutional foundation of the framework. Data and models should assist decision-makers by organizing evidence, identifying alternatives, estimating consequences, and communicating uncertainty. They should not replace legal authority, policy judgment, or accountability. The framework therefore separates predictive analysis from final policy action and requires human review of assumptions, outputs, and trade-offs.

2.2.4 Conceptual Integration

The conceptual framework follows a continuous sequence:

> **Economic and industrial data inputs → Data validation and harmonization → Detection of emerging risks → Analysis of trade, labor, manufacturing, supply-chain, and energy dependencies → Simulation of policy alternatives → Human review and selection → Monitoring of economic outcomes**

This structure links real-time information to national economic objectives without assuming that every detected signal requires intervention. Its contribution lies in creating a disciplined process through which diverse economic evidence can be translated into timely, explainable, and coordinated trade and industrial-policy decisions.

This draft consolidates the strongest material in the two uploaded manuscripts concerning production networks, trade shocks, labor intelligence, energy-manufacturing interdependence, data integration, and policy simulation.

The resulting contribution is a framework that connects economic signal detection, structural dependency analysis, and policy simulation within one decision process. Rather than treating trade exposure, workforce constraints, manufacturing capacity, supply-chain vulnerability, and energy security as separate analytical problems, PEDSF examines how changes in one domain may alter conditions in the others and how alternative interventions can be evaluated before implementation.

III. METHODOLOGY

3.1 Research Design and Approach

This study adopts a design-science and scenario-based modeling approach to develop PEDSF for U.S. trade and industrial policy. The framework combines established economic statistics with selected high-frequency indicators to detect emerging vulnerabilities, trace cross-sector effects, and compare policy responses.

PEDSF is presented as an analytical architecture rather than a completed nationwide experiment. It is intended for subsequent sector-specific and regional calibration and validation, so scenario outputs are not treated as observed national economic results.

The methodology combines nowcasting, production-network analysis, scenario modeling, and policy evaluation. Nowcasting estimates current labor, trade, manufacturing, supply-chain, and energy conditions before complete official statistics are available. Production-network analysis examines interindustry dependencies, while scenario modeling and policy evaluation compare alternative interventions, costs, uncertainty, regional effects, and spillovers.

Artificial intelligence and machine learning are limited to defined analytical tasks such as processing unstructured data, detecting anomalies, identifying non-linear relationships, and improving short-term forecasts. Economic interpretation and policy decisions remain subject to transparent assumptions and human review.

Three scenarios are evaluated: a baseline relying mainly on conventional reporting, a partial-integration model supplementing official statistics with selected high-frequency indicators, and a full-integration model applying PEDSF to detect risks, trace transmission, compare interventions, and monitor outcomes. Each may be tested against disruptions such as tariff changes, critical-input shortages, transportation interruptions, energy constraints, or specialized labor shortages. Scenario-based simulation permits policy alternatives to be assessed before operational deployment (Kancs, 2024).

This design is consistent with research that develops analytical artifacts through problem identification, model construction, and scenario-based evaluation (Inakpenu & Onaji, 2022). Related public-sector frameworks also emphasize predictive modeling, counterfactual analysis, continuous feedback, human oversight, data quality, and governance (Nayebale et al., 2026; Nyombi et al., 2025).

3.2 Analytical Model and System Architecture

The proposed framework operates through six connected analytical layers: data acquisition, data validation and harmonization, predictive signal detection, production-network and dependency analysis, policy simulation, and decision monitoring.

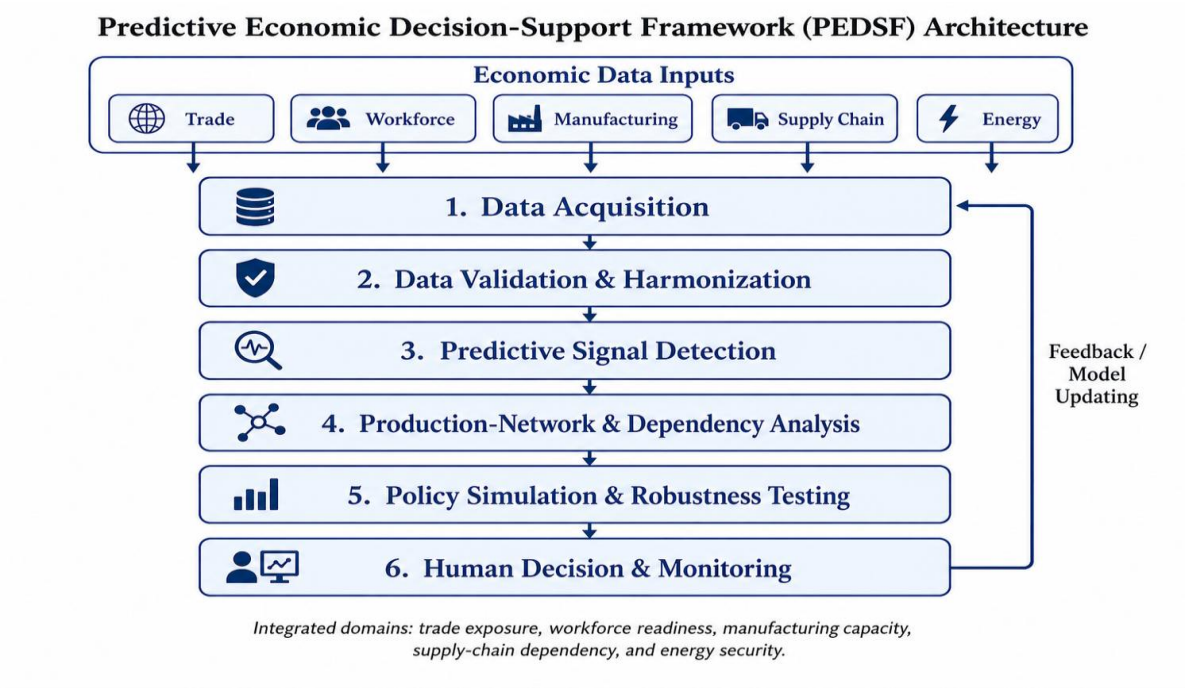


Figure 1: *Predictive Economic Decision-Support Framework (PEDSF) Architecture*

Note: The PEDSF integrates trade exposure, workforce readiness, manufacturing capacity, supply-chain dependency, and energy security through six connected analytical layers. The feedback loop represents continuous monitoring and model updating as new economic information becomes available. Author's conceptualization informed by production-network, economic-complexity, global value-chain, and interindustry-resilience literature (Acemoglu et al., 2016; Agnani et al., 2024; Balland et al., 2022; Baqaee & Farhi, 2022; Borin et al., 2025).

3.2.1 Data Acquisition

The data-acquisition layer combines official economic statistics with selected high-frequency indicators. Relevant data include international trade flows, imported intermediate inputs, tariffs, sectoral production, capacity utilization, employment, wages, occupational demand, online job postings, logistics activity, energy prices, industrial energy consumption, infrastructure conditions, investment announcements, patent activity, and interindustry transactions where legally accessible.

Official datasets establish the framework's economic baseline because they are generally collected through documented and consistent methodologies. High-frequency sources supplement these statistics by providing earlier evidence of changing industrial conditions. They are not treated as substitutes for official statistics because they may be incomplete, commercially generated, noisy, or unevenly representative across industries and regions.

3.2.2 Data Validation and Harmonization

3.2.2 Data Validation and Harmonization

The second layer standardizes the collected data according to time, industry, occupation, and geographic location. This process addresses differences in reporting frequency, industry classifications, occupational

codes, measurement units, regional coverage, missing observations, duplicate records, inflation, and seasonal patterns.

Daily, weekly, monthly, and quarterly indicators cannot be combined reliably without accounting for their different frequencies. The framework therefore permits mixed-frequency estimation where high-frequency information is expected to improve the assessment of a lower-frequency economic variable. A general representation is:

$$y_t = \alpha + \sum_{j=1}^{J} \sum_{k=0}^{K} \beta_{jk} x_{j,t-k/m} + \varepsilon_t \quad (1)$$

where y_t represents the lower-frequency economic variable of interest, such as sectoral output or employment; $x_{j,t-k/m}$ represents higher-frequency indicators such as job postings, freight activity, trade signals, or energy conditions; β_{jk} represents the estimated contribution of each lagged indicator; m represents the frequency relationship between the higher- and lower-frequency series; and ε_t is the error term.

Within PEDSF, this specification provides a general structure for incorporating timely signals without discarding the methodological value of established monthly or quarterly economic measures. The precise variables, lag structure, and parameter estimates would be determined during sector-specific empirical calibration.

Data quality is assessed before predictive analysis is conducted. Records are checked for completeness, consistency, source reliability, and relevance to the policy question. Where different classification systems are used, concordance procedures are applied to align occupations, industries, commodities, and geographic units. Personally identifiable information is excluded, while proprietary firm-level information is used only where legally available and appropriately aggregated or anonymized.

3.2.3 Predictive Signal and Structural-Change Detection

The predictive layer identifies economic changes that may precede broader industrial disruption. Dynamic-factor models, state-space estimation, anomaly detection, and change-point analysis may distinguish ordinary volatility from temporary disturbances or persistent structural shifts.

Natural language processing might turn job ads, corporate disclosures, investment statements and policy papers into signs of emerging skills, technologies, professions and investment themes. Job postings provide timely insights into the changing needs of employers, particularly in areas where new abilities are not captured by standard categories (Bone et al., 2025; Howison et al., 2024).

It can be used in cases where there are non-linear relationships or there is a lot of data , but results should be compared to simpler interpretable baselines . Adaptive systems have used supervised and unsupervised learning, graph-based modeling, anomaly detection, natural language processing, and continuous updates for identifying emerging patterns (Businge et al., 2025; Sekinobe et al., 2025; Zimbe et al., 2024, 2025). These studies support the adaptive-detection methodology, not the transfer of sector-specific performance results.

The output is a verified economic signal rather than an automatic policy recommendation. Detected changes proceed to dependency analysis before informing policy evaluation.

3.2.4 Production-Network and Dependency Analysis

The fourth layer examines how trade, labor, manufacturing, supply-chain, and energy conditions are connected. Input-output analysis provides the structural foundation for identifying direct and indirect production relationships, while network analysis helps determine whether particular industries or suppliers occupy economically consequential positions within the wider production system.

For a change in final demand or an externally imposed sectoral disturbance, the resulting change in sectoral output can be represented through the Leontief input-output relationship:

$$\Delta x = (I - A)^{-1} \Delta f \tag{2}$$

where Δx represents the resulting change in sectoral output, I is the identity matrix, A represents direct interindustry input requirements, and Δf represents the initial change in final demand or the modeled economic disturbance. The term $(I - A)^{-1}$ captures the direct and indirect production requirements transmitted through interconnected industries.

Within PEDSF, this relationship provides a structural basis for examining how an initial trade, supply-chain, or demand disturbance may propagate beyond the industry in which it originates. Production-network research similarly demonstrates that sector-specific shocks can generate wider economic consequences through input relationships and interindustry dependencies (Acemoglu et al., 2016; Baqaee & Farhi, 2022).

Trade exposure is subsequently assessed through imported intermediate inputs, supplier concentration, tariff sensitivity, domestic value added, substitution capacity, and global value-chain participation. This provides a more complete assessment than gross bilateral trade figures alone because trade statistics may not reveal the indirect production relationships embedded within complex supply chains (Borin et al., 2025).

The dependency analysis also incorporates workforce and energy conditions. A manufacturing sector may be considered vulnerable where its expansion depends on scarce technical skills, highly concentrated foreign inputs, limited transportation capacity, insufficient regional energy infrastructure, or suppliers that cannot be replaced within a reasonable period. Energy-related employment and regional labor effects are considered because industrial expansion and power-sector transitions can alter the geographic availability of workers and productive capabilities (Bücker et al., 2025).

The analysis produces sectoral and regional vulnerability indicators that show where disruptions may originate, how they may spread, and which industries or communities may experience the greatest effects.

3.2.5 Policy Simulation and Robustness Analysis

The policy-simulation layer evaluates alternative responses to the identified economic risk. Depending on the nature of the disruption, the model may compare tariff modification, supplier-diversification assistance, domestic-capacity incentives, workforce training, apprenticeship programs, infrastructure investment, regional energy expansion, or adjustment support for affected industrial communities.

Each intervention is evaluated against the baseline scenario. The framework estimates its potential effects on manufacturing output, employment, labor matching, import exposure, energy requirements, regional income, public expenditure, and connected industries. Counterfactual analysis is used to compare expected conditions with and without the proposed intervention.

The simulation does not assume that maximizing manufacturing output is the only policy objective. The evaluation also considers fiscal cost, workforce effects, energy reliability, regional distribution, implementation time, potential effects on downstream industries, and the risk that intervention may displace private investment.

Sensitivity analysis tests how the estimated results change when central assumptions are modified. These assumptions may include labor-supply elasticity, worker mobility, supplier-substitution time, input prices, energy costs, technology-adoption rates, demand growth, and disruption duration. The objective is to identify policies that remain economically reasonable under several plausible conditions rather than policies that appear optimal only under one narrow forecast.

3.2.6 Decision Output and Monitoring

The final layer translates the analysis into a policy-facing decision output. The decision interface presents the identified risk, the affected sectors and regions, the principal contributing indicators, likely transmission pathways, consequences of inaction, available interventions, uncertainty ranges, economic trade-offs, and implementation requirements.

Final policy authority remains with accountable public institutions. The framework does not autonomously activate tariffs, subsidies, training programs, procurement measures, or infrastructure investments. Its function is to organize evidence, clarify alternatives, and improve the timing and quality of human decision-making.

Following implementation, observed outcomes are compared with model projections. Differences between predicted and actual outcomes are used to identify forecasting errors, changing economic conditions, implementation delays, or incomplete assumptions. This feedback process allows the framework to improve through repeated application.

3.3 Algorithm Flowchart and Process Design

The analytical process follows a continuous sequence:

> **Policy problem definition → Data collection → Validation and harmonization → Baseline estimation → Signal detection → Dependency analysis → Scenario generation → Economic-impact estimation → Robustness testing → Human review → Implementation monitoring → Model updating**

The process begins with a clearly defined policy problem, relevant decision period, affected industries, and geographic scope. The necessary economic and high-frequency data are then collected, assessed, and harmonized. A baseline is established to represent expected economic conditions in the absence of a new intervention.

The framework then determines whether observed changes represent ordinary market variation or evidence of a structural shift. Where a material risk is confirmed, production-network analysis traces how the risk may affect suppliers, workers, industries, regions, and energy systems. Alternative policy responses are evaluated using consistent assumptions and performance measures.

The preferred intervention is determined through a balanced assessment of economic output, public cost, workforce effects, regional consequences, energy requirements, uncertainty, and potential unintended effects.

Following implementation, monitored outcomes are returned to the analytical system to improve later forecasts and simulations.

3.4 Data Sources, Processing, and Evaluation

Trade and customs data are used to measure imports, exports, tariff exposure, imported intermediate inputs, and supplier concentration. Input-output data identify interindustry purchases, sales, domestic value added, and sector multipliers. Labor-market data provide information on employment, wages, occupations, vacancies, and worker mobility. Online job postings supply more current evidence of specific skills, technologies, certifications, and experience requirements.

Table 1: *Operationalization of the PEDSF Analytical Domains*

PEDSF domain	Key indicators	Illustrative data	Analytical purpose
Trade exposure	Import dependence, tariff exposure, supplier concentration, imported intermediate inputs	Trade and customs statistics	Identify external dependencies and trade-related vulnerabilities
Workforce readiness	Employment, vacancies, wages, skills, credentials, worker mobility	Labor statistics and job postings	Detect emerging skill shortages and labor-capacity constraints
Manufacturing capacity	Output, capacity utilization, investment, inventories	Industrial and manufacturing statistics	Assess productive capacity and potential bottlenecks
Supply-chain dependency	Supplier concentration, input centrality, freight activity, lead times	Input-output, logistics, and transaction data	Trace direct and indirect disruption pathways
Energy security	Industrial energy demand, prices, reliability, infrastructure capacity	Energy and regional infrastructure data	Evaluate energy constraints affecting industrial continuity
Policy performance	Output effects, employment effects, fiscal cost, regional exposure, uncertainty	Model and scenario outputs	Compare alternative interventions and monitor implementation

Table 1 summarizes the principal variables through which PEDSF translates its five interconnected economic domains into measurable inputs for risk detection, dependency analysis, policy simulation, and subsequent evaluation.

Manufacturing indicators assess output, capacity utilization, investment, inventories, and production constraints, while logistics and energy data capture freight activity, congestion, lead times, industrial consumption, prices, grid reliability, and regional capacity. Where available, aggregated transaction data provide additional signals of changing economic activity. PEDSF integrates these sources with labor-market and industrial-production data within a common analytical structure.

Related research supports the use of digital and operational data for forecasting, inventory optimization, logistics coordination, cross-border visibility, and data-driven trade decisions (Adesanya et al., 2024; Anwansedo et al., 2024; Fowosere et al., 2025). These applications reinforce PEDSF's use of high-frequency indicators alongside conventional economic statistics.

Data processing includes cleaning, deduplication, classification harmonization, seasonal adjustment, inflation normalization, temporal alignment, and treatment of missing values. Each variable is documented by source, frequency, geographic coverage, classification, and known limitations.

Model performance is assessed through out-of-sample forecasting, benchmark comparison, sensitivity analysis, and retrospective stress testing. Outputs are classified as observed data, prior research findings, model estimates, scenario assumptions, or illustrative results. Validation covers predictive validity, structural validity, and policy validity, providing the basis for subsequent sector-specific and regional testing.

IV. RESULTS AND DISCUSSION

4.1 Presentation of Key Findings

Because this study develops a design-science and scenario-based framework, the findings represent analytical conclusions derived from the integration of the reviewed literature, proposed system architecture, and policy-simulation process. They should not be interpreted as observed national economic effects. The analysis identifies five principal findings concerning economic visibility, industrial interdependence, workforce readiness, energy security, and policy targeting.

4.1.1 Integrated Data Improve the Visibility of Emerging Industrial Risks

The first finding is that established economic statistics and high-frequency indicators perform different but complementary functions. Official statistics provide reliable and methodologically consistent measures of employment, trade, production, prices, and energy use. However, their reporting schedules and levels of aggregation may prevent policymakers from identifying developing constraints at an early stage.

High-frequency signals, such as online job postings, freight activity, investment announcements, transaction patterns, production data, and energy-demand indicators, can provide earlier evidence of changing conditions. Job-posting data, for example, may reveal a growing demand for specialized industrial skills before the change becomes visible in conventional occupational statistics (Bone et al., 2025). The extraction of skills, technologies, qualifications, and experience requirements from unstructured vacancy information can further improve the identification of emerging labor needs (Howison et al., 2024).

The framework therefore produces its strongest analytical value when high-frequency data are used to supplement, rather than replace, official datasets. A high-frequency signal may indicate that a change is developing, while established economic statistics provide the baseline against which its importance can be assessed. The combination reduces dependence on either delayed aggregate reporting or noisy real-time information alone.

This finding also establishes that the principal value of the framework is not the volume of data collected. Its value lies in the ability to connect signals from different economic domains and determine whether they point to a common industrial constraint.

4.1.2 Industrial Vulnerabilities Are Often Network-Based Rather Than Sector-Specific

The second finding is that the economic significance of an industrial disruption cannot be determined solely by the size of the initially affected firm or sector. Production systems are connected through intermediate inputs, labor, transportation, professional services, finance, digital infrastructure, and energy. A disruption affecting a relatively small but highly connected supplier may therefore create greater economic consequences than its direct output would suggest.

Production-network research supports this interpretation by showing that sector-specific shocks can spread through input relationships and affect aggregate economic performance (Acemoglu et al., 2016; Baqaee & Farhi, 2022). Similarly, interindustry resilience depends on the structure of economic connections and the ability of affected sectors to maintain or restore essential relationships following a disruption (Agnani et al., 2024).

The framework's dependency layer makes these relationships visible by examining supplier concentration, imported intermediate inputs, domestic substitution capacity, sector centrality, and downstream exposure. This approach is more informative than relying only on bilateral trade flows because gross trade statistics may not reveal the domestic and foreign value embedded within multistage production systems (Borin et al., 2025).

A tariff, export restriction, transportation interruption, or supplier failure may therefore produce different effects depending on the affected input's role within the production network. The result is that policy prioritization should consider both direct exposure and the possibility of cascading losses across connected industries.

4.1.3 Workforce Constraints Can Limit the Economic Return on Industrial Investment

The third finding concerns the relationship between workforce readiness and manufacturing competitiveness. Industrial investment does not automatically produce the expected levels of output, productivity, or regional employment. Those benefits depend partly on whether the relevant labor market can supply the combinations of technical, digital, operational, and managerial capabilities required by the investment.

Broad occupational classifications may obscure important differences among workers performing nominally similar roles. Technological change can alter the combination and relative importance of workplace skills, creating new capability requirements that are not immediately reflected in existing job titles or training systems (Alabdulkareem et al., 2018). Skills also develop in relation to technologies, productive structures, and workplace practices rather than as an independent resource supplied uniformly across the economy (Allais, 2022).

The framework addresses this problem by linking vacancy information, occupational data, wage signals, credentials, regional labor supply, and industrial investment. This permits the identification of situations in which a planned manufacturing expansion is likely to encounter labor constraints. It also supports the analysis of adjacent skills that may allow workers to transition from contracting industries into expanding industrial activities.

The broader economic implication is that workforce mismatch can reduce the return on public incentives and private capital. A subsidized facility may remain below capacity where specialized workers are unavailable, while a training program may generate limited economic value where it is based on historical occupational demand rather than current industrial requirements. Predictive labor intelligence therefore contributes to

industrial policy by improving the alignment among investment, workforce development, and regional productive capacity.

4.1.4 Manufacturing Competitiveness and Energy Security Are Interdependent

The fourth finding is that manufacturing and energy policy should not be evaluated independently. Industrial production requires reliable, affordable, and geographically accessible energy. At the same time, the expansion or relocation of manufacturing can create additional regional demand for electricity generation, transmission, storage, fuels, and supporting infrastructure.

The framework identifies energy vulnerability by connecting sectoral production requirements with regional energy prices, industrial consumption, grid capacity, reliability conditions, and infrastructure constraints. This makes it possible to assess whether a manufacturing-expansion strategy is compatible with the energy system serving the proposed location.

The relationship also includes labor and regional effects. Changes in power generation and industrial energy use can redistribute employment demand and alter the capabilities required in affected regions. Bücker et al. (2025) demonstrate that rapid changes in the U.S. power sector can produce materially different employment effects across occupations and locations. Industrial and energy transitions therefore require coordinated planning for infrastructure, production, and workforce readiness.

This finding does not imply that every manufacturing project requires a separate energy intervention. It indicates that energy availability should be treated as a core condition of industrial feasibility. A policy that expands domestic production without accounting for regional energy constraints may delay implementation, increase costs, or shift the bottleneck from imported inputs to domestic infrastructure.

4.1.5 Policy Simulation Can Improve the Targeting of Public Intervention

The fifth finding is that the framework can support more targeted policy design by comparing alternative responses to the same identified problem. Instead of assuming that a tariff, subsidy, training program, or infrastructure investment is inherently appropriate, the framework evaluates how each option may affect output, employment, trade exposure, energy demand, regional conditions, and public expenditure.

Counterfactual modeling allows policymakers to compare expected conditions under intervention with the baseline outcome expected in its absence. Model-based simulations are particularly valuable where policy choices involve several connected constraints and where implementation at full scale would be expensive or difficult to reverse (Kancs, 2024).

For example, an imported-input disruption may be addressed through tariff modification, supplier diversification, domestic-capacity support, inventory assistance, or some combination of these measures. The appropriate response depends on the availability of substitute suppliers, the time required to expand domestic production, workforce capacity, infrastructure requirements, and the economic centrality of affected downstream industries.

The finding is therefore not that predictive analysis identifies one universally optimal policy. Rather, it makes the assumptions, trade-offs, uncertainties, and spillover effects of competing interventions more visible. This can improve the allocation of public resources and reduce the risk that an intervention resolves one constraint while creating another.

4.2 Interpretation and Analysis

The findings indicate that the central industrial-policy challenge is one of coordination. Trade exposure, labor availability, manufacturing capacity, supplier concentration, and energy reliability are frequently measured through separate systems, even though they jointly determine industrial performance. The proposed framework addresses this fragmentation by creating a common analytical process through which signals from these domains can be evaluated together.

The analysis also shows that predictive capability should not be confused with certainty. The framework cannot eliminate economic uncertainty or guarantee that a disruption will occur. High-frequency data may contain noise, model relationships may change, and firms or workers may respond differently from predicted behavior. The appropriate function of the framework is therefore to identify material risks earlier, estimate plausible consequences, and clarify the range of available responses.

The distinction between prediction and causal inference is equally important. A detected association between rising job postings and industrial investment does not establish that the investment caused the labor shortage. Similarly, a relationship between energy prices and reduced industrial output may reflect several simultaneous conditions. Causal claims require an appropriate identification strategy and evidence capable of excluding reasonable alternative explanations.

Artificial intelligence has a limited but useful role within this structure. It can process unstructured information, recognize patterns, and support short-term forecasting. However, the economic relevance of its outputs depends on data quality, theoretical coherence, comparison with simpler models, and expert review. Evidence that AI can improve productivity in particular workplace contexts does not establish that it will automatically improve policy outcomes across all sectors or institutions (Brynjolfsson et al., 2025).

4.3 Policy and Implementation Implications

The findings support a phased implementation strategy. Initial applications should focus on a limited number of strategically important sectors where trade exposure, workforce requirements, manufacturing capacity, and energy dependency can be clearly defined. Possible applications include semiconductor production, advanced electrical equipment, critical industrial inputs, and energy-intensive manufacturing.

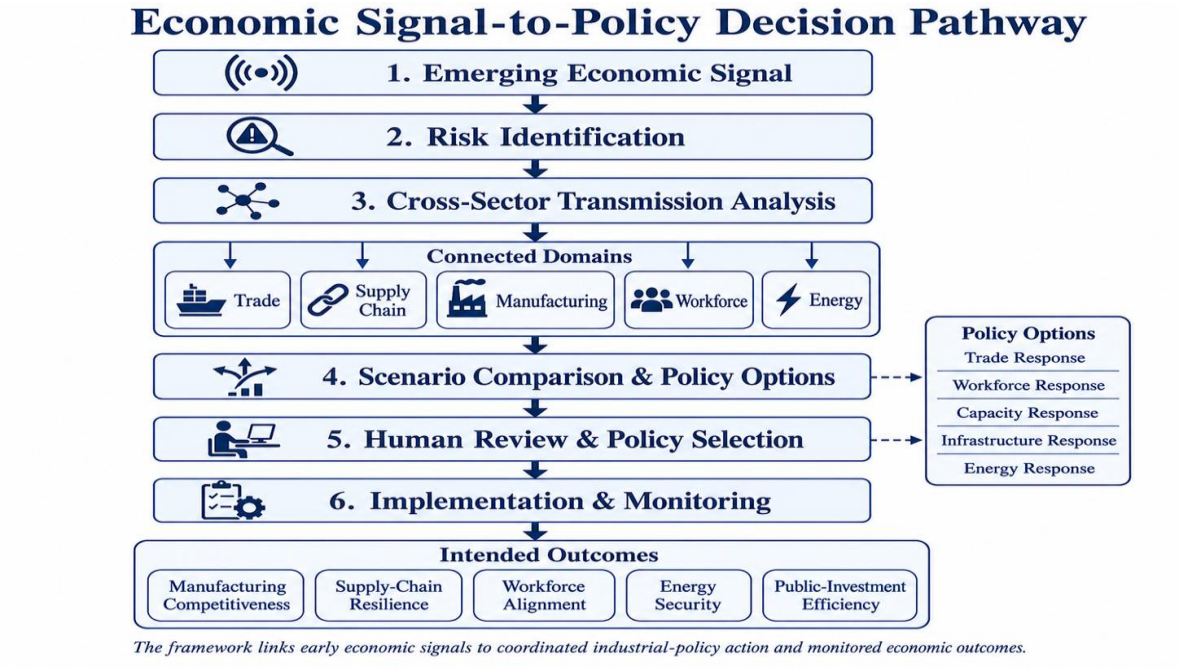


Figure 2: *Economic Signal-to-Policy Decision Pathway*

Note: The pathway illustrates how an emerging economic signal moves from risk identification and cross-sector transmission analysis to scenario comparison, human policy review, implementation, and monitoring. Policy options are evaluated across interconnected trade, supply-chain, manufacturing, workforce, and energy conditions, with intended outcomes including manufacturing competitiveness, supply-chain resilience, workforce alignment, energy security, and public-investment efficiency. Author's conceptualization.

Implementation would require cooperation among institutions responsible for trade, labor, commerce, energy, transportation, and economic statistics. The objective would not be to centralize all public data within one unrestricted system. It would be to establish compatible standards through which authorized economic indicators can be compared and analyzed across institutional boundaries.

Policy outputs should present the evidence supporting each identified risk, the assumptions used in the simulation, the estimated range of consequences, and the limitations of the analysis. Human review must occur before any recommendation influences tariffs, subsidies, workforce programs, procurement decisions, or infrastructure investment.

The framework also supports place-based policy. Trade and industrial changes produce unequal regional consequences because industries, workers, infrastructure, and energy resources are not distributed uniformly. Caliendo et al. (2019) show that trade shocks can produce different adjustment patterns across industries and locations. National policy should therefore account for regional exposure rather than assuming that aggregate growth will offset concentrated economic losses automatically.

4.4 Innovation and Research Contributions

The principal contribution of this research is not the independent use of artificial intelligence, network analysis, or economic forecasting. Each of those methods already exists. The innovation lies in integrating

five frequently separated policy domains: trade exposure, workforce readiness, manufacturing capacity, supply-chain dependency, and industrial energy security.

The framework also connects early-warning analysis with policy simulation. It does not stop after detecting an economic anomaly. It traces the relevant dependencies, evaluates competing interventions, reports uncertainty, and establishes a process for monitoring implementation. This creates a direct analytical connection between emerging economic signals and policy decisions.

A further contribution is the framework's explicit treatment of evidentiary status. Observed data, literature findings, scenario assumptions, model estimates, and illustrative outputs are classified separately. This reduces the risk that hypothetical results or borrowed statistics will be presented as independently established findings.

4.5 Scalability and Broader Impact

The framework is modular and can be adapted to different sectors, regions, and forms of disruption. The same analytical sequence can examine a tariff shock, a critical-input shortage, an industrial labor constraint, or an energy-infrastructure bottleneck, while the variables and assumptions are adjusted to the relevant context.

Scalability, however, does not mean that one model should be applied identically throughout the economy. Sector-specific production technologies, labor requirements, supplier relationships, regulatory conditions, and energy needs must determine how each application is designed.

The potential impact extends beyond an individual firm because industrial networks create cross-sector and regional spillovers. Better identification of a critical supplier may protect several downstream manufacturers. Earlier recognition of a workforce shortage may improve the return on multiple investments within an industrial cluster. Coordinating manufacturing expansion with energy planning may reduce delays affecting employers, workers, utilities, and local governments.

Accordingly, the broader significance of the framework lies in its potential to improve industrial continuity, workforce alignment, public-investment efficiency, regional resilience, and the capacity of the United States to respond to trade and supply disruptions before their effects become economy-wide.

V. ECONOMIC SIGNIFICANCE AND NATIONAL POLICY RELEVANCE

The economic significance of the proposed framework lies not merely in its capacity to generate more timely forecasts, but in its potential to improve the allocation of labor, capital, infrastructure, and public resources across interconnected sectors of the U.S. economy. By combining trade exposure, manufacturing capacity, workforce readiness, supply-chain dependency, and energy conditions within one analytical process, the framework provides a basis for identifying constraints whose effects may extend beyond an individual firm, investment, or region.

5.1 Manufacturing Output and Competitiveness

Manufacturing competitiveness depends on the coordinated availability of productive capacity, specialized labor, reliable suppliers, infrastructure, technology, and energy. Industrial incentives or capital investments may produce limited economic benefits where one or more of these complementary conditions remain unresolved. Economic-complexity research similarly indicates that productive development depends on

combinations of capabilities and institutional relationships rather than the presence of a single facility or industry (Balland et al., 2022).

The proposed framework may improve manufacturing performance by identifying emerging capacity constraints before they result in delayed production or underutilized investment. It can connect manufacturing output and capacity-utilization indicators with supplier availability, labor demand, logistics conditions, and regional energy requirements. This integrated visibility may help policymakers determine whether an industrial investment is supported by the surrounding productive system and which complementary interventions are required.

The framework's economic contribution therefore arises from its potential to support production continuity, improve the sequencing of industrial investments, and reduce the likelihood that public incentives are committed to projects whose labor, supplier, infrastructure, or energy requirements have not been adequately evaluated. Industrial policy can generate broader economic value where interventions address genuine coordination failures and reinforce productive relationships across sectors (Bartelme et al. 2025).

5.2 Trade and Supply-Chain Resilience

Trade and supply-chain disruptions can affect domestic production through both direct and indirect channels. Gross import figures may identify immediate foreign exposure, but they do not always reveal the imported intermediate inputs, domestic value added, and upstream relationships embedded in global production systems (Borin et al., 2025; Johnson & Noguera, 2017).

The proposed framework strengthens trade-policy analysis by examining supplier concentration, tariff sensitivity, substitution capacity, production-network centrality, and the time required to develop alternative sources. This allows policymakers to distinguish between imports that are readily replaceable and inputs whose interruption could disrupt several downstream industries.

The broader economic importance of this capability lies in reducing the risk of cascading production losses. Research on production networks demonstrates that sector-specific shocks can spread through input relationships and generate effects beyond the industry in which the disruption originates (Acemoglu et al., 2016; Baqaee & Farhi, 2022). Earlier identification of highly connected suppliers or critical inputs may therefore support more proportionate tariff decisions, supplier-diversification strategies, inventory planning, and domestic-capacity investments.

5.3 Workforce and Human-Capital Efficiency

The economic return on industrial investment also depends on the availability of workers with capabilities aligned to changing technologies and production processes. Broad occupational classifications may not adequately distinguish among workers with different combinations of mechanical, digital, analytical, automation, and process-control skills. Technological change can reorganize workplace tasks and alter the relationship among skills more rapidly than conventional classifications and training systems can respond (Alabdulkareem et al., 2018).

The proposed framework may improve workforce allocation by combining occupational data with job postings, employer requirements, wage signals, credentials, regional labor availability, and planned industrial investments. This can help identify emerging skill shortages, transferable capabilities, and potential transition pathways before labor constraints begin to delay production.

Its significance extends beyond improving recruitment for individual employers. Better alignment between workforce programs and industrial demand may increase the economic return on training expenditures, reduce persistent vacancies, support worker mobility, and strengthen the capacity of regional industrial clusters. Because skills are shaped by productive structures and workplace organization, workforce policy must be connected to the industries and technologies in which those skills will be applied (Allais, 2022).

5.4 Energy Security and Industrial Continuity

Energy security is a fundamental condition of manufacturing continuity. Industrial expansion may increase regional demand for electricity, fuels, transmission capacity, storage, and supporting infrastructure. A manufacturing strategy that does not account for these requirements may shift economic vulnerability from imported inputs to domestic energy constraints.

The framework connects industrial-location and expansion decisions with regional energy prices, consumption patterns, infrastructure capacity, and reliability conditions. It may therefore help identify whether proposed manufacturing growth is compatible with the energy system serving the relevant region and whether additional investment is required.

The economic significance of this integration is reinforced by evidence that changes in the power sector can produce different employment and adjustment effects across U.S. regions and occupations (Bücker et al., 2025). Coordinated manufacturing, workforce, and energy planning may consequently reduce implementation delays, protect production continuity, and improve the use of infrastructure resources.

5.5 Public-Investment and Fiscal Efficiency

Industrial incentives, workforce programs, infrastructure investments, and energy projects involve substantial public resources. Their economic value depends on whether they address binding constraints, complement related investments, and produce benefits beyond the immediate recipient.

The framework may improve fiscal efficiency by allowing policymakers to compare the expected economic effects of competing interventions under consistent assumptions. A proposed subsidy, training program, tariff adjustment, or infrastructure investment can be evaluated according to its potential effects on output, employment, supply-chain exposure, regional development, energy demand, and connected industries.

This process does not guarantee that a particular intervention will succeed. It provides a more disciplined basis for determining where public investment may produce the greatest economic spillovers and where an intervention may merely transfer costs between sectors. Interindustry resilience measures are especially relevant because they help identify sectors whose continuity supports wider portions of the economy (Agnani et al., 2024).

5.6 Regional and Systemic Economic Effects

The national policy relevance of the framework arises from the fact that industrial disruptions and policy interventions do not remain confined to one enterprise. They may affect suppliers, workers, transportation systems, utilities, downstream manufacturers, regional tax bases, and public services.

Trade shocks can produce substantially different adjustment patterns across industries and locations because workers and productive resources do not move immediately or uniformly (Caliendo et al., 2019). The

framework's regional analysis can help identify communities that are highly dependent on particular industries, exposed to critical-input disruptions, or insufficiently prepared for new manufacturing investments.

By making these cross-sector and regional relationships more visible, the framework may support earlier and more targeted interventions that preserve productive capacity, improve workforce alignment, reduce infrastructure bottlenecks, and strengthen the resilience of industrial clusters. Its broader economic contribution is therefore the creation of a structured decision process through which localized risks can be evaluated according to their potential effects on national manufacturing competitiveness, trade resilience, energy security, and long-term economic stability.

VI. CONCLUSION

6.1 Summary of the Study

This study developed a predictive economic decision-support framework for modernizing U.S. trade and industrial policy. The framework responds to a central policy challenge: trade exposure, workforce readiness, manufacturing capacity, supply-chain dependency, and energy security are often analyzed through separate systems even though they jointly influence industrial performance.

The study finds that official economic statistics remain essential but may be strengthened by carefully validated high-frequency indicators. When labor-market signals, trade data, production information, logistics activity, supplier relationships, and energy conditions are analyzed together, policymakers can obtain earlier and more detailed evidence of emerging industrial constraints. Production-network research further demonstrates that disruptions may spread beyond the sector in which they originate, making cross-sector dependency analysis necessary for effective policy design (Acemoglu et al., 2016; Baqaee & Farhi, 2022).

The framework therefore combines data harmonization, predictive signal detection, input-output and network analysis, policy simulation, robustness testing, and human review. Its principal contribution is not the use of artificial intelligence alone, but the integration of multiple economic domains into a governed and transparent decision process. Artificial intelligence supports selected tasks such as processing unstructured information and identifying non-linear patterns, while final policy authority remains with accountable institutions.

6.2 Recommendations

The framework should initially be applied through limited sectoral and regional pilots rather than immediate nationwide deployment. Early applications should focus on industries where trade exposure, workforce requirements, supplier concentration, manufacturing capacity, and energy dependency can be clearly measured.

Implementation should preserve official statistics as the analytical baseline while adding reliable high-frequency indicators where they provide meaningful early-warning value. Federal institutions responsible for trade, labor, commerce, transportation, energy, and economic statistics should establish interoperable data standards and clearly defined access controls.

Policy simulations should report their assumptions, uncertainty ranges, expected spillover effects, implementation costs, and possible unintended consequences. Recommendations affecting tariffs, subsidies, training programs, procurement, or infrastructure should remain subject to economic review, legal authority, and human approval.

6.3 Limitations and Future Research

This study presents a conceptual and scenario-based framework rather than completed nationwide empirical findings. It does not independently establish specific increases in gross domestic product, productivity, employment, or energy efficiency. Any such outcomes would require empirical calibration and validation.

Future research should test the framework using sector-specific and regional data, compare its forecasting performance with simpler benchmark models, and evaluate whether high-frequency indicators provide meaningful warning advantages. Further work should also examine data quality, privacy, cybersecurity, algorithmic transparency, institutional coordination, and the distributional effects of proposed interventions.

The long-term value of the framework will depend on whether it improves real policy decisions, not merely predictive accuracy. Its success should therefore be measured by the quality, timeliness, transparency, and economic relevance of the decisions it supports.

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AI-ENABLED MEDICAID INTEROPERABILITY: SECURE HEALTH INFORMATION EXCHANGE AND PREDICTIVE ANALYTICS FOR COORDINATED CARE

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Abstract

Medicaid is a particularly important setting for interoperable health information because beneficiaries frequently receive services across hospitals, primary care, behavioral health, pharmacies, long-term services and supports, managed care organizations, community-based providers, and state Medicaid agencies. The fragmentation of these information environments can limit timely access to longitudinal information and constrain analytics needed for care coordination, population health management, and program administration. This paper reframes secure health information exchange around a Medicaid-centered architecture that combines standards-based interoperability, artificial intelligence (AI), Zero Trust Architecture (ZTA), privacy-preserving federated learning, and predictive analytics. The framework uses HL7 FHIR-based exchange to connect Medicaid payer, provider, and state data environments; AI-assisted semantic mapping to normalize heterogeneous information; and predictive models to identify patterns such as care gaps, potentially avoidable utilization, and emerging risk that can support earlier human intervention. Security is treated as an enabling layer rather than a separate endpoint, with resource-specific authorization, anomaly detection, secure aggregation, differential privacy, and auditable exchange mechanisms. The proposed validation environment uses Synthea-generated synthetic longitudinal records and Medicaid-oriented variables and workflows to evaluate semantic accuracy, predictive discrimination, exchange latency, security resilience, privacy protection, and operational usefulness. The paper also introduces a Medicaid Interoperability and Predictive Analytics Framework (MIPAF) that extends the original Intelligent Interoperability Index by incorporating predictive utility and care-coordination measures. The framework is intended as a design and evaluation model rather than a claim of demonstrated clinical effectiveness.

Keywords: Medicaid, Interoperability, Artificial Intelligence, Health Information Exchange, Predictive Analytics, Zero Trust Architecture, Federated Learning, Semantic Interoperability, Blockchain, Healthcare Operations, Privacy-Preserving Analytics, Care Coordination

1. INTRODUCTION

1.1 Background of the Study

The central problem addressed in this study is not simply the movement of health records between organizations, but the ability of a Medicaid ecosystem to transform distributed data into secure, timely, and actionable information. Medicaid operates across state agencies, managed care organizations, providers, hospitals, pharmacies, behavioral health organizations, community-based organizations, and other service networks. CMS describes Medicaid health information exchange as a mechanism that states can align with Medicaid program strategies, health IT capacity, and common interoperability standards. CMS also requires Medicaid programs and Medicaid managed care plans to participate in standards-based interoperability policies, including FHIR-based APIs.

The 2020 CMS Interoperability and Patient Access rule established FHIR-based API requirements affecting Medicaid fee-for-service and managed care environments, while the 2024 CMS Interoperability and Prior Authorization final rule expanded the interoperability architecture through Provider Access, Payer-to-Payer, and Prior Authorization APIs. These developments create a policy and technical foundation on which AI-enabled Medicaid analytics can be built. The opportunity is therefore to move from interoperability as data availability toward interoperability as an analytical capability: data should be exchanged in standardized form, protected at every access point, and made usable for predictive and operational decision support.

1.2 Objectives of the Study

The purpose of this study is to develop and analytically evaluate an integrated framework for secure and intelligent health information exchange using Artificial Intelligence, Zero Trust Architecture, and Federated Learning. The primary studies objectives are to:

1. Develop a Medicaid-centered interoperability architecture using HL7 FHIR and AI-assisted semantic mapping to connect heterogeneous payer, provider, and state data.
2. Design security controls combining Zero Trust access, anomaly detection, privacy-preserving federated learning, secure aggregation, and auditable exchange.
3. Develop predictive-analytics pathways for Medicaid use cases such as care-gap identification, potentially avoidable utilization, care-transition risk, and population-level service needs.
4. Evaluate interoperability and predictive performance using synthetic longitudinal data and defined technical, privacy, security, and operational metrics.
5. Extend the original Intelligent Interoperability Index into a broader Medicaid-focused framework that incorporates predictive utility and care-coordination performance.

1.3 Problem Statement

Despite decades of standardization efforts, healthcare interoperability continues to face a persistent tension between data availability and information security. While clinicians require immediate access to comprehensive patient records to deliver informed care, sharing that data introduces significant vulnerabilities. Traditional perimeter-based security models may grant excessive implicit trust after a user or device gains network access, allowing a compromised identity or endpoint to reach additional resources. A Zero Trust approach instead requires resource-specific authentication and authorization without relying on network location as the basis for trust (Rose et al., 2020). Further complicating the challenge of interoperability, is a lack of semantic intelligence whereby upon arrival of clinical data, it is presented in forms the receiving system cannot interpret without manual intervention, thereby delaying information use and potentially contributing to clinical or operational errors.

1.4 Research Questions

1. How can AI-assisted semantic mapping and FHIR-based exchange improve secure information flow across Medicaid payer, provider, and state environments?
2. How can Zero Trust Architecture, federated learning, secure aggregation, and anomaly detection protect Medicaid information while enabling cross-organizational analytics?

3. How can interoperable Medicaid data support predictive analysis of care gaps, utilization patterns, and emerging beneficiary risk?
4. Which measures should be used to evaluate semantic interoperability, predictive performance, security resilience, privacy protection, exchange latency, and operational usefulness?
5. How can predictive outputs be incorporated into Medicaid workflows while preserving explainability, human oversight, fairness, and appropriate governance?

1.5 Scope and Delimitations

The study focuses on Medicaid and Medicaid/CHIP-aligned information environments in the United States. It considers payer-provider exchange, payer-to-payer exchange, state Medicaid data, clinical information, claims and encounter data, and selected operational information relevant to predictive analytics. The study does not claim to establish clinical effectiveness, eligibility determinations, medical necessity decisions, or production-level fraud detection. Predictive models are treated as decision-support components subject to human review.

2. Literature Review

2.1 Review of Related Literature

2.1.1 Medicaid Interoperability

The evolution of HIE has progressed from point-to-point interfaces to platform-based ecosystems. The earliest standards, most notably HL7 version 2, were almost exclusively syntactic in nature, defining the structure of messages, but leaving the interpretation of clinical concepts to the end-user. The introduction of the Fast Healthcare Interoperability Resources (FHIR) standard by HL7 has begun to move interoperability into the realm of modern web technologies, featuring RESTful APIs and resource-oriented models (Jayathissa & Hewapathirana, 2023). Although FHIR provides a standardized and web-based structure for exchanging health information, its implementation may still require terminology services, concept mapping, ontology development, and governance mechanisms to make heterogeneous clinical data consistently interpretable across institutions (Rosenau et al., 2022). Earlier research has demonstrated that clinical NLP can support the extraction and normalization of information from unstructured EHR narratives into standardized FHIR resources. In an evaluation of the NLP2FHIR pipeline, F-scores ranged from 0.69 to 0.99 across different representations of Condition, Procedure, Medication Statement, and Family Member History resources, demonstrating technical feasibility while also showing that mapping performance varies according to the clinical resource and data element being processed (Hong et al., 2019).

2.1.2 Medicaid Data as an Analytics Foundation

T-MSIS provides a national Medicaid and CHIP data architecture containing enrollment, demographics, utilization and cost, payment, provider, managed-care, and third-party-liability information. T-MSIS Analytic Files further organize these data for research and analysis. In the proposed architecture, these administrative data are complemented by clinical and exchange data

exposed through FHIR-based interfaces. The analytical value comes from linking longitudinal dimensions without requiring indiscriminate centralization of raw clinical data.

Adversarial instructions embedded in retrieved content may influence downstream application behaviour, bypass intended controls, disclose information, manipulate connected functions, or trigger unauthorized actions through indirect prompt injection (Greshake et al., 2023). Finally, the dependence of clinical operations on interconnected electronic systems creates significant availability risks. Ransomware that encrypts or disables EHR systems can interrupt access to critical patient information, delay procedures, disrupt hospital operations, and require diversion of patients to other facilities (Argaw et al., 2020).

2.1.3 AI and Predictive Analytics

AI and machine-learning techniques can supplement conventional cybersecurity monitoring by identifying patterns and deviations that may indicate suspicious or unauthorized activity. For example, statistical and machine-learning methods can analyze EHR audit logs and organizational context to identify access events that deviate from expected user–patient relationships or established access patterns, helping privacy officers prioritize potentially inappropriate activity for investigation (Boxwala et al., 2011; Menon et al., 2014). Machine-learning techniques can strengthen cybersecurity monitoring by identifying patterns and deviations in network or system activity that may indicate unauthorized access, misuse, or other potential security incidents (Buczak & Guven, 2016). NLP techniques may support the extraction of time-sensitive threat indicators from unstructured incident reports, advisories, and security documentation, thereby improving situational awareness within the HIE environment (Manoharan & Sarker, 2022).

2.2 Theoretical and Conceptual Framework

2.2.1 Zero Trust Architecture and Federated Learning Models

The theoretical basis of this study is predicated on the convergence of Zero Trust Architecture and Federated Learning models. Zero Trust Architecture removes implicit trust based on network location and requires access decisions to consider the identity, device, resource, and context associated with each request (Hasan, 2024; Rose et al., 2020). Within an HIE environment, this approach supports granular authorization, micro-segmentation, and continuous evaluation of access to individual resources.

Federated learning complements ZTA by enabling healthcare institutions to train a shared model while retaining patient data within their local environments. Rather than transferring raw clinical records to a central repository, participating institutions transmit locally generated model updates for aggregation into a consensus model (Sheller et al., 2020). Together, Zero Trust and federated learning may reduce unnecessary data exposure by combining resource-specific access control with collaborative model training that does not require centralization of raw institutional records (Alsamhi et al., 2024).

2.2.2 Socio-Technical Theory and Digital Health Transformation

Digital health transformation is not exclusively a technical process; it is also socio-technical. Socio-technical theory emphasizes that successful implementation depends on the interaction between technical components, such as algorithms and infrastructure, and social components, including clinicians, patients, organizational practices, and governance policies. Clinical adoption of AI-supported HIE depends not only on model performance but also on workflow integration, usability, clinician confidence, and the ability of users to understand how system outputs should inform clinical or operational decisions (Kelly et al., 2019; Amann et al., 2020). Accordingly, the framework should combine technical security with usable workflows, appropriately interpretable outputs, and clearly assigned human responsibilities. Explainability should be designed around the needs of clinicians, patients, technical personnel, and other intended users rather than treated solely as a technical property of the model (Amann et al., 2020).

3. Design-Science Methodology and Framework Development

3.1 Research Design and Approach

The study adopts a design-science approach to develop an integrated architecture for secure and intelligent health information exchange. The framework is examined analytically against identified interoperability, privacy, cybersecurity, and operational requirements. A simulation-based validation environment is also specified for subsequent empirical evaluation. By simulating decentralized health data environments, the performance resilience of ZTA-FL architectures can be tested against common attack vectors, while measuring the efficiency of the semantic data mapping.

3.1.1 Quantitative Modeling and Simulation Parameters

The proposed validation environment will simulate a network of five healthcare institutions with heterogeneous legacy data structures. The proposed simulation will use 10,000 synthetic longitudinal health records generated with Synthea, an open-source patient-simulation platform designed to produce realistic synthetic electronic health record data for research, system development, and interoperability testing (Walonoski et al., 2018). Simulation parameters include:

- **Network latency:** Will be modelled under varying distributions and service conditions.
- **Attack scenarios:** Will include SQL injection, credential misuse, lateral movement, prompt injection, membership inference, and model poisoning where applicable.
- **Data heterogeneity:** Will include HL7 v2 messages, C-CDA documents, unstructured clinical text, and FHIR resources.

3.1.2 Data Sourcing and Pre-processing for Synthetic Health Records

Synthetic data provide an alternative for developing and testing healthcare information systems where the use of real PHI is restricted, impractical, or unnecessary. Consistent with the Synthea-based generation process described above, the simulation will use Synthea-generated records as its primary dataset. GAN- and VAE-based models are recognized as alternative synthetic-data

approaches: medGAN can generate high-dimensional discrete patient records, while the EHR Variational Autoencoder can generate longitudinal sequences of clinical encounters, diagnoses, medications, and procedures (Choi et al., 2017; Biswal et al., 2021). Synthetic output will nevertheless be evaluated for statistical fidelity, clinical plausibility, and disclosure risk rather than presumed to be anonymous. During federated training, calibrated differential-privacy noise may be applied to clipped model updates to reduce the risk that information about individual records can be inferred from those updates. The selected clipping threshold, noise multiplier, and privacy budget should be reported as part of the proposed validation protocol (Guerra-Manzanares et al., 2023).

3.2 Analytical Model and System Architecture

The proposed framework is organized into supporting architectural layers designed to address workload isolation, semantic interoperability, privacy-preserving collaboration, access control, anomaly detection, and auditability. Figure 1 illustrates the interaction among these components and the movement of information from heterogeneous healthcare data sources to authorized receiving systems.

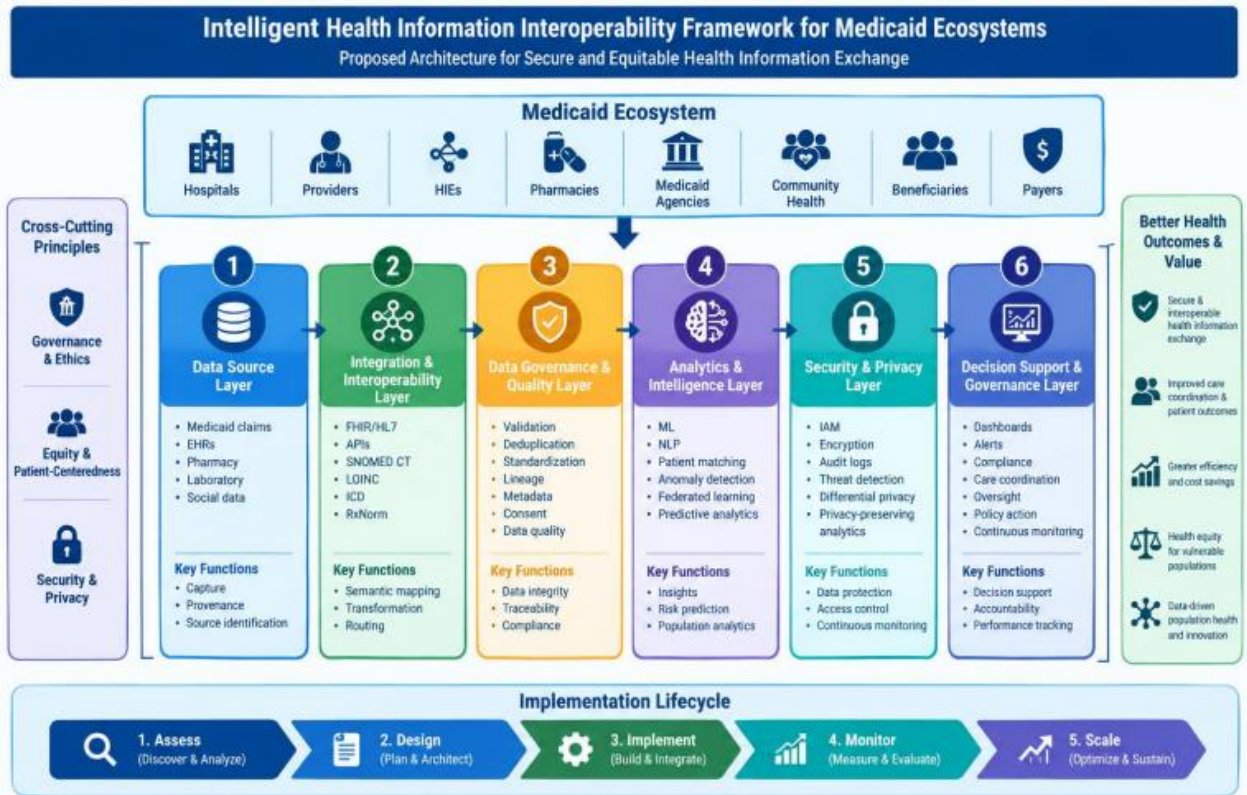


Figure 1. Proposed Architecture for Secure and Intelligent Health Information Exchange

The proposed Medicaid Interoperability and Predictive Analytics Framework (MIPAF) contains six interacting layers:

1. Medicaid Data Layer — eligibility/enrollment, claims, encounters, pharmacy, provider, prior

authorization, clinical, and relevant community-service information.

2. Interoperability Layer — HL7 FHIR resources, APIs, terminology services, semantic mapping, identity

resolution, and data-quality validation.

3. Secure Exchange Layer — Zero Trust authentication and authorization, least privilege, encryption, policy

enforcement, and workload isolation.

4. Predictive Intelligence Layer — risk stratification, care-gap prediction, utilization forecasting, anomaly

detection, and population-level pattern analysis.

5. Privacy-Preserving Learning Layer — federated learning, secure aggregation, differential privacy, and

local model governance.

6. Governance and Action Layer — explainability, human review, auditability, fairness monitoring,

workflow integration, and outcome measurement.

The conceptual flow is: Medicaid data sources → FHIR/semantic normalization → secure authorization → longitudinal data integration → predictive analytics → explainable risk or opportunity signals → human review and care-management action → feedback and model monitoring. This positions interoperability as the infrastructure that enables predictive analysis, rather than treating interoperability and AI as separate projects.

3.2.1 Neural Network Architecture for Real-time Anomaly Detection

For security monitoring, the proposed framework will use an unsupervised variational autoencoder trained on baseline network-flow features associated with legitimate HIE transactions. For each incoming observation x, the model will generate a reconstructed observation $\hat{x}$ and calculate the reconstruction error as

$$E(x) = \frac{1}{d}\sum_{k=1}^{d}(x_k - \hat{x}_k)^2$$

where x_k represents the observed value of feature k, $\hat{x}_k$ represents the corresponding reconstructed value, and d is the number of input features. A higher reconstruction error indicates that the observation differs more substantially from the normal traffic patterns learned during model training.

The anomaly-classification rule will be expressed as:

$$A(x) = \begin{cases} 1, & E(x) > \tau \\ 0, & E(x) \leq \tau \end{cases}$$

where $A(x) = 1$ denotes an anomalous observation, $A(x) = 0$ denotes an observation classified as normal, and τ is the anomaly threshold calibrated using validation data. Events classified as anomalous may be routed for additional authentication, temporary access restriction, or analyst review, depending on institutional security policy.

Observations classified as anomalous may be subjected to additional authentication, temporary access restriction, transaction blocking, or analyst review, depending on the severity of the detected activity and the applicable institutional security policy. Variational autoencoders have been used to identify deviations in network-flow records without requiring fully labelled attack datasets. However, the proposed model must be validated using representative HIE or FHIR traffic before claims regarding real-time detection effectiveness can be made (Nguyen et al., 2019).

3.2.1.1 Evaluation of the Anomaly-Detection Model

The proposed model will be compared with a **rule-based alerting baseline** using precision, recall, F1-score, false-positive rate, detection latency, and the number of events requiring analyst review. The evaluation will determine whether the model improves the detection of suspicious HIE activity without creating excessive false alerts, processing delays, or analyst workload.

Where inferential analysis is appropriate, the study will report the sample size, test assumptions, effect size, confidence interval, and exact p-value.

3.2.2 Secure Aggregation of Federated Model Updates

In each federated-learning round t, participating hospital i trains the current global model on its local dataset and generates a local model update, denoted by $\Delta w_i^{(t)}$. To account for differences in institutional dataset sizes, the update may be weighted as:

$$u_i^{(t)} = \frac{n_i}{\sum_{j=1}^{K} n_j} \Delta w_i^{(t)}$$

where n_i represents the number of training records held by hospital i, and K is the number of participating hospitals.

To prevent the coordinating server from directly observing an institution's individual update, each participating institution will add pairwise random masks to its weighted contribution:

$$\bar{u}_i^{(t)} = u_i^{(t)} + \sum_{\substack{j=1 \\ j \neq 1}}^{K} r_{ij}^{(t)}$$

where $\bar{u}_i^{(t)}$ is the masked update submitted by institution i, and $r_{ij}^{(t)}$ is a pairwise random mask shared between institutions i and j.

The pairwise masks will be constructed so that the mask assigned by one institution is cancelled by the corresponding mask assigned by the other institution:

$$r_{ij}^{(t)} = -r_{ji}^{(t)}$$

This antisymmetric relationship ensures that the pairwise random values cancel when all participating updates are aggregated.

When the coordinating server sums the masked institutional updates, the pairwise masks cancel as follows:

$$\sum_{i=1}^{K} \bar{u}_i^{(t)} = \sum_{i=1}^{K} \left(u_i^{(t)} + \sum_{\substack{j=1 \\ j \neq 1}}^{K} r_{ij}^{(t)} \right) = \sum_{i=1}^{K} u_i^{(t)}$$

The coordinating server therefore receives the aggregate contribution required for model updating without directly obtaining each institution's unmasked update.

The aggregated contribution will then be applied to the global model according to:

$$w^{(t+1)} = w^{(t)} + \eta \sum_{i=1}^{K} \bar{u}_i^{(t)}$$

where $w^{(t)}$ is the global model at round t, $w^{(t+1)}$ is the updated global model, and η is the learning rate. Because the pairwise masks cancel during aggregation, the aggregated masked updates are equivalent to the aggregated weighted updates.

This formulation establishes the functional operation of the proposed secure-aggregation mechanism but does not independently establish complete privacy or security. Its protection depends on assumptions concerning secure key exchange, participant collusion, client dropout, cryptographic implementation, and protocol integrity. Secure aggregation also does not independently prevent model poisoning or inference attacks against the resulting global model; complementary differential-privacy, validation, and anomaly-detection controls are therefore required (Bonawitz et al., 2017).

3.2.3 Integration of Blockchain for Immutable Audit Trails

The audit and provenance layer may use a permissioned distributed ledger to maintain tamper-evident records of exchange activities. The ledger would not store clinical data directly. Instead, it

could record transaction hashes, timestamps, verified actor or service identifiers, authorization outcomes, consent references, and provenance metadata. Smart contracts or equivalent policy mechanisms may enforce predefined access conditions, while the resulting records support retrospective verification and compliance review (Thazhath et al., 2022).

3.3 Proposed Security, Privacy, and Performance Evaluation

The proposed framework will be evaluated across five dimensions: semantic performance, security resilience, privacy protection, latency efficiency, and exchange reliability. Semantic mapping will be assessed using precision, recall, and F1-score. Anomaly detection will be evaluated using detection rate, false-positive rate, F1-score, detection latency, and the number of alerts requiring analyst review. Operational performance will be assessed using end-to-end exchange latency, communication volume, resource utilization, and the proportion of successful exchanges.

Membership-inference resistance will be assessed by measuring an adversary's ability to determine whether particular records were included in model training. The evaluation will compare the baseline federated model with a differential-privacy configuration and report the attack model, true-positive rate, false-positive rate, attack advantage, clipping threshold, noise multiplier, and privacy budget (ε,δ)(\varepsilon,\delta)(ε,δ) (Shokri et al., 2017; Nasr et al., 2019; Abadi et al., 2016).

The resulting measures will provide the inputs required for the proposed Intelligent Interoperability Index. Figure 2 summarizes the validation workflow, including synthetic-data generation, heterogeneous data formats, simulated institutional nodes, traffic scenarios, and the evaluation dimensions applied to the framework.

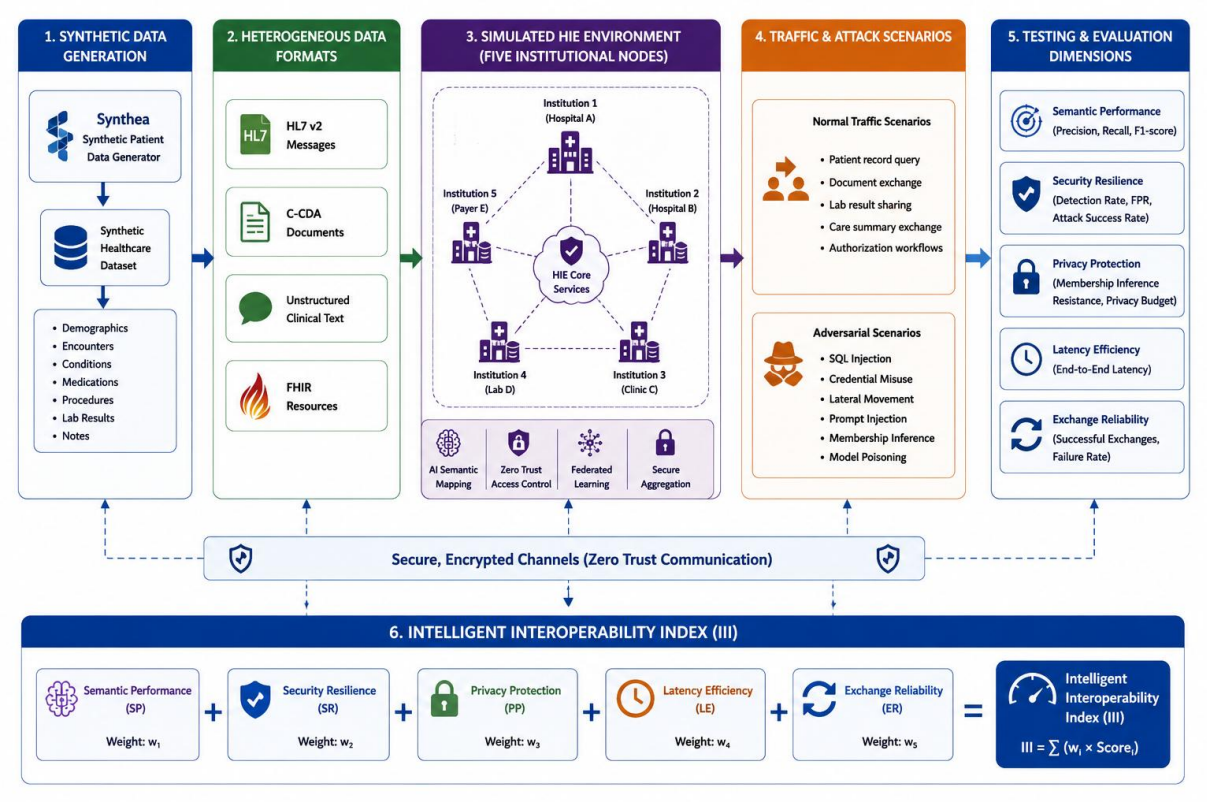


Figure 2. Proposed Validation Workflow for the Intelligent HIE Framework

The diagram presents the proposed process for generating synthetic healthcare records, configuring heterogeneous institutional nodes, introducing normal and adversarial traffic, evaluating semantic, security, privacy, latency, and exchange-reliability outcomes, and incorporating the resulting measures into the Intelligent Interoperability Index.

4. Analytical Evaluation and Discussion

4.1 Analytical Evaluation of the Proposed Framework

4.1.1 Medicaid Interoperability and Proposed Evaluation Metrics

Prior studies provide evidence that FHIR-based clinical-data normalization is technically feasible, but they do not establish a performance result for the present framework. Hong et al. (2019) reported F-scores ranging from 0.69 to 0.99 across selected FHIR element representations, while Williams et al. (2023) demonstrated a five-stage harmonization pipeline for transforming raw hospital records into standardized FHIR-based and AI-ready data. However, the latter study also required independent manual validation of the semantic mappings, indicating that automated harmonization should be supported by syntactic validation and expert review. Accordingly, the semantic-mapping accuracy of the framework proposed in this study must be established through its own comparative evaluation rather than inferred from results reported in earlier studies.

Table 1: Framework Requirements and Evaluation Plan

Identified challenge	Framework response	Proposed evaluation metric
Semantic inconsistency	AI-assisted FHIR mapping	Precision, recall and F1-score
Excessive implicit trust	Zero Trust access control	Unauthorized-access and policy-violation rates
Centralized data exposure	Federated learning	Data locality and model performance
Exposure of local updates	Secure aggregation and differential privacy	Membership-inference resistance and privacy budget
Suspicious system activity	Anomaly detection	F1-score, false-positive rate and detection latency
Weak traceability	Audit and provenance layer	Audit completeness and verification time
Exchange delays	Communication-efficient aggregation	End-to-end latency and transmitted data volume

4.2 Interpretation and Analysis

4.2.1 Comparative Analysis of AI Models versus Heuristic Systems

Rule-based systems can perform reliably where terminology, mappings, and expected input structures are well defined. Their limitations become more apparent when clinical text contains spelling variation, abbreviations, ambiguous expressions, or previously unseen contextual patterns. Contextual language models may improve adaptability in such situations, but their outputs remain dependent on training data, prompt design, terminology constraints, and context-specific validation. Accordingly, AI-assisted mapping should complement rather than automatically replace controlled terminology services, mapping rules, syntactic validation, and expert review (Schmiedmayer et al., 2024). Because semantic mapping and AI-supported clinical interpretation can produce errors that are not adequately represented by aggregate performance measures alone, transformed records and clinically consequential outputs should remain reviewable by qualified users. The interface should provide appropriate provenance, uncertainty information, limitations, and escalation procedures for ambiguous or potentially unsafe outputs (Kelly et al., 2019; Amann et al., 2020).

4.2.2 Impact on Interoperability Latency and Data Integrity

End-to-end interoperability latency refers to the time required to retrieve, transform, authorize, transmit, validate, and make exchanged information usable within the receiving system. Encryption, secure aggregation, audit logging, and distributed model training may introduce additional computational and communication overhead. The proposed framework should therefore evaluate communication-efficient aggregation, controlled update frequency, client selection, and model-update compression to reduce communication rounds and transmitted data volume without materially degrading model performance (McMahan et al., 2017; Kairouz et al., 2021).

4.3 Policy and Implementation Implications

4.3.1 Regulatory Compliance and HIPAA Alignment in AI Systems

Access controls within the HIE should be configured so that each user, service, or AI component receives only the information required for its authorized function. This approach supports the HIPAA minimum-necessary standard where it applies and aligns with Zero Trust principles requiring resource-specific authentication and authorization rather than implicit trust based on network location (U.S. Department of Health and Human Services, 2013; Rose et al., 2020). Tamper-evident audit records may support compliance review by providing timestamped evidence of access requests, authorization decisions, consent references, and data-exchange events. However, auditability alone does not establish or guarantee compliance with HIPAA or other regulatory requirements (Thazhath et al., 2022).

4.3.2 Strategic Framework for Institutional Adoption

Institutional adoption should follow a phased process that begins with clearly defined clinical or operational needs, stakeholder participation, and assessment of data quality and workflow requirements, followed by prospective evaluation, controlled deployment, post-implementation monitoring, and multidisciplinary governance (Wiens et al., 2019; Kelly et al., 2019). Implementation should be accompanied by role-specific education and workflow redesign so that clinicians and health-information personnel understand the system's intended purpose, operating procedures, limitations, data-quality responsibilities, and escalation requirements (Topol, 2019).

4.4 Innovation and Research Contributions

4.4.1 Development of the Intelligent Interoperability Index (III)

A central contribution of the study is the proposed Intelligent Interoperability Index, a composite evaluation model intended to assess the maturity and performance of an HIE implementation across several dimensions.

- **(Semantic Accuracy):** The F1-score of automated mapping of clinical data.

- **(Latency Efficiency):** For example, the normalized rate of speed at whuch cross-institutional queries are undertaken.
- **(Security Resilience):** For example the percentage of neutralized cyber-attacks.
- **(Data Siloing):** The rate of failures during handshake protocol between two systems.

The III is proposed as a structured benchmarking instrument for future validation and institutional decision-making. It should not be treated as a standardized measure until its components, weighting method, reliability, and external validity have been empirically assessed.

Table 2: Intelligent Interoperability Index Components

III component	Definition	Proposed measure	Direction
Semantic performance	Accuracy of clinical-data transformation	Mapping F1-score	Higher is better
Latency efficiency	Speed of actionable cross-system exchange	Normalized end-to-end latency	Higher normalized score is better
Security resilience	Ability to detect or resist defined attacks	Detection rate adjusted for false positives	Higher is better
Exchange reliability	Successful completion of valid exchanges	Successful exchanges divided by attempted exchanges	Higher is better
Privacy protection	Resistance to unintended information disclosure	Membership-inference advantage or privacy-budget measure	Lower risk is better

Because the components are measured using different units, each measure must first be normalized to a common scale between 0 and 1. For indicators in which higher values represent better performance, the normalized score will be calculated as:

$$Z_j = \frac{x_j - x_j^{\min}}{x_j^{\max} - x_j^{\min}}$$

Where x_j is the observed value of component j, while $x_j^{\min}$ and $x_j^{\max}$ represent the minimum and maximum benchmark values established during validation.

For indicators in which lower values represent better performance, including end-to-end latency and membership-inference risk, the normalized score will be calculated as:

$$Z_j = \frac{x_j^{\max} - x_j}{x_j^{\max} - x_j^{\min}}$$

This transformation ensures that a higher normalized score consistently represents better performance across all III components.

After normalization, the Intelligent Interoperability Index will be calculated as:

$$III = w_{SP}SP + w_{LE}LE + w_{SR}SR + w_{ER}ER + w_{PP}PP$$

subject to:

$$w_{SP} + w_{LE} + w_{SR} + w_{ER} + w_{PP} = 1$$

where:

- SP represents normalized semantic performance;
- LE represents normalized latency efficiency;
- SR represents normalized security resilience;
- ER represents normalized exchange reliability;
- PP represents normalized privacy protection; and
- $w_{SP}, w_{LE}, w_{SR}, w_{ER}, w_{PP}$ represent the respective component weights.

The weighting method should be established through expert consultation, sensitivity analysis, or empirical validation rather than assigned arbitrarily. The III is therefore proposed as a structured benchmarking instrument for future validation and institutional decision-making. It should not be treated as a standardized measure until its components, benchmark ranges, weighting method, reliability, and external validity have been empirically assessed.

4.5 Scalability and Broader Impact

4.5.1 Global Interoperability Standards and Cross-Border Exchange

Because FHIR provides standardized, resource-oriented representations for health information and DIDs provide a standardized architecture for decentralized identifiers, the proposed framework may support exchange across organizational or national boundaries where participating systems implement compatible profiles, terminology bindings, identity methods, security controls, and

governance requirements (Ayaz et al., 2021; World Wide Web Consortium, 2022). Healthcare organizations should evaluate the framework against established characteristics of trustworthy AI, including validity and reliability, safety, security and resilience, accountability and transparency, explainability and interpretability, privacy enhancement, and fairness with harmful bias managed (National Institute of Standards and Technology, 2023).

4.5.2 Proposed Economic and Operational Evaluation

Accordingly, the economic value of the proposed HIE should be evaluated using measurable outcomes such as changes in duplicate laboratory or imaging tests, emergency-department utilization and cost, information-retrieval time, hospital admissions, implementation expenses, maintenance costs, and workflow efficiency. Existing reviews report potential benefits in several of these areas but emphasize that the available economic evidence remains heterogeneous and frequently low in strength (Hersh et al., 2015; Menachemi et al., 2018).

5. Conclusion and Recommendations

5.1 Conclusion

The central proposition of the proposed framework is that secure interoperability can serve as the infrastructure for predictive Medicaid analytics. FHIR-based exchange and semantic normalization make distributed information more usable; Zero Trust, privacy-preserving learning, anomaly detection, and auditability protect that information; and predictive analytics can transform longitudinal data into signals for care coordination, population health management, and operational planning.

The proposed MIPAF and MIPAI provide a structured way to evaluate this integration without assuming that AI automatically improves outcomes. The Synthea-based validation environment can test technical and analytical performance before deployment with real Medicaid data. Future empirical work should determine whether the architecture improves measurable outcomes such as care-coordination timeliness, avoidable utilization, data-quality performance, workflow efficiency, and privacy/security resilience.

Accordingly, the practical contribution of this study is a testable architecture and evaluation pathway rather than a claim of clinical or programmatic effectiveness. Future empirical work should determine whether implementation improves measurable outcomes such as care-coordination timeliness, avoidable utilization, data-quality performance, workflow efficiency, and privacy/security resilience, while also examining implementation cost and effects across relevant beneficiary groups.

5.2 Recommendations

1. **Adopt Granular Zero Trust Controls:** Healthcare institutions should apply resource-specific authentication, least-privilege access, and micro-segmentation across clinical-data workflows.

2. **Evaluate Federated Learning:** Federated learning should be considered where institutions need to develop shared models without centralizing raw clinical records, subject to infrastructure, privacy, data-quality, and communication requirements.
3. **Validate Synthetic Data:** Synthetic datasets should be assessed for clinical plausibility, statistical fidelity, analytical utility, and disclosure risk before use in system development or testing (Pezoulas et al., 2024).
4. **Maintain Explainability and Human Oversight:** AI-supported outputs should communicate their purpose, limitations, and appropriate use and remain subject to validation, monitoring, governance, and qualified human review (Amann et al., 2020; National Institute of Standards and Technology, 2023).
5. **Establish Continuous Governance:** Multidisciplinary teams should monitor system performance, access activity, data quality, privacy risks, and emerging cybersecurity threats throughout implementation.

5.3 Limitations and Future Work

The study remains a design and validation framework rather than a production Medicaid implementation. Several limitations therefore constrain the conclusions that can be drawn. It does not use real protected health information or production HIE traffic, and the Intelligent Interoperability Index has not undergone external validation. Its security, performance, operational value, and regulatory alignment therefore remain dependent on implementation quality, institutional infrastructure, threat assumptions, and context-specific evaluation.

Future studies should implement and compare the framework using synthetic or appropriately de-identified datasets and assess semantic-mapping accuracy, exchange latency, communication efficiency, security resilience, privacy protection, and operational usability. They should also quantify the overhead introduced by secure aggregation, differential privacy, encryption, anomaly detection, and audit logging across institutions with varying hardware, bandwidth, and data distributions (Kaissis et al., 2020; Kairouz et al., 2021). Further work may examine lightweight federated learning for resource-constrained environments and post-quantum security where justified by emerging risks (Kim et al., 2023).

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REAL-TIME PREDICTIVE ECONOMIC INTELLIGENCE AND DECISION-SUPPORT FRAMEWORK FOR U.S. TRADE POLICY: QUANTIFYING IMPACTS ON CRITICAL SUPPLY-CHAIN RESILIENCE AND DOMESTIC MANUFACTURING COMPETITIVENESS

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Abstract

Growing geopolitical uncertainty, concentrated sourcing, transportation disruptions, trade-policy volatility, and dependence on globally distributed production networks have increased the economic importance of timely supply-chain intelligence for the United States. Conventional trade-policy analysis remains indispensable, but many established approaches rely on economic data that become available only after disruptions have begun affecting production, inventories, prices, and trade flows. This paper develops a Real-Time Predictive Economic Intelligence and Decision-Support Framework (RPEI-DSF) for integrating high-frequency supply-chain information with machine learning, computable general equilibrium modeling, agent-based simulation, and risk-adjusted economic decision rules. Rather than treating predictive accuracy as the principal measure of analytical value, the framework evaluates whether information arrives early enough to support economically meaningful intervention. The study adopts an integrative conceptual and evidence-synthesis methodology supported by recent U.S. manufacturing, freight, tariff, semiconductor, and medical-product evidence. Five analytical layers are proposed: data acquisition and validation; predictive risk estimation; network and disruption simulation; macroeconomic and sectoral impact assessment; and policy decision optimization. A Supply-Chain Risk Exposure metric and a decision-adjusted economic value function are introduced to connect disruption probability, economic exposure, intervention lead time, actionability, resilience, and implementation cost. Evidence indicates that digital visibility and predictive analytics can strengthen supply-chain adaptability, although their economic value depends on data quality, institutional coordination, model interpretability, and the availability of feasible policy responses. U.S. tariff experience further demonstrates that interventions can simultaneously increase domestic production while raising input prices or reducing downstream output, emphasizing the need for system-wide rather than single-industry optimization. The resulting RPEI-DSF provides a replicable analytical architecture for evaluating trade-policy alternatives, critical-input vulnerabilities, and domestic manufacturing resilience without assuming that more protection, more data, or more prediction is inherently welfare enhancing.

Keywords: Predictive Economic Intelligence; Trade Policy; Supply-Chain Resilience; Domestic Manufacturing; Machine Learning; Computable General Equilibrium; Agent-Based Modeling; Economic Decision Support; Supply-Chain Visibility; Trade-Policy Uncertainty

1. INTRODUCTION

The competitiveness of U.S. manufacturing increasingly depends on economic relationships extending well beyond the boundaries of individual firms. Modern production systems rely on multilayer supplier networks, international transportation infrastructure, cross-border intermediate goods, semiconductor capacity, energy inputs, specialized machinery, pharmaceuticals, critical minerals, and digitally connected logistics systems. These networks generate substantial efficiency during normal conditions but can transmit shocks rapidly when transportation networks fail, suppliers experience capacity constraints, geopolitical relationships deteriorate, or trade-policy conditions change.

The scale of the underlying economic system makes supply-chain disruption a macroeconomic rather than merely operational issue. The U.S. freight transportation system handled approximately 20 billion tons of goods valued at $25 trillion during 2024, illustrating the magnitude of economic activity potentially exposed to transportation and supply-network disturbances (Bureau of Transportation Statistics [BTS], 2026). In June 2026 alone, U.S. manufacturers reported approximately $656.5 billion in new orders, $652.1 billion in shipments, $1.591 trillion in unfilled orders, and $962.9 billion in inventories (U.S. Census Bureau, 2026). Changes in information availability, supplier reliability, logistics capacity, or trade policy can therefore affect significant volumes of economic activity.

Traditional supply-chain risk research emphasizes identification, assessment, mitigation, recovery, and resilience (Christopher & Peck, 2004; Tang, 2006; Ho et al., 2015). The ripple-effect literature further demonstrates that disruptions originating at one node can propagate throughout interconnected supply networks and generate nonlinear consequences beyond the initially affected supplier or industry (Ivanov et al., 2014). The challenge for policymakers is consequently not only to determine whether a shock exists, but to determine where it is propagating, which industries are economically critical, what response is feasible, and whether intervention creates greater economic value than inaction.

The same problem applies to trade-policy decisions. Tariffs, export restrictions, subsidies, sourcing incentives, strategic stockpiles, domestic production incentives, and trade agreements can alter production location, input costs, inventories, investment, import dependence, and employment. Yet policy interventions involve trade-offs. The U.S. International Trade Commission (USITC, 2023), for example, found that Section 232 tariffs reduced imports and increased U.S. production of affected steel and aluminum products, but also increased domestic prices and reduced production among some downstream users of those materials. Such results demonstrate why policy success cannot be evaluated using a single indicator such as domestic output or import reduction.

Economic analysis must therefore evaluate interactions among resilience, efficiency, production costs, domestic capacity, consumer and producer welfare, employment, trade exposure, and downstream effects.

A second challenge is informational timing. Much official economic information remains monthly, quarterly, or annual. These statistics are authoritative and indispensable for economic measurement, but supply-chain disruptions may develop over hours or days. IoT devices, shipment information, customs records, port activity, inventory systems, satellite observations, procurement data, firm disclosures, news analytics, and digital supplier networks can provide earlier indicators of stress. Edge computing can reduce processing delays for high-frequency data (Shi et al., 2016), while big-data analytics and machine learning can extract predictive patterns from complex data environments (Sivarajah et al., 2017; Baryannis et al., 2019).

The research challenge is not simply technological. An accurate prediction that arrives after a factory has already stopped production has limited economic value. Similarly, an accurate warning has little policy value when policymakers have no feasible intervention. This paper therefore distinguishes **predictive accuracy** from **decision-adjusted economic value**.

The study addresses three research questions:

RQ1. How can real-time and high-frequency economic information be transformed into economically actionable intelligence for U.S. trade and supply-chain policy?

RQ2. How can machine learning, agent-based modeling, and computable general equilibrium analysis be integrated rather than used as disconnected analytical tools?

RQ3. Which indicators should determine whether a predictive intervention improves supply-chain resilience and domestic manufacturing competitiveness?

To answer these questions, the paper develops the Real-Time Predictive Economic Intelligence and Decision-Support Framework (RPEI-DSF). Its contribution is threefold. First, it establishes an integrated architecture connecting real-time signals to economic-policy decisions. Second, it introduces a risk-adjusted valuation structure linking predictive information with avoided economic loss. Third, it demonstrates why trade-policy interventions must be evaluated across upstream industries, downstream manufacturers, supply-chain resilience, and broader welfare simultaneously.

2. Literature Review and Theoretical Background

2.1 Supply-Chain Risk, Resilience, and Disruption Propagation

Supply-chain resilience refers broadly to the ability of a network to prepare for, respond to, recover from, and adapt following disruptive events. Christopher and Peck (2004) emphasized visibility, collaboration, agility, and risk-aware organizational culture as foundations of resilient networks. Tang (2006) subsequently demonstrated that robust supply-chain strategies can provide operational benefits during both stable and disrupted conditions rather than treating resilience purely as redundant cost.

Ponomarov and Holcomb (2009) conceptualized resilience as an adaptive capability involving preparedness, response, recovery, and connectedness. Ho et al. (2015) showed that supply-chain risk encompasses supply, demand, manufacturing, transportation, financial, informational, and environmental sources, reinforcing the need for multidimensional rather than single-risk assessment.

A critical advancement occurred through research on the ripple effect, which recognizes that disturbances propagate through supply networks rather than remaining localized. Ivanov et al. (2014) demonstrated that network design, capacity, inventory, sourcing structure, and recovery strategy determine how disruptions spread across supply chains. Subsequent research connected digital technologies with ripple-effect control and supply-chain risk analytics (Ivanov et al., 2019).

The viable-supply-chain perspective extends this logic from short-term recovery toward survival under structural change. Ivanov (2022) argues that long-term viability integrates agility, resilience, and sustainability. This perspective is particularly relevant for U.S. critical supply chains because a system capable of recovering from one disturbance may remain structurally exposed to repeated geopolitical, technological, climate, or public-health shocks.

2.2 Trade Exposure and Policy Uncertainty

Supply-chain resilience cannot be separated from trade economics. International specialization can increase productivity and reduce costs, but concentrated import exposure may impose adjustment costs on specific industries and regions. Autor et al. (2013) demonstrated substantial labor-market effects associated with import competition, illustrating that aggregate trade gains do not eliminate geographically concentrated adjustment pressures.

Trade-policy uncertainty creates an additional transmission mechanism. Handley and Limão (2017) showed that reductions in policy uncertainty can influence firm entry, trade flows, prices, and welfare. Caldara et al. (2020) similarly found that increases in trade-policy uncertainty reduced investment and economic activity in the United States.

These findings suggest that trade-policy intelligence should consider not only actual tariffs but also anticipated policy changes, probability distributions around future restrictions, and firms' responses to uncertainty. Predictive economic intelligence is therefore potentially valuable before a formal policy change occurs.

2.3 Digitalization, Visibility, and Predictive Analytics

Digitization has expanded the amount and velocity of supply-chain information. Industry 4.0 technologies facilitate real-time monitoring, automation, connectivity, and data integration across production and logistics networks (Fatorachian & Kazemi, 2021).

Big-data analytics provides the computational foundation for extracting useful information from high-volume and heterogeneous datasets, although data quality, integration, governance, and analytical complexity remain significant constraints (Sivarajah et al., 2017). Baryannis et al. (2019) identify artificial intelligence as increasingly relevant to supply-chain risk detection, prediction, assessment, and mitigation.

More recent evidence reinforces the connection between digital capability and resilience. Dubey et al. (2023) find that digital adaptability and agility contribute to supply-chain resilience and that government effectiveness can moderate these relationships. Zheng et al. (2023) demonstrate how predictive analytics can support flexible supply networks and production-capacity decisions.

Network visibility is particularly important. Bowen and Siegler (2024), analyzing approximately 16,000 supply-network relationships, show how deeper-tier network mapping can identify hidden critical suppliers that would be missed by traditional first-tier visibility. Wu et al. (2024) further demonstrate that data-driven digital transformation can improve supply-chain performance through resilience and robustness mechanisms.

The healthcare sector provides a particularly important example. Tiwari et al. (2024) find that digital technologies and supply-chain visibility can enhance healthcare supply-chain resilience under environmental dynamism. The National Academies of Sciences, Engineering, and Medicine (NASEM, 2022) similarly emphasize transparency, analytics, preparedness, diversification, inventory strategy, and capacity buffering in strengthening medical-product supply chains.

Data availability alone is insufficient. Van Schilt et al. (2024) show that missing or sparse data can sharply reduce supply-chain visibility. This matters for predictive policy systems because false precision created from incomplete data can be more dangerous than explicitly acknowledging uncertainty.

2.4 Economic Modeling and Decision Support

Real-time monitoring identifies current conditions, while predictive modeling estimates future conditions. Neither alone determines the macroeconomic effect of policy.

Computable general equilibrium models provide a structured method for estimating sectoral, trade, price, employment, and welfare consequences of economic policy. Dixon and Rimmer (2002)

demonstrate their applicability to forecasting and policy analysis, while the GTAP database provides internationally comparable input-output, trade, production, tax, and sectoral information supporting applied general-equilibrium models (Aguiar et al., 2019).

Agent-based models offer a complementary perspective. CGE models examine economy-wide equilibrium effects, while ABM can represent heterogeneous firms, suppliers, inventories, routing decisions, production constraints, and adaptive behavior. The two approaches therefore operate at different analytical resolutions.

The RPEI-DSF proposed here treats these methods as complementary:

Machine learning identifies what may happen.

Agent-based simulation investigates how the disruption may propagate.

CGE analysis estimates broader economic consequences.

Decision optimization evaluates what should be done.

2.5 Research Gap

Despite substantial literature on trade policy, supply-chain resilience, artificial intelligence, and economic simulation, three gaps remain.

First, most research investigates these fields independently. Supply-chain analytics often focuses on firm performance, while trade-policy analysis emphasizes sectoral or macroeconomic outcomes. Second, predictive-model performance is typically evaluated through statistical accuracy rather than the economic value of information. Third, policy interventions are frequently evaluated after implementation rather than within continuously updated analytical architectures.

RPEI-DSF addresses these gaps by integrating real-time information, predictive risk, disruption propagation, macroeconomic modeling, and policy optimization into a unified framework.

3. Methodology

3.1 Research Design

This paper adopts an integrative conceptual and evidence-synthesis research design rather than presenting unverified primary empirical results. The framework is informed by peer-reviewed literature, official U.S. manufacturing and transportation statistics, medical-product resilience evidence, and retrospective U.S. tariff-impact analysis.

The objective is methodological: to define how a deployable predictive economic decision-support system should integrate data, modeling, risk measurement, policy simulation, and validation.

Four analytical propositions guide the framework:

P1: Reducing information latency increases the potential economic value of supply-chain interventions when earlier warning creates additional response options.

P2: Greater supply-network visibility improves disruption-risk assessment, subject to data quality and appropriate model calibration.

P3: Trade-policy interventions must be evaluated across both protected industries and downstream users because production gains in one sector may create cost increases elsewhere.

P4: Critical-product policy should incorporate social and service-continuity consequences that are not fully represented by conventional production-cost metrics.

3.2 RPEI-DSF Architecture

The framework contains six interconnected layers.

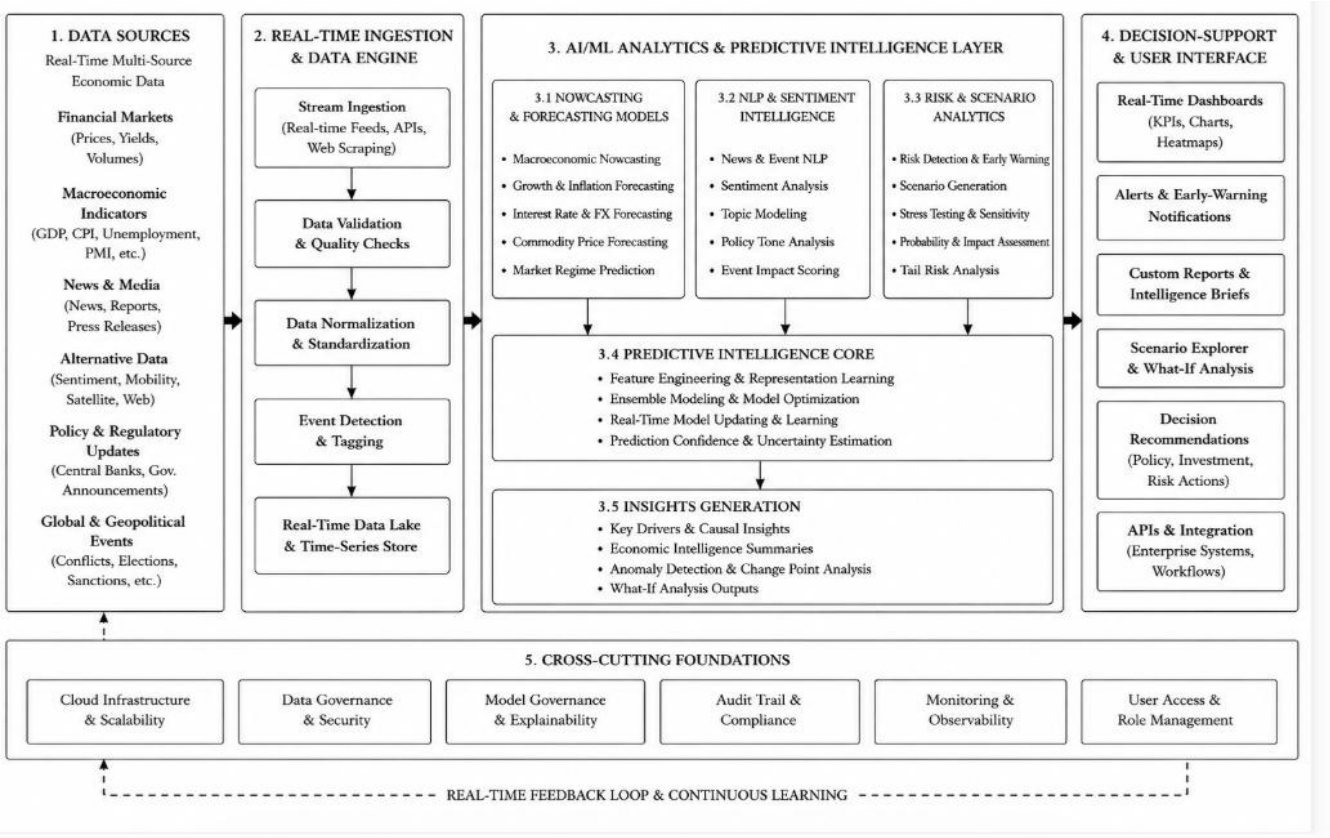


Figure 1. Real-Time Predictive Economic Intelligence and Decision-Support Architecture

Layer 1: Data Acquisition

Customs and trade flows, supplier information, inventories and orders, freight and port activity, production indicators, prices and labor data, geopolitical and policy signals, and critical-product availability.↓

Layer 2: Data Quality and Integration

Cleaning → harmonization → entity matching → missing-data assessment → latency measurement → validation

Layer 3: Predictive Intelligence

Demand forecasting → disruption probability → supplier failure risk → congestion prediction → policy-risk indicators

Layer 4: Economic and Network Simulation

Supply-network mapping → ABM disruption propagation → CGE sectoral effects → scenario analysis

Layer 5: Decision Optimization

Expected avoided loss → policy cost → downstream effects → resilience impact → welfare consequences

Layer 6: Policy Recommendation and Feedback

Diversify sourcing | adjust inventories | reroute | expand capacity | qualify suppliers | modify trade instrument | monitor only

Observed outcomes feed back into the predictive models.

The framework therefore operates as a continuous analytical loop rather than a one-time forecasting exercise.

3.3 Supply-Chain Risk Exposure

For sector (j), Supply-Chain Risk Exposure can be represented as:

$$SCRE_j = \sum_{i=1}^{n} w_{ij} E_{ij} (1 - R_{ij})$$

Where:

- $SCRE_j$= Supply-Chain Risk Exposure for sector j
- w_{ij}= economic importance or weight of input $i$for sector j
- E_{ij}= exposure of sector $j$to disruption of input i
- R_{ij}= resilience level associated with input i
- n= total number of critical inputs evaluated

Exposure may incorporate import concentration, supplier concentration, geographical concentration, transportation dependence, substitutability, inventory coverage, and lead time.

The metric should not be interpreted as a universal fixed 0–100 score. Its scale depends on operationalization and should be normalized when cross-sector comparison is required.

3.4 Information Latency and Economic Value

The economic contribution of predictive intelligence arises when additional warning time allows economically beneficial action.

Let:

$$V_{\text{RPEI}} = \sum_{s=1}^{S} p_s[L_s^0 - L_s^A(\tau_s)] - C_D - C_M - C_A$$

Where:

- V_{RPEI}= economic value generated by the Real-Time Predictive Economic Intelligence framework
- p_s= probability of disruption scenario s
- L_s^0= expected economic loss under scenario $s$without intervention
- $L_s^A(\tau_s)$= residual economic loss after intervention, given warning lead time τ_s
- C_D= data infrastructure and acquisition cost
- C_M= modeling, maintenance, and governance cost
- C_A= cost of implementing the intervention
- S= total number of disruption scenarios considered

A prediction is economically actionable only when:

$$p_s \, \Delta L_s(\tau_s) > C_A + C_F$$

Where:

- p_s= probability of disruption scenario s
- $\Delta L_s(\tau_s)$= economic loss avoided through intervention, given warning lead time τ_s
- C_A= cost of implementing the intervention
- C_F= expected cost of false alarms or unnecessary intervention

This formulation prevents a common analytical mistake: equating greater prediction accuracy with greater economic value. A moderately accurate signal delivered early enough to reroute a critical shipment may be more economically valuable than a highly accurate prediction generated after the disruption has occurred.

3.5 Economic Policy Impact Function

Trade-policy evaluation requires a broader objective function:

A cleaner journal-style version is:

$$NB_p = \Delta Y_p + \Delta W_p + \Delta R_p + \Delta E_p - C_p - D_p$$

Where:

- NB_p= net economic benefit of policy option p
- ΔY_p= change in domestic output resulting from policy p
- ΔW_p= change in overall economic welfare
- ΔR_p= improvement in supply-chain resilience
- ΔE_p= employment or strategic-capacity benefit
- C_p= direct implementation and administrative cost of the policy
- D_p= downstream costs, distortions, retaliation effects, or other adverse consequences

No policy is considered optimal merely because it reduces imports. Similarly, an intervention that raises domestic production but generates larger downstream losses may fail the net-benefit test.

3.6 Analytical Modules

Machine-Learning Module

The predictive layer may employ random forests, gradient boosting, recurrent neural networks, probabilistic models, anomaly detection, or other techniques appropriate to the data-generating process. Model selection should depend on predictive objective, frequency, explainability, and the consequences of false positives and false negatives.

Because policy applications require institutional accountability, interpretability must accompany predictive performance. Explainable-AI techniques can support examination of feature importance and model behavior (Guidotti et al., 2019).

Agent-Based Module

The ABM layer represents firms, suppliers, transportation nodes, consumers, and public agencies as heterogeneous agents. Scenario experiments can include supplier failure, port congestion, demand surges, geopolitical restrictions, transportation outages, or critical-product shortages.

Important outputs include:

- disruption propagation,
- production interruptions,
- inventory depletion,
- substitution behavior,
- recovery time,
- sourcing changes, and
- network bottlenecks.

CGE Module

The CGE layer translates sector-level shocks into wider economic consequences. Inputs can include tariff changes, import costs, production constraints, factor mobility, substitution elasticities, labor-market effects, and interindustry relationships.

Outputs can include:

- sectoral output,
- imports and exports,
- employment,
- prices,
- household welfare,
- investment, and
- trade balances.

3.7 Evaluation Indicators

Dimension	Primary indicators	Policy interpretation
Supply risk	supplier concentration, import dependence, SCRE	vulnerability
Visibility	network coverage, data completeness, data latency	information quality
Prediction	precision, recall, RMSE, calibration	predictive reliability
Resilience	recovery time, alternative sourcing, inventory coverage	adaptive capability
Manufacturing	output, capacity utilization, investment, production cost	competitiveness
Trade	imports, exports, trade balance, source diversification	external exposure
Welfare	consumer cost, producer benefit, downstream loss	net economic effect
Policy responsiveness	detection-to-decision time	institutional agility
Critical goods	availability, stockout duration, service continuity	societal consequence

3.8 Validation Strategy

A deployable RPEI-DSF should undergo four forms of validation.

First, **historical back-testing** should examine whether the predictive module would have detected known events before substantial economic consequences occurred.

Second, **out-of-sample validation** should measure forecasting performance using unseen data.

Third, **sensitivity analysis** should test alternative elasticities, disruption probabilities, substitution rates, network structures, and model assumptions.

Fourth, **policy validation** should compare simulated consequences against observed post-policy outcomes whenever natural experiments or historical policies are available.

This approach ensures that a decision-support framework evolves through empirical evidence rather than relying on predetermined improvement targets.

4. Results and Evidence-Based Analytical Findings

4.1 Finding 1: Supply-Chain Intelligence Has Large Potential Economic Reach

The scale of U.S. manufacturing and freight activity indicates that even small improvements in disruption detection or recovery can affect significant economic flows. June 2026 manufacturer data recorded $656.5 billion in new orders and $652.1 billion in shipments, while unfilled orders exceeded $1.59 trillion (U.S. Census Bureau, 2026).

These figures do not establish that RPEI-DSF would save a predetermined percentage of economic activity. They demonstrate the scale of the system to which improved decision intelligence could apply.

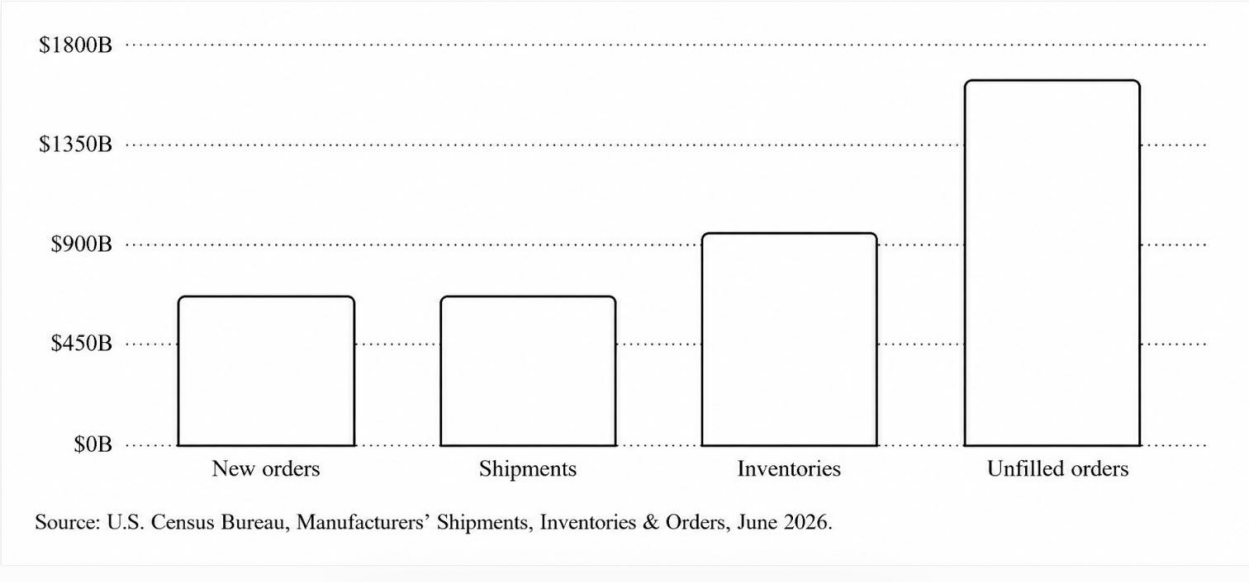


Figure 2. Selected U.S. Manufacturing Indicators, June 2026

New Orders: **$656.5 billion**
Shipments: **$652.1 billion**
Inventories: **$962.9 billion**
Unfilled Orders: **$1,590.6 billion**

The large unfilled-order stock is especially relevant because delayed components, transportation interruptions, or critical-input shortages can extend production queues even when final demand remains strong.

4.2 Finding 2: Trade Policies Generate Cross-Sector Trade-Offs

USITC's retrospective analysis of tariffs provides an empirical illustration of why RPEI-DSF must evaluate system-wide effects.

For affected steel products, Section 232 tariffs reduced imports by approximately 24%, increased domestic prices by 2.4%, and increased U.S. production by 1.9% during the period analyzed (USITC, 2023). For aluminum, imports declined approximately 31%, domestic prices increased 1.6%, and domestic production increased 3.6%.

The same report estimated that downstream industries using steel and aluminum experienced an average price increase of approximately 0.2% and production decline of 0.6%.

For semiconductors affected by Section 301 tariffs, USITC estimated a much larger import decline, together with increases in U.S. semiconductor prices and production.

These outcomes demonstrate the central RPEI-DSF proposition:

> **A trade intervention can simultaneously strengthen one measure of domestic capacity and weaken another measure of manufacturing competitiveness.**

Consequently, policy optimization should not target import reduction alone.

4.3 Finding 3: Visibility Creates Value Through Earlier Intervention

The literature consistently associates digitalization, deeper network visibility, and analytical capability with greater resilience and adaptability (Ivanov et al., 2019; Dubey et al., 2023; Bowen & Siegler, 2024; Wu et al., 2024).

The mechanism can be represented as:

Visibility

Earlier detection expands the range of feasible responses, limits disruption propagation, shortens recovery time, and ultimately reduces economic losses.

However, this sequence is conditional. Van Schilt et al. (2024) demonstrate how missing and sparse data can materially reduce supply-chain visibility. RPEI-DSF therefore treats data quality as part of the economic model rather than an external IT concern.

4.4 Finding 4: Critical Supply Chains Require Sector-Specific Objective Functions

Semiconductor, pharmaceutical, automotive, and steel networks share common resilience principles but differ substantially in economic consequences.

A shortage of steel may raise costs and reduce manufacturing throughput. A semiconductor shortage can interrupt multiple industries simultaneously because semiconductors are embedded across automotive, electronics, telecommunications, defense, energy, and industrial equipment.

Medical products require an additional dimension because economic cost does not fully represent the consequence of shortage. NASEM (2022) emphasizes the need for awareness, mitigation, preparedness, and response measures specifically oriented toward continuity of medically necessary products. FDA reported that its activities helped prevent 330 potential drug shortages during calendar year 2025, while four new shortages were identified (FDA, 2026).

RPEI-DSF should therefore incorporate product criticality and substitutability:

$$\boxed{Priority_i = f(P_i, E_i, C_i, S_i^{-1}, T_i)}$$

Where:

- $Priority_i$= intervention priority assigned to critical input or product i
- P_i= probability of disruption
- E_i= economic exposure associated with the disruption
- C_i= criticality of the input or product
- S_i^{-1}= inverse substitutability, meaning priority increases as substitutes become less available
- T_i= expected recovery time

Higher criticality, lower substitutability, and longer recovery time should increase monitoring and intervention priority.

5. Discussion

5.1 From Predictive Accuracy to Decision-Adjusted Economic Value

The principal theoretical contribution of RPEI-DSF is its shift from **prediction-centric analytics** toward **decision-adjusted economic intelligence**.

A forecasting model may achieve high predictive accuracy yet contribute little economic value if the prediction arrives too late. Conversely, an earlier signal with somewhat lower statistical accuracy may justify preventive action when the potential loss is extremely large and the intervention is relatively inexpensive.

This distinction is especially important in trade and supply-chain policy, where decision windows differ by intervention. Rerouting transportation may require hours. Reallocating inventories may require days. Qualifying alternative suppliers can require months. Expanding semiconductor fabrication capacity requires years.

The value of warning time therefore depends on the structure of the policy response.

5.2 Implications for Domestic Manufacturing

Domestic manufacturing competitiveness should not be equated with maximum domestic content. Competitiveness involves productivity, reliable access to inputs, cost structure, technological capability, labor availability, innovation, capacity utilization, and resilience.

The USITC tariff evidence illustrates this distinction. Protection may increase domestic output among upstream producers while simultaneously raising costs for downstream manufacturers. RPEI-DSF improves policy analysis by tracing those effects across the supply network before identifying a preferred intervention.

For example, where a concentrated imported input presents national vulnerability, the policy set should not automatically default to tariffs. The framework can compare:

The framework evaluates a range of policy and resilience options, including supplier diversification, trusted-partner sourcing, domestic production incentives, strategic inventory, capacity reservations, recycling or substitution, targeted tariffs, infrastructure investment, and, where intervention is not yet justified, enhanced monitoring without immediate policy action.

The economically optimal response may combine several instruments.

5.3 Implications for Trade Policy

Trade policy increasingly operates in an environment characterized by geopolitical competition, national-security concerns, industrial policy, and supply-chain concentration. Handley and Limão (2017) and Caldara et al. (2020) demonstrate that policy uncertainty itself influences investment and trade.

RPEI-DSF can therefore support a shift from purely retrospective trade analysis toward scenario-based policy preparation.

Suppose an increase in geopolitical risk raises the probability that a critical input will become unavailable. The framework would first identify affected products and industries. Network analysis would determine downstream dependence. Predictive models would estimate disruption probability. ABM would assess propagation. CGE would estimate broader economic consequences. Policymakers could then compare the expected economic value of diversification, stockpiling, domestic capacity, negotiation, tariff intervention, or other measures.

This architecture does not automate trade policy. It structures evidence for human decision-makers.

5.4 Institutional and Governance Requirements

A federal-scale RPEI-DSF would require governance as much as technology.

First, participating institutions would require common data definitions and secure interoperability. Relevant information is dispersed across trade, transportation, manufacturing, public-health, procurement, commercial, and firm-level systems.

Second, access permissions must protect proprietary, personal, and national-security information.

Third, predictive outputs require uncertainty intervals and transparent assumptions. High-stakes policy recommendations should not be generated by opaque models without explanation.

Fourth, policy analysts should distinguish correlation from causal impact. A model capable of forecasting port congestion does not automatically determine the economic effect of a tariff intervention.

Fifth, RPEI-DSF requires a human-in-the-loop governance structure. Algorithms can rank scenarios and compare alternatives, but policy choices involve distributional, strategic, legal, and political considerations that extend beyond mathematical optimization.

5.5 Proposed Policy Dashboard

A policy dashboard derived from RPEI-DSF should prioritize a small number of decision-relevant indicators:

Indicator	Example decision question
Critical-input concentration	Are too many industries dependent on one supplier or country?
Warning lead time	How long before disruption becomes economically binding?
Alternative capacity	Can domestic or allied suppliers replace affected output?
Inventory coverage	How long can production continue?
Downstream exposure	Which industries suffer if the input price rises?
Recovery time	How long before normal production resumes?
Expected avoided loss	What economic loss can intervention prevent?
Intervention cost	What does mitigation cost?
False-alarm cost	What is lost if the warning is incorrect?
Net economic benefit	Does intervention create positive expected value?

The purpose of this dashboard is not to produce a single politically neutral "correct" policy. Rather, it makes trade-offs visible and comparable.

6. Policy and Managerial Implications

For policymakers, implementation should begin with narrowly defined critical-supply-chain pilots rather than immediate economy-wide deployment. Semiconductor manufacturing, selected medical products, critical industrial inputs, and high-consequence transportation corridors provide logical environments for testing.

An initial implementation could integrate existing official manufacturing, trade, transportation, and critical-product data. The second stage could incorporate commercial logistics, supplier, inventory, and high-frequency data through controlled public-private partnerships. Predictive models could then be back-tested against historical disruptions before supporting live policy evaluation.

Industry participants would benefit from similar architecture at firm or sector level. Manufacturers can integrate supplier-risk scores, demand forecasts, inventory levels, transportation information, and alternative sourcing options into decision thresholds. Government need not receive unrestricted proprietary data; federated, aggregated, or appropriately anonymized architectures can support public-sector situational awareness while protecting commercial information.

Importantly, resilience should not become synonymous with excessive redundancy. Inventory buffers, duplicated suppliers, excess capacity, and domestic substitution involve costs. The analytical objective is to determine where redundancy is economically justified because the expected disruption loss exceeds the cost of resilience.

7. Limitations and Future Research

This paper develops an analytical framework rather than presenting results from a fully deployed national RPEI-DSF. Several limitations therefore remain.

First, real-time private-sector data can be expensive, proprietary, inconsistent, or incomplete. Public information provides strong economic benchmarks but may not achieve the frequency required for certain disruption decisions.

Second, model uncertainty remains unavoidable. Machine-learning forecasts may degrade when geopolitical or economic relationships change. CGE models depend on elasticity assumptions and structural specifications. ABM outcomes depend on behavioral rules and network representation.

Third, integrating models across different temporal and spatial scales presents substantial methodological challenges. A port disruption may develop hourly, manufacturing data may be monthly, and investment responses can occur over years.

Fourth, national-security and commercial-security concerns may limit detailed supply-network transparency.

Future research should empirically implement RPEI-DSF for selected critical industries and compare predicted and realized disruption outcomes. Particular attention should be given to the economic value of warning lead time, optimal thresholds for intervention, uncertainty calibration, distributional consequences, and differences between high-criticality and ordinary commercial supply chains.

Research should also examine whether digital-twin architectures can improve synchronization between real-world supply networks and policy simulations and whether explainable-AI methods can make complex predictive systems sufficiently transparent for public-sector decision-making.

8. Conclusion

U.S. trade policy and domestic manufacturing competitiveness increasingly depend on the ability to understand disruptions before their full economic consequences materialize. Traditional economic models remain essential but can be strengthened when combined with high-frequency supply-chain information, predictive analytics, network simulation, and explicit economic decision rules.

This paper develops RPEI-DSF as an integrated architecture connecting data visibility, predictive risk estimation, disruption propagation, macroeconomic analysis, and policy optimization.

Its central proposition is that the value of predictive economic intelligence should not be measured by forecasting accuracy alone. Economic value emerges when reliable information arrives sufficiently early to permit an intervention whose expected avoided loss exceeds its cost.

The framework also demonstrates why trade-policy decisions must be evaluated systemically. Policies that reduce imports or increase upstream domestic production may simultaneously increase downstream costs. Conversely, resilience investments that appear inefficient under normal conditions may generate substantial value when expected disruption losses are incorporated.

RPEI-DSF therefore reframes the objective of real-time trade analytics. The goal is neither maximum protection nor maximum data collection. It is to provide policymakers and industry with timely, explainable, risk-adjusted evidence for choosing interventions that strengthen critical supply-chain resilience while preserving the productivity and competitiveness of U.S. manufacturing.

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DEVELOPING AN ADVANCED COMMUNICATIONS AND NETWORK-RESILIENCE FRAMEWORK FOR STRENGTHENING THE ECONOMIC RESILIENCE OF U.S. CRITICAL INFRASTRUCTURE

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Abstract

U.S. electricity customers experienced about eleven hours of service interruption in 2024, nearly twice the prior-decade average, with major weather events accounting for roughly 80% of outage duration [1]. Modern restoration increasingly depends on communications pathways linking field devices, control centers, wireless systems, fiber, and enterprise networks. Yet reliability engineering and regional economic-loss modeling remain largely disconnected, limiting utilities' ability to monetize the resilience value of communications investments. This paper proposes the Advanced Communications and Network-Resilience Framework, which links communications-layer degradation to restoration performance and economic consequence. The framework combines a criticality-weighted Telemetry Observability Index, a Restoration Time Inflation Function, customer interruption cost curves [2], dynamic inoperability input-output modeling [3], [4], and stochastic capital-allocation optimization. It is evaluated on a synthetic metropolitan distribution system under storm, derecho, ice-storm, and cyber-physical scenarios consistent with recent federal advisories [5]. Illustrative results indicate that targeted communications hardening can materially improve observability, reduce expected annual economic loss, and produce benefit-cost ratios exceeding annualized capital costs. National transferability scenarios suggest potentially significant avoided losses, while sensitivity analysis identifies observability elasticity of restoration as the principal empirical uncertainty. The framework offers Sector Risk Management Agencies [6], federal grid-resilience programs [7], and bulk electric-system cybersecurity initiatives [8] a defensible basis for valuing diverse, redundant, and secure communications infrastructure as an economic-resilience investment.

Keywords: Critical Infrastructure Resilience; Grid Communications; Telemetry Observability; Economic Loss Propagation; Resilience Investment Optimization

1. INTRODUCTION

1.1 The changing character of an outage

An electric distribution outage in 1995 was primarily a physical problem. Crews patrolled feeders, located damage, completed repairs, and restored service. Restoration time was largely determined by travel, materials, crew availability, and physical access. Information systems played a limited supporting role. In 2026, an outage is increasingly a cyber-physical event. Modernized distribution systems depend on automated reclosers, sectionalizers, fault-location and service-restoration schemes, distributed energy resources, and continuous telemetry. Operators rely on communications networks to identify faulted sections, verify equipment states, manage voltage during restoration, and direct crews toward repairs that restore the greatest number of customers. These functions are therefore conditional on the availability and integrity of communications pathways.

Traditional reliability indices do not adequately represent this dependency. The System Average Interruption Duration Index records customer-minutes of interruption but does not distinguish between outages prolonged by physical damage and those prolonged because operators lose visibility or control when communications infrastructure fails. Consequently, the economic contribution of communications resilience can remain largely invisible within conventional reliability-based investment analysis. The exposure is material. In 2024, U.S. electricity customers averaged approximately eleven hours of interruption, nearly twice the preceding decade's average, with about 80 percent attributable to major events [1]. Major-event interruption duration approached nine hours in 2024 compared with roughly four hours annually from 2014 through 2023, while non-major-event interruptions remained near two hours [1]. These severe events can simultaneously affect power and communications assets exposed to common hazards. Economic dependence on uninterrupted electricity is also increasing. Data centers consumed approximately 4.4 percent of U.S. electricity in 2023 and are projected to consume 6.7 to 12 percent by 2028 [9].

1.1.1 A current illustration: northern Illinois, 2026

Northern Illinois illustrates the growing frequency and sequencing of severe events. The August 9–12 storms represented the twentieth major weather event affecting Commonwealth Edison customers in 2026, reportedly the highest annual count in more than two decades, with at least fifty-two tornadoes confirmed across the service territory [39], [40]. June storms produced approximately 684,000 customer outages [39], while a late-July outbreak affected more than 530,000 customers. The August sequence produced approximately 410,000 outages, with gusts reaching 96 miles per hour, followed by additional storms while restoration activities were still underway [40].

These events are not presented as evidence of any specific communications failure. Rather, they demonstrate the real-world relevance of compounding hazards, where subsequent events may arrive before physical restoration is complete or backup communications autonomy has recovered.

1.2 The unsolved area

Three established research communities address portions of this problem but not the complete relationship. Power-system resilience research provides mature frameworks, resilience metrics, and joint power-communications restoration models [10], [11], [12], [13], [14], [15], but generally expresses outcomes in engineering terms such as load restored, energy not served, and restoration duration. Regional economics provides established methods for translating disruption into economic consequence, including static and dynamic economic-resilience concepts [16], [17], dynamic inoperability input-output modeling [3], [4], [18], and customer interruption-cost estimation using nationally representative utility survey data [2]. These methods generally treat outage duration as an input rather than explaining its communications-dependent determinants.

Communications engineering evaluates availability, diversity, routing, fault prediction, latency, and delivery performance [19], [20], but rarely translates those measures into the economic consequences experienced by the critical infrastructure being supported. The unresolved problem is therefore the transfer function between communications degradation, restoration duration, and economic loss.

1.3 Contributions

This paper makes six contributions. It: (1) formalizes the observability-to-economics problem as a two-stage stochastic optimization over a layered multigraph; (2) defines a criticality-weighted Telemetry Observability Index incorporating shared-risk-link-group exposure; (3) introduces a

Restoration Time Inflation Function and identification strategy using historical outage data; (4) defines the Marginal Economic Value of Observability and Communications-Economic Resilience Ratio; (5) specifies a replicable reference implementation; and (6) develops transparent national adoption scenarios for estimating potential economic and infrastructure consequences.

The framework is proposed rather than empirically validated. Its synthetic case study and illustrative parameters are intentionally transparent because the central argument is that the empirical relationship between communications observability and restoration performance remains insufficiently measured

2. Background and Related Work

2.1 Reliability indices and the measurement boundary

U.S. distribution reliability practice relies on IEEE Std 1366 indices [21]. These measures capture outage outcomes but not their causes. Consequently, improvements produced by stronger communications observability cannot be directly attributed or independently verified, causing benefit-cost analyses to undervalue investments whose primary mechanism is informational.

2.2 Economic consequence modelling

Economic-loss methods include customer interruption-cost models based on survey-derived damage functions [2], [22], [23] and inoperability input-output models that propagate disruption through interconnected economic sectors [18], including dynamic recovery formulations [3], [4]. National laboratory applications demonstrate their operational relevance [24]. However, these approaches treat outage duration and recovery as externally supplied inputs rather than communications-dependent variables.

2.3 Cyber-physical interdependence

Power-communications co-simulation is increasingly established [25], [26], alongside restoration models incorporating cyber rerouting [15], emergency communications [14], device-to-device links [13], network criticality [27], and graph-based resilience methods [19], [20], [28]. Yet their objectives remain predominantly engineering-based rather than economically calibrated.

2.4 Regulatory and policy environment

Federal critical-infrastructure policy increasingly emphasizes cascading and cross-sector risk [6], [29], while network-security monitoring requirements expand operational visibility [8] and federal grid-resilience programs require demonstrable benefits [7]. Recent state-sponsored telecommunications compromises further establish communications failure as a credible common-mode threat [5], [30].

2.5 Statement of the gap

The unresolved need is a defensible monetary mapping from communications resilience to restoration performance and economic consequence.

Capability	Representative basis	Output units	Permits monetized communications business case
Distribution reliability indices	IEEE Std 1366; federal annual survey [1], [21]	customer-minutes	No. No causal decomposition by mechanism.
Resilience trapezoid and derived metrics	Conceptual frameworks and metric taxonomies [10], [11], [12]	performance-hours	No. Physical performance only; no cost kernel.
Customer interruption cost estimation	Survey-based sector cost curves [2], [22], [23]	US dollars	No. Duration is an exogenous input.
Dynamic inoperability input-output	Leontief-based propagation with recovery rates [3], [4], [18]	US dollars	No. Initial inoperability is an exogenous input.
Cyber-physical restoration optimization	Joint cyber-power restoration formulations [13], [14], [15]	MWh restored	Partially. Objective is energy, not economic loss.
Communications availability engineering	Path diversity, availability modelling, fault prediction [19], [20]	availability, latency	No. No consequence mapping.
Proposed framework (ACNRF)	Coupled observability, restoration, and economic kernel	US dollars per observability point	Yes, conditional on empirical calibration of the coupling parameters.

Table 1. Existing capabilities and the residual gap in monetizing communications resilience.

3. Problem Formulation

3.1 Layered system model

Let the physical distribution system be a directed graph G_P = (V_P, E_P) whose vertices are substations, switching devices, distributed energy resource points of interconnection, and load aggregation points, and whose edges are line sections. Let the communications system be a graph G_C = (V_C, E_C) whose vertices are field endpoints, aggregation nodes, backhaul hubs, and the control centre, and whose edges are fiber spans, wireless links, and routed circuits. The two graphs are bidirectionally coupled.

Forward dependency: $\Phi : V_P \rightarrow 2^{VC}$ assigns to each monitored power asset the set of communications vertices whose joint failure would render that asset unobservable. Reverse dependency: $\Psi : V_C \rightarrow V_P$ assigns to each communications vertex the power asset supplying it, subject to a backup autonomy $\tau_b(v)$ measured in hours.

The coupling is the source of the analytical difficulty. A communications node that loses commercial power operates on battery for the duration of its backup autonomy and then fails, removing observability from the very assets an operator needs in order to restore the power that would recharge it. Availability models that treat the two networks as independent will systematically overstate resilience under exactly the long-duration major events that dominate the 2024 interruption statistics [1].

3.2 Telemetry observability

For monitored asset i and time t, define the quality-graded observability

$$q_i(t) = a_i(t) \cdot f_L(\ell_i(t)) \cdot f_\rho(\rho_i(t)) \in [0, 1] \quad (1)$$

where the three factors are, respectively, end-to-end path availability, a penalty on measured end-to-end latency, and a penalty on packet delivery ratio over the reporting interval. The latency and delivery penalties are

$$f_L(\ell) = \exp(-\lambda \cdot \max(0, \ell - L_i^{max}) / L_i^{max}), \quad f_\rho(\rho) = \min(1, (\rho / \rho_i^{min})^\gamma) \quad (2)$$

with $\lambda > 0$ governing the severity of the latency penalty and $\gamma > 0$ the severity of the loss penalty. The requirement thresholds for latency and delivery ratio are function-specific and are set from the operational requirement, not from the network's capability. Representative values are given in Table 3.

3.3 Path availability with shared-risk correction

Let P denote the set of routed paths from asset i to the control centre. Under an independence assumption the availability is the standard parallel expression. That assumption is untenable for utility networks, in which nominally diverse paths frequently share a duct bank, a bridge crossing, a pole line, or a single hub building. Let $\theta \in [0, 1]$ denote the shared-risk-link-group overlap fraction, computed as the proportion of route-kilometres common to two or more of those paths, weighted by hazard exposure. Then

$$a_i = (1 - \theta_i) \cdot [\, 1 - \prod_{p \in P_i} (1 - A_p) \,] + \theta_i \cdot \max_{p \in P_i} A_p \quad (3)$$

Equation (3) interpolates between full diversity at $\theta = 0$ and complete common-mode dependence at $\theta = 1$. Its merit is that θ is directly computable from the geographic information system route inventory a utility already maintains for permitting and construction sequencing, so the correction applies to an existing asset base without new instrumentation. In the author's programme experience, nominally redundant urban routes commonly exhibit θ between 0.2 and 0.5 because of shared manhole and duct infrastructure, so the correction is not a marginal refinement.

3.4 The observability index and its envelope

Define criticality weights proportional to the product of connected load, sector interruption cost intensity, and switching consequence. The criticality-weighted Telemetry Observability Index is

$$TOI(t) = (\Sigma_{i \in M} w_i \, q_i(t)) / (\Sigma_{i \in M} w_i) \quad (4)$$

over the monitored set M, and the Communications Resilience Envelope over an event window of length T is its normalized integral

$$CRE = (1 / T) \int_0^T TOI(t) \, dt \quad (5)$$

Equation (5) is the communications analogue of the resilience trapezoid area used in power system resilience assessment [10]. A separate index TOI_crit is computed over the subset of assets whose

function is required for restoration, since system-average observability can remain high while the specific observability needed for restoration is lost.

3.5 The coupling problem

With the observability layer defined, the unsolved question can be stated precisely. Let D(t) denote the observability deficit, one minus the critical-asset observability index, and let the ideal restoration duration be that which would obtain under complete observability. The problem is to determine the functional form and parameters of a mapping

$$T_r = T_r^0 \cdot \Lambda(D; \alpha, \beta) + \Delta(D) \quad (6)$$

where Λ is the restoration time inflation factor and Δ captures any additive dispatch penalty arising from blind crew routing. Neither Λ nor its parameters have been estimated for United States distribution systems in the open literature. Everything downstream of equation (6) is standard; everything upstream is measurable; equation (6) alone is the gap.

Symbol	Definition	Units
G_P, G_C	Physical power graph and communications graph	-
Phi, Psi	Forward and reverse dependency mappings between layers	-
tau_b(v)	Backup power autonomy of communications vertex v	Hours
q_i(t)	Quality-graded observability of monitored asset i	dimensionless, [0,1]
a_i, l_i, rho_i	Path availability, end-to-end latency, packet delivery ratio	-, ms, fraction
theta_i	Shared-risk-link-group overlap fraction for asset i	dimensionless, [0,1]
w_i	Criticality weight of monitored asset i	dimensionless
TOI(t), TOI_crit(t)	Weighted observability index, all assets and restoration-critical subset	dimensionless, [0,1]
CRE	Communications resilience envelope over the event window	dimensionless, [0,1]
D(t)	Observability deficit, 1 minus TOI_crit	dimensionless
alpha, beta	Observability elasticity and convexity exponent of restoration	-
T_r, T_r^0	Realized and ideal restoration duration	Hours

Symbol	Definition	Units
q_j(t)	Inoperability of economic sector j	fraction of as-planned output
k_j	Sector recovery rate in the dynamic inoperability kernel	per day
x	Binary vector of communications investment decisions	-
EL	Total economic loss, direct plus propagated	US dollars
MEVO	Marginal economic value of observability	US dollars per percentage point
CERR	Communications-economic resilience ratio	dimensionless

Table 2. Notation used throughout the framework. In this table and in the running prose, subscripts and superscripts are written in plain form (for example T_r, q_0, C_dir) for typesetting portability; the displayed equations use full mathematical setting.

Grid function	Latency requirement L_max	Delivery ratio rho_min	Availability target	Typical bearer
Line differential and teleprotection	under 10 ms	0.9999	0.99999	Dedicated fiber, SDH or OTN
Synchrophasor streaming	20 to 50 ms	0.999	0.9999	Fiber, private wireless
FLISR peer-to-peer messaging	under 100 ms	0.999	0.9999	Fiber ring, private LTE
SCADA supervisory polling	1 to 4 s	0.99	0.999	Fiber, private or public cellular
Volt/VAR and capacitor control	2 to 10 s	0.99	0.999	Private LTE, mesh radio
DER telemetry and curtailment	1 to 5 s	0.99	0.999	Private LTE, public cellular
AMI interval and last-gasp	minutes	0.95	0.99	Mesh, cellular
Crew field applications	seconds	0.95	0.99	Public cellular, satellite backup

Table 3. Representative function-specific communications requirements used to set the thresholds in equation (2). Values reflect commonly cited operational design targets and should be replaced by the utility's own protection and automation standards in any applied use.

4. The Advanced Communications and Network-Resilience Framework

4.1 Architecture

The framework is organized in five layers, shown in Figure 1. Measured state propagates upward from the telemetry layer to the capital allocation layer. A prioritization and investment signal propagates downward. Each interface is a defined data contract rather than an informal handoff, which is what permits independent implementation of any single layer.

Figure 1. ACNRF five-layer reference architecture

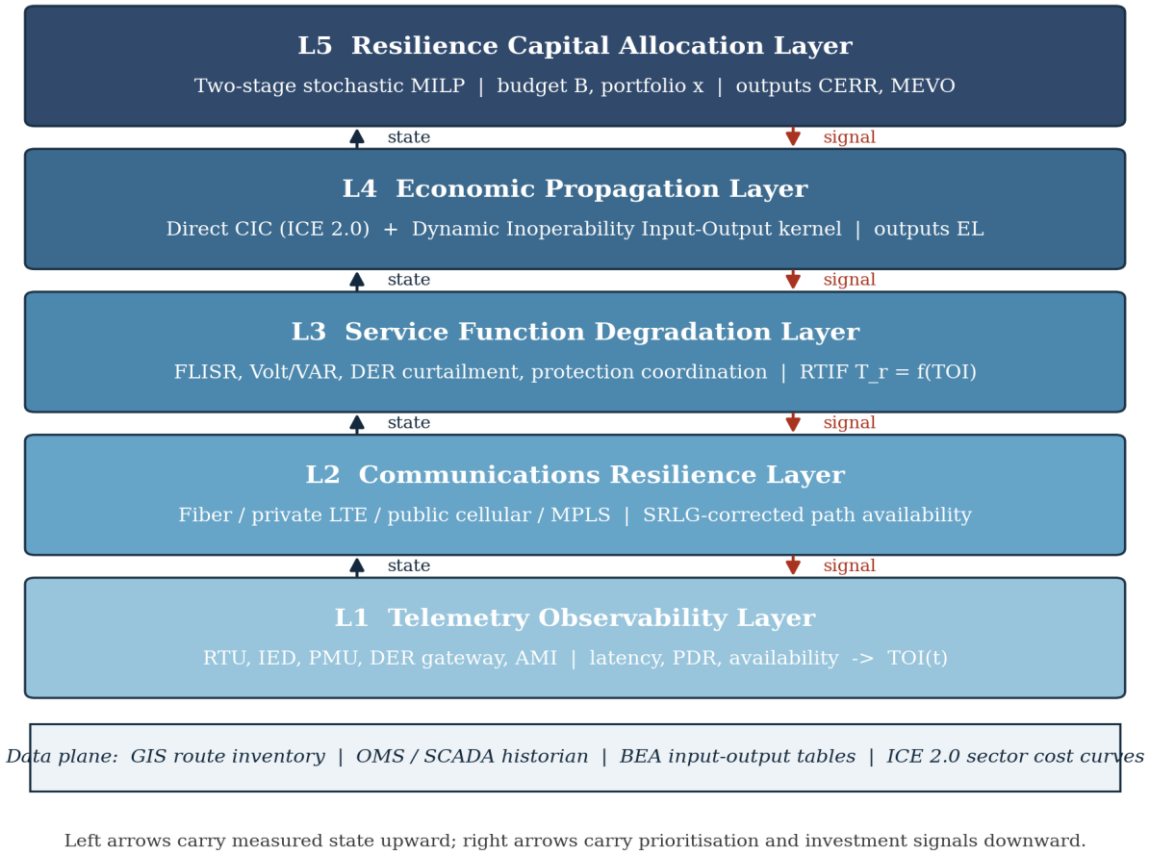


Figure 1. Five-layer reference architecture of the Advanced Communications and Network-Resilience Framework. Upward arrows carry measured state; downward arrows carry prioritisation and investment signals. The data plane draws on asset inventories and public economic data that most utilities already possess.

4.2 Layer 1 and Layer 2: from network telemetry to an observability state

Layers 1 and 2 operationalize equations (1)–(5) using network-management, routing, GIS, performance-monitoring, and security-monitoring data [8]. Backup autonomy is modeled dynamically: communications nodes remain available until batteries are exhausted, then fail until power or generator support returns, producing delayed observability degradation and highlighting autonomy as a critical design parameter.

4.3 Layer 3: the restoration time inflation function

Layer 3 is the framework's central and least certain component. The proposed parametric form is

$$\Lambda(D; \alpha, \beta) = 1 + \alpha \cdot D^{\beta}, \quad \alpha > 0, \ \beta > 0 \tag{7}$$

so that equation (6) becomes T_r = T_r^0 (1 + α D^β) + Δ(D). The parameter α is the observability elasticity of restoration: the proportional lengthening of restoration at total observability loss. The exponent β governs convexity, that is, whether a small observability deficit is nearly harmless with damage concentrating only at large deficits, which corresponds to β > 1, or whether even modest deficits are costly, which corresponds to β < 1. Figure 3 shows the family.

The form is monotone and bounded below by unity, which is physically necessary; it nests the null hypothesis of no coupling at α = 0, making that hypothesis testable; and it is identifiable from two variables utilities already record.

4.3.1 Identification strategy

Parameters can be estimated from historical outage-management, supervisory-control, and communications records. For each event, reconstruct observability deficit and compare actual restoration duration with a matched communications-independent counterfactual, then estimate equation (8) using robust nonlinear regression. Common-hazard endogeneity can be reduced through matching and strengthened using staged upgrades in a difference-in-differences design.

$$\ln\left(T_r(e) / \hat{T}_r^{0}(e) \right) = \ln(1 + \alpha D_e^{\beta}) + \varepsilon_e \tag{8}$$

4.4 Layer 4: the economic propagation kernel

Layer 4 converts restoration duration into monetary loss in two tiers.

4.4.1 Direct customer interruption cost

Energy not served for asset i is ENS_i = L_i · T_r,i, where L_i is interrupted load. Direct cost aggregates sector cost curves over customer classes s:

$$C_{dir} = \Sigma_s \Sigma_{i \in s} N_{i,s} \cdot c_s(T_{r,i}) + \Sigma_s \Sigma_{i \in s} ENS_{i,s} \cdot e_s(T_{r,i}) \tag{9}$$

where N is customer count, c_s is the per-event fixed cost component, and e_s is the per-kilowatt-hour variable component, both functions of duration. The functional forms and their parameterization follow the survey-based estimation practice underlying the national interruption cost calculator [2], [22], [23]. The updated calculator, developed from surveys across twenty-four utility service territories conducted between 2022 and 2024, provides a defensible and publicly documented source for these curves [2].

4.4.2 Propagated regional loss

Direct cost understates total consequence because interrupted sectors fail to supply their downstream customers. The dynamic inoperability input-output kernel [3], [4] evolves a sector inoperability vector q(t) as

$$q(t+1) = q(t) + K\,[\,A^* q(t) + c^*(t) - q(t)\,], \quad q(0) = q_0 \tag{10}$$

where A* is the interdependency matrix derived from national input-output accounts and rescaled by sector output, c*(t) is the exogenous perturbation, and K = diag(k_1, …, k_n) contains sector recovery rates. The initial condition q_0 is set from the electricity-dependence-weighted share of sector output interrupted, which is precisely where the observability layer enters: a longer restoration produces a larger q_0 and a longer tail. Total propagated loss over a horizon H is

$$C_{ind} = \Sigma_j x_j \Sigma_{t=0}^{H} q_j(t) \cdot \Delta t \quad (11)$$

with x_j the sector's as-planned output per unit time. Figure 4 shows representative trajectories. Total economic loss is EL = C_dir + C_ind, and care must be taken to avoid double counting the direct business interruption already captured in the sector cost curves, which is handled by netting the first-order term of C_ind against the commercial and industrial component of C_dir.

4.5 Layer 5: capital allocation

Let j index candidate communications investments, each with capital cost c_j and binary decision x_j. Let omega index hazard scenarios with probabilities pi_omega. The two-stage stochastic program is

$$\min_x \Sigma_j CRF \cdot c_j x_j + \Sigma_\omega \pi_\omega EL(\omega, x) \quad (12)$$

subject to a budget constraint, minimum observability constraints on defined critical asset classes, and logical constraints linking dependent investments:

$$\Sigma_j c_j x_j \le B; \quad TOI_{crit}(\omega, x) \ge TOI^{min} \quad \forall \omega \in \Omega_{design}; \quad x_j \le x_k \quad \forall (j,k) \in \Pi; \quad x \in \{0,1\}^n \quad (13)$$

where CRF is the capital recovery factor, Pi the set of prerequisite pairs, and Omega_design the subset of scenarios against which a firm observability floor is required. The loss function EL(omega, x) is nonlinear in x through equations (3), (7), and (10). Two tractable treatments exist: evaluate EL on a precomputed scenario grid and embed it as a piecewise-linear function using special ordered sets of type two, which is exact on the grid; or decompose so the second stage evaluates EL by simulation and generates Benders-type cuts from subgradients, which scales better but requires care since EL is not convex in general. For the tens of candidate actions typical of one service territory, the piecewise-linear treatment solves to optimality in seconds and is recommended.

4.6 Verification and validation protocol

A framework with an unmeasured central parameter must specify falsifiable tests. Three validation tiers are proposed. **Verification** confirms that each computational layer reproduces known analytical cases and that setting (\alpha=0) returns the no-coupling baseline. Internal validation uses temporal cross-validation, estimating parameters on historical events and testing whether predicted restoration durations outperform damage-conditioned historical benchmarks. External validation evaluates economic credibility by comparing direct interruption costs with utility claims and customer surveys, while benchmarking indirect-to-direct loss ratios against published inoperability studies. Results materially outside established ranges should be treated as evidence of model misspecification or parameterization error.

4.7 Decision quantities

Two derived quantities are the framework's practical output. The Marginal Economic Value of Observability is the local sensitivity of expected annual loss to critical-asset observability,

$$MEVO = -\partial E[EL] / \partial TOI_{crit}, \text{ expressed in US dollars per percentage point} \quad (14)$$

and the Communications-Economic Resilience Ratio is the benefit-cost ratio of a candidate portfolio evaluated over the full hazard set,

$$CERR(x) = (E[EL(0)] - E[EL(x)]) / (CRF \cdot \Sigma_j c_j x_j) \quad (15)$$

MEVO answers the planning question of where the next dollar should go. CERR answers the regulatory question of whether the portfolio as a whole is prudent. Both are expressed in units that a commission, a grant reviewer, and a chief financial officer already use, which is the point.

5. Algorithms and Computational Treatment

Planning and restoration should prioritize assets by the economic consequence of lost observability, not solely by electrical size or customers restored. The Observability-Weighted Criticality Ranking (OWCR) estimates the economic loss avoided when an asset's observability is restored, incorporating power-communications dependencies, backup autonomy, restoration delay, and regional consequences. During outages, Observability-Aware Restoration Sequencing (OARS) applies the same principle to crew deployment, ranking feasible repairs by expected economic loss avoided relative to completion time. This allows communications repairs with no immediate customer restoration to outrank power repairs when restored visibility materially accelerates broader system recovery and reduces overall economic disruption.

6. Key Performance Indicator System

A framework that is not instrumented does not change behaviour. Table 4 defines the closed KPI set, organized by layer, with the computation, the unit, an indicative target, and the data source. The set is deliberately small enough to be reported quarterly and specific enough that each indicator has a single owner.

#	Indicator	Computation	Unit	Indicative target	Source system
1	Telemetry Observability Index	Equation (4), all monitored assets	fraction	at least 0.98 blue sky	NMS, SCADA historian
2	Critical-asset TOI	Equation (4) over restoration-critical subset	fraction	at least 0.99 blue sky; at least 0.90 in design event	NMS, OMS
3	Communications Resilience Envelope	Equation (5) over 72-hour window	fraction	at least 0.95 for design event	Model output
4	SRLG overlap fraction	Shared route-km divided by total route-km, hazard weighted	fraction	at most 0.15 for critical paths	GIS route inventory
5	Path Diversity Index	Mean count of SRLG-disjoint paths per critical asset	count	at least 2.0	NMS, GIS
6	Telemetry latency p99	99th percentile end-to-end one-way delay by function class	milliseconds	within Table 3 threshold	Network performance monitoring
7	Packet delivery ratio	Delivered divided by offered telemetry	fraction	at or above function	NMS, protocol

#	Indicator	Computation	Unit	Indicative target	Source system
		datagrams		threshold	gateway
8	Node backup autonomy	Discharge-tested runtime at design load	hours	at least 24 for hub sites	Battery monitoring, test records
9	Observability Restoration Time	Hours from event onset to TOI_crit above 0.90	hours	at most 8	OMS, NMS correlation
10	Restoration Time Inflation Factor	Equation (7) evaluated at realised deficit	ratio	at most 1.10 in design event	Model output
11	Observability-attributable ENS	ENS difference between realised and full-observability counterfactual	MWh	trending down year over year	Model output, OMS
12	Mean time to detect anomalous east-west traffic	Median detection latency inside the security perimeter	minutes	at most 15	INSM platform
13	Marginal Economic Value of Observability	Equation (14)	US$ per percentage point	reported, not targeted	Model output
14	Communications-Economic Resilience Ratio	Equation (15)	ratio	at least 1.5 for funded portfolios	Model output
15	Economic Resilience Index	1 minus realised loss divided by no-mitigation loss	fraction	at least 0.25	Model output
16	Diverse route-km delivered	Constructed route-km meeting the SRLG disjointness test	kilometres	programme specific	Construction close-out records

Table 4. Closed key performance indicator set for the framework. Indicators 1 through 8 are measured, 9 through 12 are observed during and after events, and 13 through 16 are model outputs used in planning and regulatory filings.

Two design choices in Table 4 deserve comment. Indicator 4, the shared-risk overlap fraction, is placed in the measured set rather than the modelled set because it is the single most common source of overstated resilience and because it is verifiable by audit against construction records. Indicator 12 is included not because internal network security monitoring is a resilience measure in the

conventional sense but because the compliance deployment now under way [8] produces the observability telemetry the rest of the set consumes and treating it as a shared asset rather than a sunk compliance cost materially improves the economics of both programmes.

7. Reference Implementation: the ACNR-Sim Toolchain

7.1 Module architecture

The framework is specified as an executable toolchain so that the claims in this paper are falsifiable. The reference implementation is a Python package with six modules and a command-line entry point. It depends only on open scientific libraries and an open-source mixed-integer solver, so that a utility planning group or a regulatory staff analyst can run it without licence acquisition.

Module	Responsibility	Principal inputs	Principal outputs
acnr.topology	Build the layered multigraph; ingest GIS route inventory; compute SRLG overlap	GIS shapefiles, NMS topology export	G_P, G_C, Phi, Psi, theta
acnr.hazard	Generate correlated damage realisations for wind, ice, flood, and adversary scenarios	Fragility curves, hazard intensity fields	Damage sets per scenario
acnr.observe	Evaluate equations (1) through (5) over the event window with autonomy state machine	Topology, damage, latency and PDR statistics	TOI(t), TOI_crit(t), CRE
acnr.restore	Apply the RTIF and run Algorithm 2 for crew sequencing	TOI trajectory, damage set, crew roster	T_r per asset, ENS
acnr.economy	Direct interruption cost and DIIM propagation	Sector cost curves, A*, K, sector outputs	C_dir, C_ind, EL
acnr.invest	Build and solve the two-stage MILP; compute MEVO and CERR	Candidate portfolio, budget, scenario weights	x*, MEVO, CERR, frontier

Table 5. Reference implementation module structure.

7.3 Analyst-facing application

The toolchain is intended to reach planners as a lightweight application with three read-only views over the same model artefacts. A network diversity map renders SRLG overlap on the route inventory and flags critical assets whose nominal redundancy fails the disjointness test, which is in practice the most actionable single output. A scenario explorer replays the observability trajectory of Figure 2 against a chosen hazard and portfolio. A frontier view of the kind in Figure 5 overlays CERR isoquants so a reviewer can see which portfolios clear a prudence threshold.

8. Illustrative Case Study

8.1 System and scenario definition

The framework is exercised on a synthetic metropolitan distribution system structurally representative of a large Midwestern urban and near-suburban service area. No client, site, customer, or proprietary data are used, and the parameters in Table 6 are typical rather than drawn from any particular utility.

Parameter		Value	Parameter	Value
Distribution substations		42	Fiber route-kilometres	640
Feeder-kilometres		1,180	Fiber rings	12
Monitored field devices		3,600	Communications hub sites	8
Restoration-critical devices		1,140	Mean SRLG overlap, critical paths	0.31
Customers served		210,000	Mean path diversity index	1.7
Peak load		1,450 MW	Median hub backup autonomy	8 hours
Large commercial and industrial customers		3,100	Nominal blue-sky TOI	0.982
Data centre load on system		185 MW across 6 sites	Nominal blue-sky critical TOI	0.986

Table 6. Synthetic case study system parameters.

ID	Scenario	Annual frequency	Character	Joint communications damage
S1	Routine convective storms	0.85 per year	Localised feeder damage, 4 to 10 hour restoration	Limited; a small number of pole-mounted radios lost
S2	Derecho	0.20 per year	Widespread wind damage, 200-plus damage locations, multi-day restoration	Severe; OPGW cuts on 3 rings, hub battery exhaustion at hour 11
S3	Severe ice storm	0.05 per year	Structural failures, extended access constraints, 5-day restoration	Severe and prolonged; mobile generation required at 6 hub sites
S4	Coordinated cyber-physical	0.04 per	Edge device compromise degrading routed telemetry	Targeted; telemetry integrity suspect rather

ID	Scenario	Annual frequency	Character	Joint communications damage
	intrusion	year	during a moderate weather event	than absent, forcing manual verification

Table 7. Hazard scenario set. Scenario S4 is patterned on the class of sustained state-sponsored access to communications infrastructure described in recent joint federal advisories [5], [30], in which the operative harm is loss of trust in telemetry rather than loss of telemetry.

8.2 Candidate portfolios

Six nested portfolios were evaluated, from a minimal action to a comprehensive rebuild. Costs are order-of-magnitude estimates consistent with published utility construction unit costs and are used here only to establish relative economics.

Portfolio	Content	Capital cost (US$ M)	Critical TOI in S2	CRE in S2
Baseline	No action	0.0	0.711	0.881
A	Extend hub backup autonomy from 8 to 24 hours at all 8 hubs	12.4	0.784	0.907
B	A plus SRLG remediation on the 3 worst-overlapping rings	21.8	0.826	0.925
C	B plus third diverse fiber path to 4 highest-consequence hubs	34.6	0.861	0.940
D	C plus third diverse path to remaining 4 hubs and private wireless overlay for 240 critical devices	58.0	0.882	0.964
E	D plus mesh radio tertiary bearer for 900 additional devices	79.5	0.894	0.971
F	E plus full ring rebuild to SRLG overlap below 0.10 system wide	104.2	0.901	0.975

Table 8. Candidate investment portfolios and their communications-layer outcomes under scenario S2.

8.3 Observability and restoration results

Figure 2 shows the observability trajectory for the baseline and for portfolio D under scenario S2. The characteristic features are the delayed collapse at hour eleven as hub batteries exhaust, the depressed plateau at 0.711 for the baseline against 0.870 for portfolio D, and the substantially faster observability restoration under the mitigated case, which reaches the 0.90 critical threshold at approximately hour thirty against approximately hour fifty for the baseline.

Applying equation (7) with the illustrative parameters alpha equal to 0.62 and beta equal to 1.35 gives a restoration time inflation factor of 1.106 for the baseline event-average deficit of 0.271, and 1.035 for portfolio D at a deficit of 0.118. In other words, the model attributes approximately a seven percent reduction in restoration duration to the communications portfolio, holding all physical repair work constant. Figure 3 shows how that attribution varies with the convexity exponent, which is the parameter about which the profession currently knows least.

Figure 2. Observability resilience trapezoid, derecho scenario S2

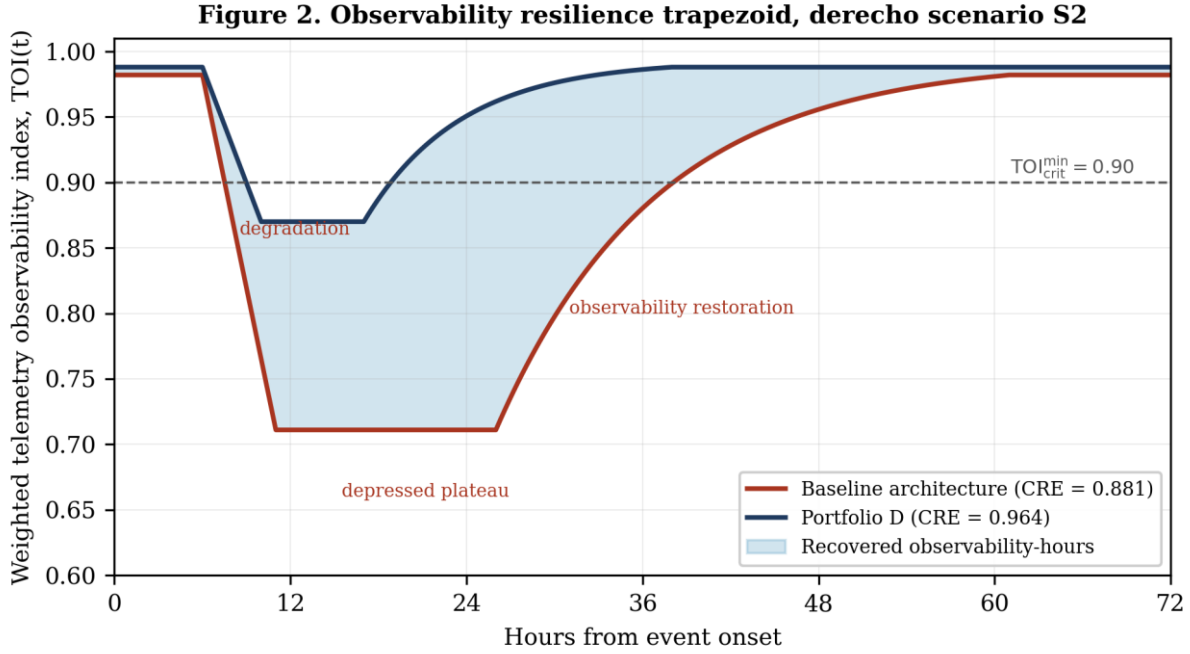


Figure 2. Observability resilience trapezoid for scenario S2. The shaded region is the recovered observability-hours attributable to portfolio D and is the physical quantity the framework monetizes.

Figure 3. Restoration time inflation function, sensitivity to convexity exponent

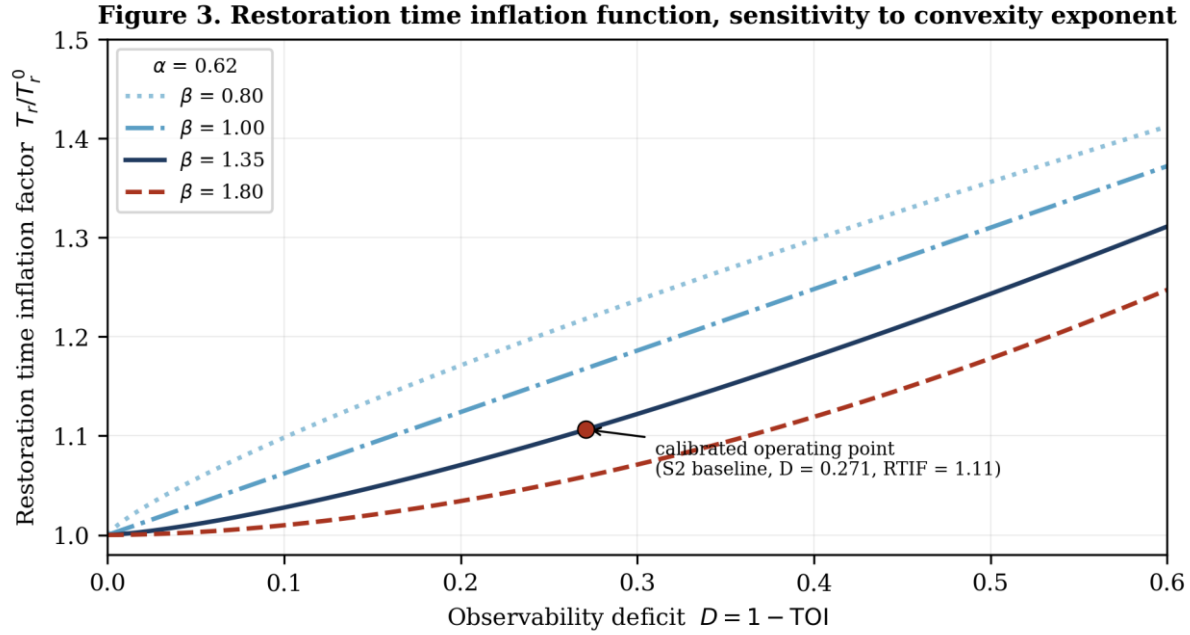


Figure 3. Restoration time inflation function family. The four curves share alpha equal to 0.62 and differ in the convexity exponent. The spread at moderate deficits is the practical reason that empirical estimation of beta is a research priority.

8.4 Economic results

Table 9 decomposes the economic loss for scenario S2. Direct customer interruption cost is computed from sector cost curves of the form documented for the national interruption cost calculator [2], [22]. Propagated loss is computed from the dynamic inoperability kernel with six aggregated sectors, whose trajectories are shown in Figure 4.

Figure 4. DIIM sector inoperability trajectories, scenario S2 baseline

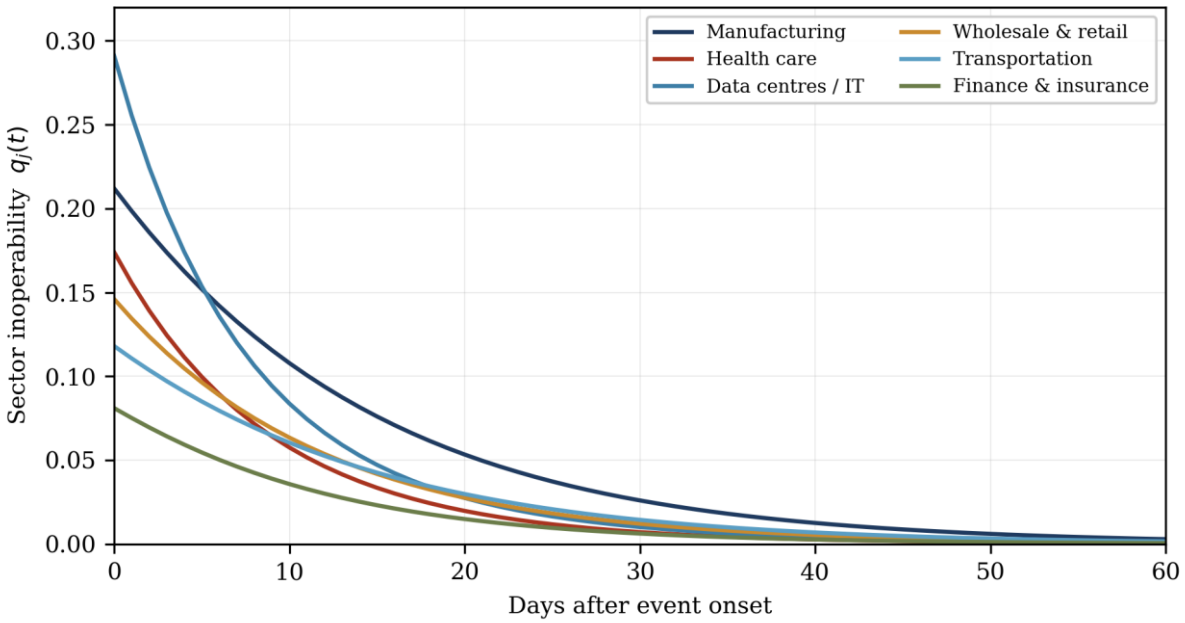


Figure 4. Sector inoperability trajectories under scenario S2, baseline case. The data centre and information technology aggregate shows both the highest initial inoperability and, because of its high recovery rate, one of the shortest tails, which is a structural feature of the input-output kernel and not an artefact of parameterisation.

Loss component	**Baseline (US$ M)**	**Portfolio D (US$ M)**	**Avoided (US$ M)**
Energy not served (GWh)	8.9	6.1	2.8
Direct cost, residential	18.4	12.9	5.5
Direct cost, small commercial	41.7	30.6	11.1
Direct cost, large commercial and industrial	97.3	74.1	23.2
Direct cost, data centre and critical facility	26.9	18.4	8.5
Subtotal, direct	184.3	136.0	48.3
Propagated regional loss, net of overlap	46.9	43.2	3.7

Loss component	Baseline (US$ M)	Portfolio D (US$ M)	Avoided (US$ M)
Total economic loss, scenario S2	231.2	179.2	52.0

Table 9. Economic loss decomposition for scenario S2. The propagated component is reported net of the first-order business interruption already captured in the commercial and industrial direct cost, following the overlap treatment described in Section 4.4.2.

Aggregating across the full hazard set gives the expected annual figures in Table 10, which are the quantities that enter the benefit-cost test.

Scenario	Frequency (per year)	Baseline loss (US$ M)	Portfolio D loss (US$ M)	Avoided per event (US$ M)	Contribution to avoided EAL (US$ M/yr)
S1 Routine storms	0.85	21.4	14.9	6.5	5.53
S2 Derecho	0.20	231.2	179.2	52.0	10.40
S3 Ice storm	0.05	410.0	296.0	114.0	5.70
S4 Cyber-physical	0.04	520.0	383.0	137.0	5.48
Total avoided expected annual loss					27.11

Table 10. Hazard-weighted expected annual loss and the avoided-loss numerator of the benefit-cost ratio.

With a capital recovery factor of 0.1019, corresponding to a twenty-year life at an eight percent weighted average cost of capital, the annualized capital charge for portfolio D is 5.91 million dollars. Equation (15) therefore gives a Communications-Economic Resilience Ratio of 27.11 divided by 5.91, or approximately 4.6. Equation (14), evaluated across the fourteen percentage point improvement in event-average critical observability delivered by portfolio D, gives a Marginal Economic Value of Observability of approximately 1.94 million dollars per percentage point.

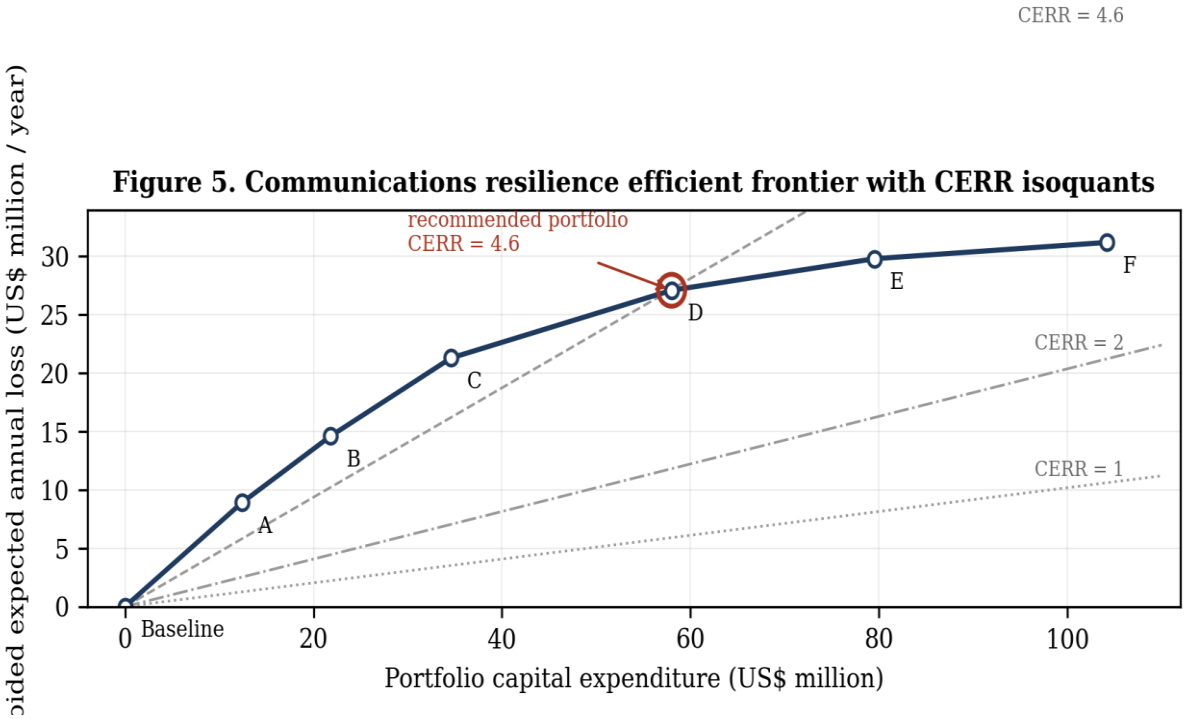


Figure 5. Efficient frontier across the six candidate portfolios with CERR isoquants. Portfolios E and F remain benefit-positive but exhibit sharply diminishing marginal returns, because at that point the binding constraint has shifted from communications availability to physical repair capacity.

9. Projected National Economic and Infrastructural Impact

Sections 3 through 8 establish that the framework closes on a single service territory. This section scales that result to the United States. The purpose is not to forecast. It is to establish the order of magnitude of the national consequence of the measurement gap, so that the priority of closing it can be judged against the cost of closing it. Every figure in this section is a projection from the illustrative parameterization of Section 8, and inherits the uncertainty quantified in Figure 11.

9.1 Scaling method and the addressable base

The national base is the 161.7 million United States electricity customer accounts reported in the federal annual industry survey [37]. The case study system serves 210,000 customers and yields an avoided expected annual loss of 27.11 million dollars for 58 million dollars of capital: 129.10 dollars per customer-year of avoided loss at 276.19 dollars per customer of capital.

Multiplying that unit benefit across the national base would be indefensible. The case study is an urban system with high automation density, a substantial shared-risk deficit to remediate, and 185 MW of data centre load whose interruption costs are far above average. Three corrections are therefore applied. The addressable base is segmented into three tiers by automation density, since the restoration time inflation of equation (7) can only bite where there are automated functions to lose. Each tier receives a transferability factor scaling the per-customer benefit downward from the case study, and a capital factor scaling the per-customer cost, since lower-density systems require less communications plant per customer. Adoption penetration is then applied by tier under three scenarios. Table 11 reports the segmentation and Table 12 the scenario results.

Tier	Description	Customers	Transferability factor	Avoided loss per customer-year	Capital per customer
A	Large investor-owned utilities with high distribution automation density and substantial measurable observability deficit	89.0 M	0.75	$96.82	$234.76
B	Mid-size investor-owned utilities and large municipal systems with partial automation	45.3 M	0.45	$58.09	$193.33
C	Small municipal systems and rural cooperatives with low automation density	27.5 M	0.20	$25.82	$151.90

Table 11. Addressable base segmentation. Transferability factors are the author's judgment, disclosed so a reader may substitute their own; the tier shares are approximate and reflect the concentration of United States customer accounts in large investor-owned systems.

Scenario	Penetration by tier (A / B / C)	Customers reached	Avoided loss (US$B/yr)	Capital (US$B)	Annualised charge (US$B/yr)	CERR
Conservative	25% / 10% / 3%	27.6 M	2.43	6.2	0.63	3.85
Central	55% / 30% / 12%	65.8 M	5.62	14.6	1.49	3.78
Ambitious	80% / 55% / 30%	104.3 M	8.55	22.8	2.32	3.68

Table 12. National projection under three adoption scenarios. Capital is a cumulative programme total; the annualised charge applies a capital recovery factor of 0.1019 corresponding to a twenty-year life at an eight percent weighted average cost of capital.

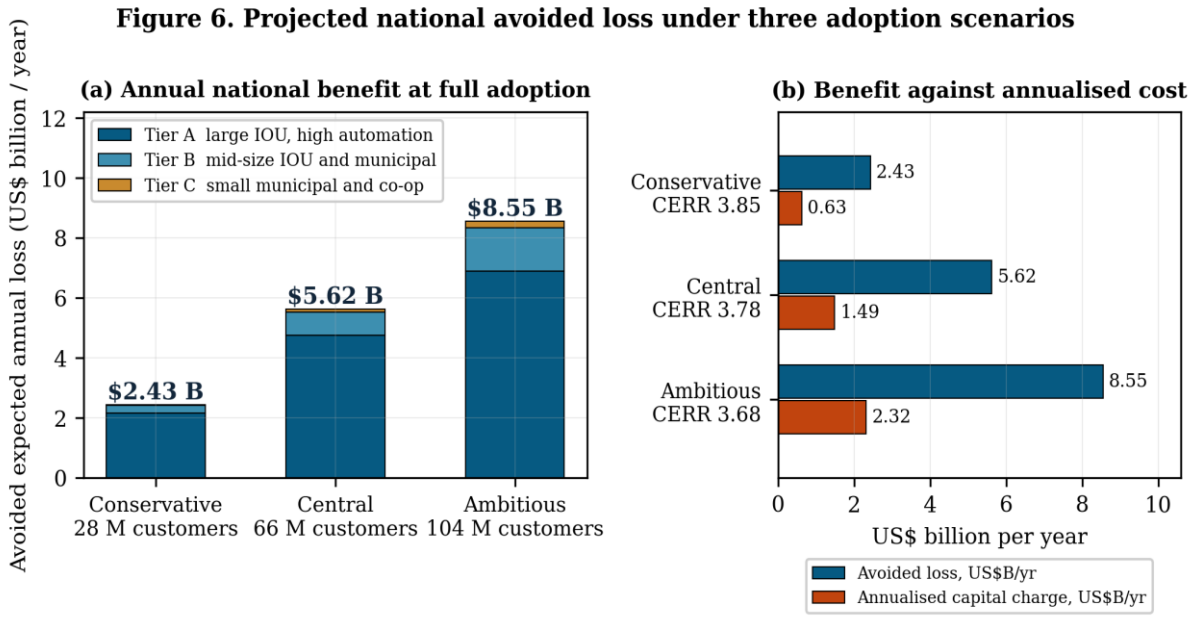


Figure 6. Projected national avoided expected annual loss by adoption scenario, decomposed by utility tier, with the corresponding annualised capital charge and benefit-cost ratio. Tier A supplies between eighty and eighty-eight percent of the benefit in every scenario, because it combines the largest customer count with the highest transferability.

9.2 Magnitude in context

The central scenario projects $5.62 billion annually in avoided economic loss, reaching about 66 million customer accounts through $14.6 billion in cumulative capital, with a Communications-Economic Resilience Ratio of 3.78. Conservative and ambitious scenarios project $2.43 billion and $8.55 billion annually. These estimates remain modest relative to national exposure: major-outage customer costs averaged over $67 billion annually from 2018–2024 and reached $121 billion in 2024, while major outages increased from 4,666 to 6,533 and average duration rose from 9.6 to 11.8 hours [38]. Commercial and industrial customers incurred approximately $6,031 per outage in 2024 [38].

9.3 Deployment path and public capital exposure

Figure 7 shows the central scenario on a logistic adoption path from 2027 through 2037. Two features matter for policy. Annual capital outlay peaks near 2.5 billion dollars in the early 2030s and then declines as the addressable base is exhausted, so the programme is self-limiting rather than open-ended. And the run-rate benefit crosses above the annual outlay around 2032, five to six years into deployment, after which the programme is cash-positive in economic terms while capital is still being spent. Cumulative avoided loss over the eleven-year window is 32.5 billion dollars against 14.6 billion of capital; discounted at eight percent, the benefit-cost ratio over the window alone is 1.9, rising thereafter because the assets continue to deliver after the capital programme ends.

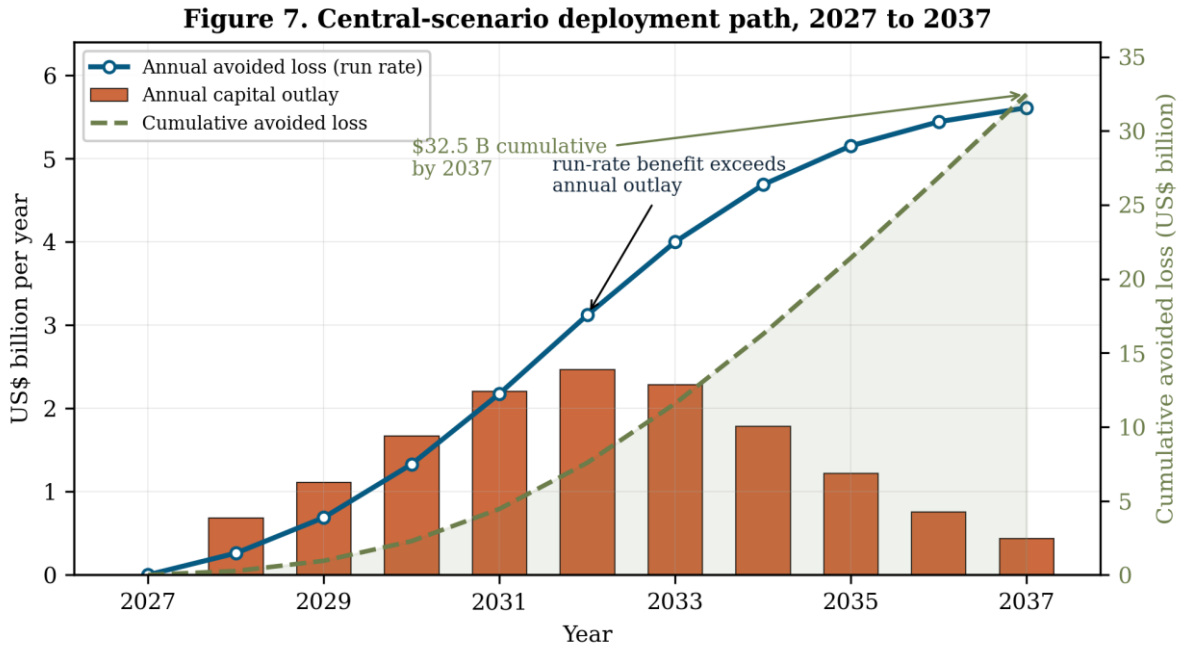


Figure 7. Central-scenario deployment path. Annual capital outlay is self-limiting; the run-rate benefit crosses above it in the early 2030s.

9.4 Sector incidence and employment

Because the economic kernel of Section 4.4 is sector-resolved, the projected benefit can be attributed to the industries that receive it. Figure 8 allocates the central-scenario benefit using the sector structure of the dynamic inoperability kernel and the direct cost shares of Table 9. Manufacturing receives the largest share at approximately 1.36 billion dollars per year, followed by the data centre, information technology, and communications aggregate at 1.05 billion. Health care and social assistance receives 0.68 billion, which understates its social significance because the framework monetizes only interruption cost and not health outcomes.

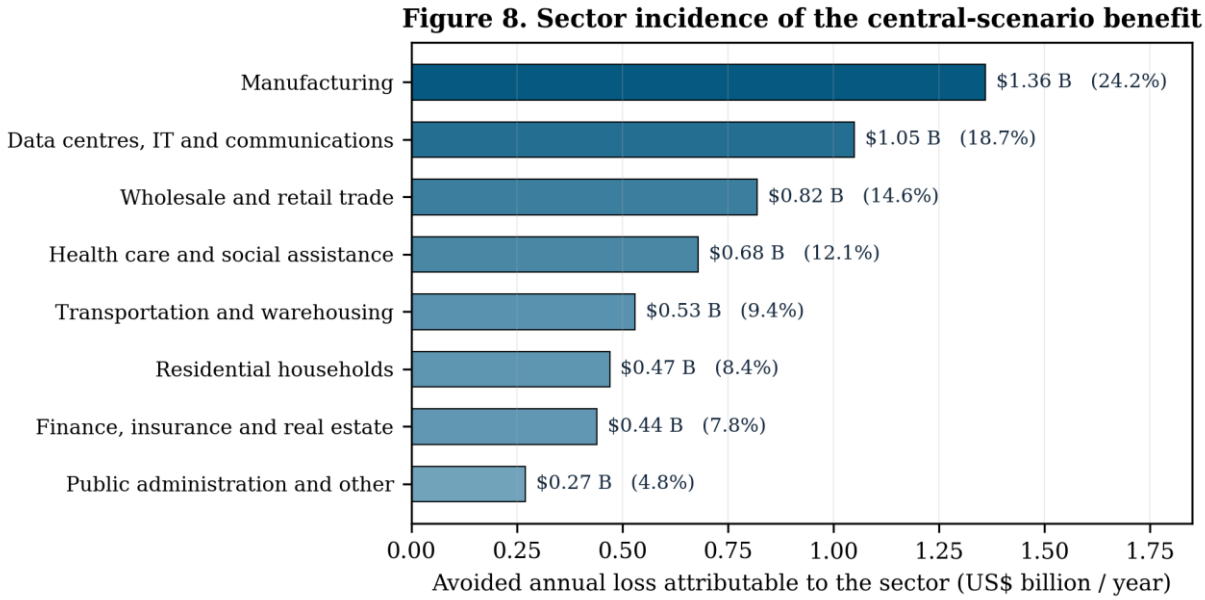


Figure 8. Sector incidence of the central-scenario benefit. Manufacturing and the data centre aggregate together receive approximately forty-three percent, reflecting both high interruption cost intensity and high electricity dependence.

The $14.6 billion central-scenario capital programme would generate substantial domestic economic activity through fiber deployment, splicing, tower work, radio commissioning, battery installation, engineering, and project management. Using 7.0–11.5 job-years per $1 million invested, it supports approximately 102,000–168,000 job-years, or 10,000–17,000 annual full-time-equivalent positions over ten years.

9.5 Public capital efficiency

The framework's largest near-term fiscal effect may be on how existing appropriations are spent rather than on how much is spent. Federal grid resilience programmes have obligated capital at the ten-billion-dollar scale [7], and award scoring rewards demonstrated resilience benefit without a common denominator that distinguishes genuine route diversity from parallel capacity on a shared route. Figure 9 quantifies the arithmetic. If CERR screening reallocated twenty percent of a 10.5 billion dollar appropriation from projects with an effective ratio near 1.4 to projects near 3.2, the additional avoided loss is approximately 0.39 billion dollars per year from the same appropriated dollars, with no increase in outlay. At a thirty-five percent reallocation the figure approaches 0.67 billion.

Figure 9. Capital efficiency gain from CERR-based award screening

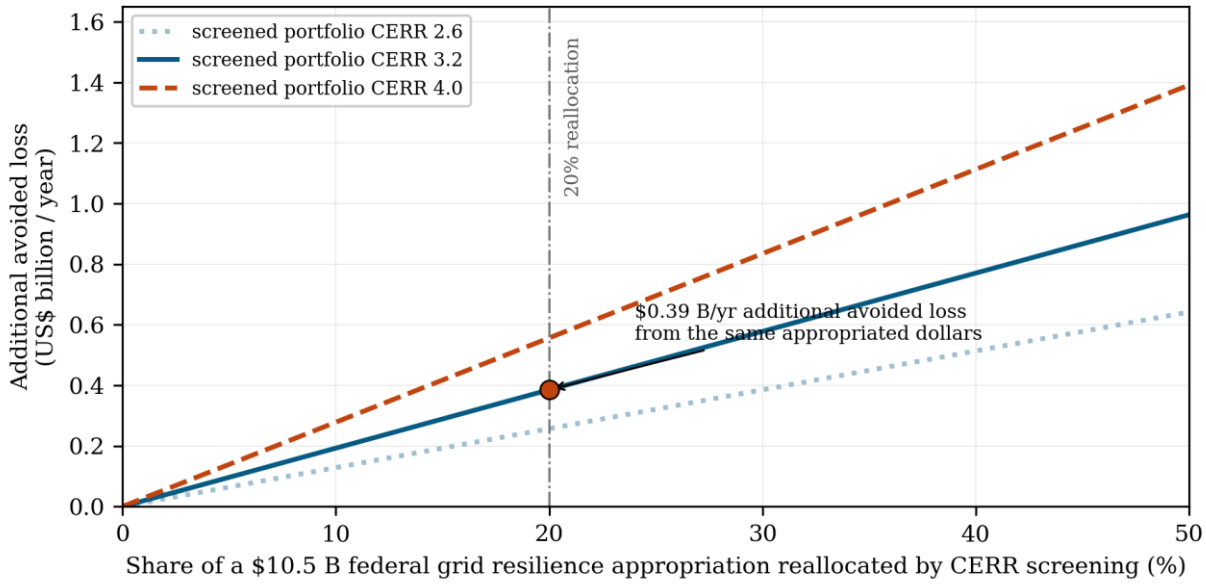


Figure 9. Additional avoided loss obtainable by reallocating a share of a federal appropriation toward higher-CERR projects. The gain requires no additional appropriation, only a scoring denominator.

9.6 Geographic incidence

Outage exposure is highly concentrated. The national analysis found the highest single-state annual customer cost rising from 7.8 billion dollars in 2018 to 38.9 billion in 2024, with Texas accumulating more than 80 billion over the study period and Louisiana, California, Michigan, and Virginia persistently costly irrespective of weather [38]. Figure 10 compares each state's share of national major-outage customer cost against its projected share of the central-scenario benefit.

Figure 10. Geographic concentration of exposure and projected benefit

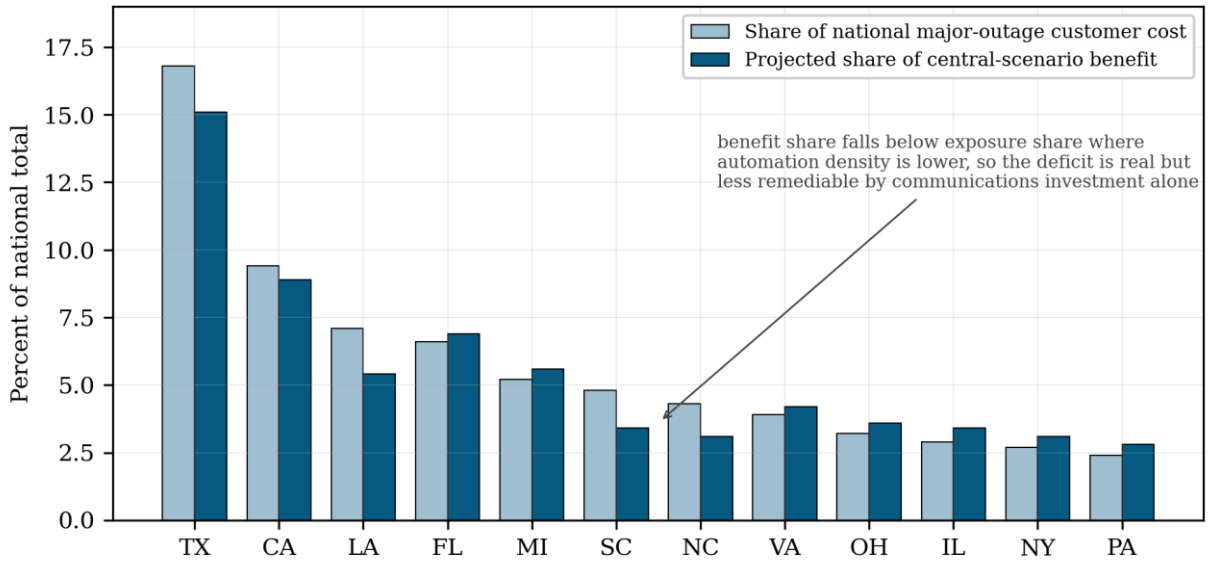


Figure 10. Geographic concentration of exposure and projected benefit. Where projected benefit share falls below exposure share, the observability deficit is real but less remediable by communications investment alone, because there is less automation whose loss the deficit degrades.

The divergence between the two bars is the policy-relevant signal. States where projected benefit share falls materially below exposure share are those whose losses are dominated by physical damage on systems with limited automation. For those states the correct inference is not that communications investment is worthless but that its benefit is contingent on the automation investment it serves, which is an argument for sequencing rather than for abandonment. States where the bars are close, or where benefit share exceeds exposure share, are systems in which observability is already the binding constraint.

9.7 Infrastructural impact

Economic figures describe consequence; the physical programme describes what would actually be built. Scaling the case study portfolio to the central scenario gives the deliverables in Table 13. These are the tangible national outcomes: roughly 90,000 kilometres of genuinely diverse fiber route, about 2,500 communications hub sites carried from eight-hour to twenty-four-hour autonomy, and approximately 1.1 million monitored field devices brought under a measured observability indicator for the first time.

Infrastructural deliverable	Case study system	Central scenario, national	Character of the outcome
Substations within scope	42	approximately 13,200	Observability instrumented and reported at substation granularity
Diverse fiber route added	288 km	approximately 90,000 km	Route-km meeting the shared-risk disjointness test, not merely parallel capacity
Communications hubs at 24-hour autonomy	8	approximately 2,500	Ride-through beyond the battery cliff that drives the Figure 2 plateau
Critical devices on a diverse bearer	240	approximately 75,000	Restoration-critical devices with an independent secondary path
Monitored devices under a TOI indicator	3,600	approximately 1.1 M	Devices whose observability becomes a reported, auditable quantity
Shared-risk overlap on critical paths	0.31 to 0.12	programme dependent	The measured reduction in common-mode exposure

Table 13. Infrastructural deliverables at national scale under the central adoption scenario, obtained by scaling the case study portfolio by customers reached.

Two of these outcomes are institutional rather than physical, and are arguably more durable. The first is that the shared-risk overlap fraction becomes a reported design quantity, which changes what utilities build rather than merely how they describe it. The second is that approximately 1.1 million field devices acquire an observability figure that appears in a planning document and can be audited, which is the precondition for any subsequent empirical work on the coupling parameter. A national deployment would, as a by-product, generate the dataset that would allow the framework's own central assumption to be tested and, if necessary, refuted.

9.8 Conditions under which the projection fails

The projection depends on four empirically testable conditions. First, if observability elasticity is near zero, restoration remains dominated by physical repair constraints and projected benefits fall sharply, reinforcing the importance of the identification strategy in Section 4.3.1. Second, persistent crew or access constraints may limit gains from improved observability, as reflected in the diminishing returns shown in Figure 5. Third, adoption may lag because of rate-case outcomes, competing capital priorities, supply-chain constraints, or skilled-labour shortages, reducing penetration below Table 12 assumptions. Fourth, lower-cost alternative communications technologies could reduce required capital while increasing benefit-cost performance.**10. Discussion**

10.1 What the results do and do not establish

The numerical results are model outputs under stated assumptions, not empirical claims. Their purpose is to demonstrate internal consistency, unit reconciliation, and the practical usefulness of the proposed decision metrics. A CERR of 4.6 would indicate a strong benefit-cost case, while a MEVO approaching $2 million per percentage point could directly support capital prioritization. The contribution is that these quantities can be computed systematically.

The results also reveal the framework's principal uncertainty. Figure 11 shows that MEVO is most sensitive to the observability elasticity (\alpha), followed by the convexity parameter (\beta) and sector cost multiplier. This is significant because (\alpha) and (\beta) remain empirically unestimated, whereas sector costs are supported by national survey data [2] and the economic structure by established national accounts.

Figure 11. Tornado sensitivity of the marginal economic value of observability

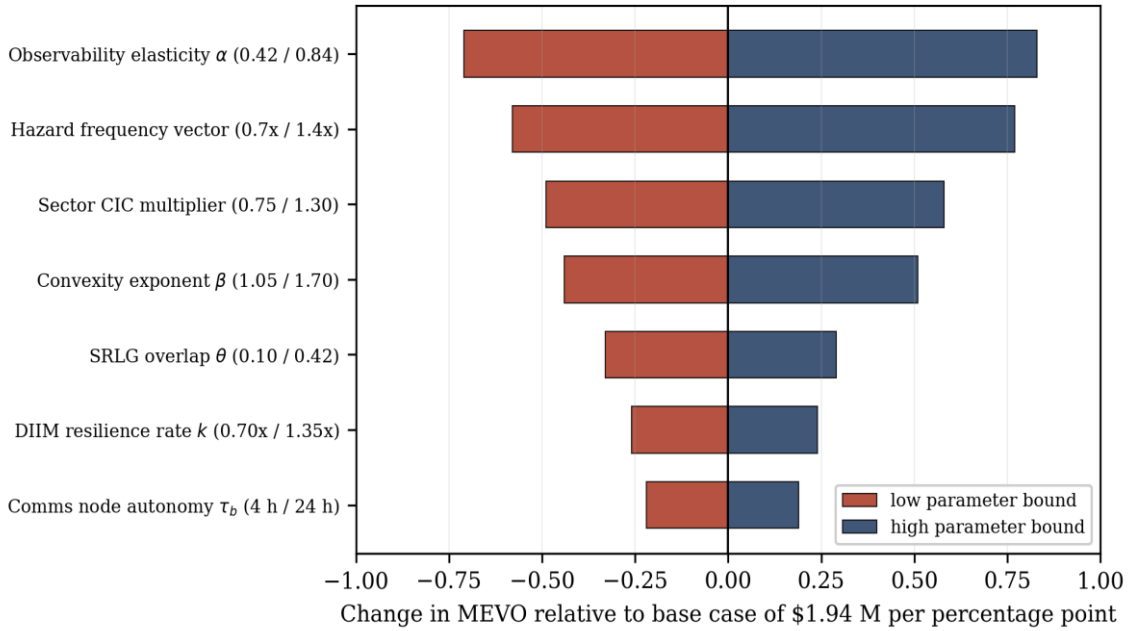


Figure 11. Tornado sensitivity of the marginal economic value of observability. The two coupling parameters introduced by this framework account for the largest share of output uncertainty, which is the empirical agenda the paper proposes.

Parameter	Low	Base	High	Basis for the range
Observability	0.42	0.62	0.84	Assumed; no published estimate exists.

Parameter	Low	Base	High	Basis for the range
elasticity, alpha				Range spans plausible values from restoration practice.
Convexity exponent, beta	1.05	1.35	1.70	Assumed; range spans near-linear to strongly convex response.
Sector interruption cost multiplier	0.75	1.00	1.30	Dispersion across survey territories in the national cost estimation programme [2].
SRLG overlap, theta	0.10	0.31	0.42	Observed variation between well-designed and legacy urban route structures.
DIIM recovery rate scaling	0.70x	1.00x	1.35x	Dispersion in published sector recovery rate estimates [3], [4], [18].
Hub backup autonomy	4 h	8 h	24 h	Range from minimum practice to hardened design.
Hazard frequency vector	0.70x	1.00x	1.40x	Uncertainty in major-event frequency; national interruption statistics show substantial interannual variation [1].

Table 14. Sensitivity parameter ranges.

10.2 Why the coupling parameter has not been estimated

Three explanations for why a quantity this consequential remains unmeasured are plausible and not mutually exclusive. The first is data locality: outage records and communications performance records sit in different systems owned by different departments with no shared event key, so the join that equation (8) requires is organizationally rather than technically difficult. The second is the absence of a consumer: because reliability indices do not decompose by mechanism, no existing planning or regulatory process would use alpha if it were known. The third is that identification requires a system in transition, and the current wave of distribution automation has only recently produced the necessary cross-sectional variation.

The third explanation implies a closing window. As distribution automation approaches saturation, the cross-sectional variation in observability that permits identification will shrink. The estimation should be done now.

10.3 Relationship to existing engineering formulations

The framework does not replace the cyber-physical restoration optimizations developed in the power systems literature [13], [14], [15]; it sits above them. Those formulations solve, at high fidelity, how to sequence repairs given a damage state and a communications topology. The framework supplies the objective function they should be optimizing, in monetary units, and the investment layer determining which topology they are handed in the first place. Utilities already operating such tools should substitute them for the greedy heuristic of Algorithm 2 while retaining the economic kernel of Layer 4.

The framework is likewise agnostic about the source of its availability inputs. Where a co-simulation environment exists [25], [26], the Layer 1 trajectory can be produced at far higher fidelity than equation (3) permits; where machine learning fault prediction is in production [19], [20], its outputs can replace the fragility-based hazard model. The contribution is the coupling and the decision layer, not the constituent physics.

10.4 Comparison against alternative resilience capital

A benefit-cost ratio is meaningful only when compared with investments competing for the same capital. Utility resilience portfolios commonly include vegetation management, undergrounding, pole and conductor hardening, and distribution automation. Communications investment does not substitute for these measures. Rather, it complements automation by providing the connectivity required for automated assets to deliver their intended resilience benefits.

Vegetation management and hardening reduce physical damage, while undergrounding reduces exposure. Automation shortens restoration duration, but its effectiveness depends on reliable communications. This dependency explains why communications capital is often undervalued: its benefit is realized through another asset class, causing conventional attribution methods to credit the switching equipment while overlooking the network that enables it.

Accordingly, communications investments should be evaluated alongside the automation they support rather than against hardening measures addressing different failure mechanisms. In the case study, hub backup autonomy delivers 33 percent of avoided expected annual loss while representing only 21 percent of recommended portfolio capital. This illustrates how relatively modest communications investments can materially increase the resilience value of larger automation portfolios.

11. Practical and Policy Implications

11.1 Utility planning practice

The immediate practical implication is a change in how communications capital is queued. Under current practice, fiber and wireless projects compete for capital against physical hardening projects using a benefit measure that cannot represent their mechanism of action, and they consequently lose. Under the framework, the same projects are ranked by Algorithm 1 on marginal economic consequence, and the ranking will differ substantially from an asset-size ranking. In the case study, the highest-consequence single action is not the largest fiber build but the extension of hub backup autonomy, which is inexpensive, unglamorous, and delivers 33 percent of the total avoided expected annual loss for 21 percent of the capital of the recommended portfolio.

A second implication concerns project scoping. The shared-risk overlap fraction of Table 4 is measurable at design stage and is often the difference between a redundant route and a genuinely diverse one. In the author's programme experience across substation, fiber, and telecommunications delivery, nominal redundancy that fails the disjointness test is common and arises for rational construction reasons: shared duct is cheaper, shared manholes are already permitted, and shared crossings are the only crossings. The framework does not make those choices wrong. It makes their resilience cost visible when the choice is made rather than after the event that exploits it.

11.2 Regulatory and rate proceedings

The framework supplies state commissions a testable structure rather than an assertion. A utility filing a communications capital request must disclose its observability index, shared-risk overlap, estimated coupling parameters with standard errors, and resulting CERR. Each is auditable: intervenors can challenge the coupling estimate econometrically, the overlap fraction against construction records, or the cost curves against the national survey basis. That is a substantial improvement on the present position, in which the benefit is asserted qualitatively because no quantitative structure exists to contest.

The framework also supplies a natural prudence threshold. Because CERR is a ratio of avoided expected annual loss to annualized capital charge, a value below unity indicates that the portfolio destroys value at the stated hazard frequencies, and the utility should be required to justify the frequencies rather than the portfolio.

11.3 Federal programme design

Grid resilience grant programmes have deployed capital at very large scale, with more than seven billion dollars announced across the first two rounds of one such programme and further rounds since opened [7]. The framework offers programme designers three instruments: CERR is comparable across applicants of very different size because it is a ratio; the shared-risk overlap fraction distinguishes applications purchasing genuine diversity from those purchasing parallel capacity on a common route, a distinction current rubrics cannot make; and observability restoration time gives a post-award performance measure verifiable from operational records rather than self-reported. Section 9.5 quantifies the capital efficiency at stake.

At the national level, the recurring risk management planning cycle established by current policy [6], [29] requires cross-sector consequence assessment. Energy and communications are mutually dependent in a way that resists sector-specific metrics: an energy metric cannot value a communications asset, and vice versa. Monetized regional loss is the natural common currency, and the framework lets sector risk management agencies compute it consistently in both directions.

11.4 Alignment with mandatory security investment

Internal network security monitoring is now a mandatory reliability standard for high and medium impact bulk electric system cyber systems, with deadlines in 2028 for control centres and 2030 for other applicable systems [8]. Utilities treat this as a compliance cost; the framework reframes it as shared infrastructure. Sensors deployed for the standard observe east-west traffic within the security perimeter and therefore produce, at no marginal cost, the latency, delivery, and reachability statistics equations (1) and (2) require. A utility that architects its deployment with the observability index in mind obtains a resilience planning capability as a by-product of a compliance obligation. One that does not will pay twice.

11.5 A staged adoption sequence

A utility adopting the framework does not need to implement all five layers before obtaining value. The layers are ordered so that each stage produces a usable output on its own, which matters because a programme that requires full implementation before any benefit is visible will not survive its first budget cycle.

Stage one computes the shared-risk overlap fraction from the existing geographic information system and reports it for critical paths. This requires no new instrumentation, no economic modelling, and no coupling parameter, and it typically identifies within weeks a set of assets whose nominal redundancy fails the disjointness test. Stage two adds latency and delivery measurement from the network monitoring platform, producing the graded observability index of equation (1) and a blue-

sky baseline. Stage three reconstructs observability during historical events from alarm and polling records, which yields the observability restoration time indicator and, critically, the paired dataset from which the coupling parameters can be estimated.

Only at stage four does the economic layer engage, and only at stage five the capital optimization. A utility that stops after stage three has still acquired a measured resilience indicator, an auditable diversity metric, and the empirical basis for its own coupling estimate, which is a substantially better position than the one it started from. The staging also distributes cost: stages one through three draw on data and systems the utility already owns, and the incremental spend is analytical rather than capital.

Policy Instrument	Current Limitation	Framework Contribution
State Rate Proceedings	Communications benefits are often qualitative and lack a contestable valuation structure.	CERR provides auditable inputs, disclosed coupling parameters, and statistical uncertainty.
Federal Resilience Grants	Scoring may not distinguish redundancy from genuine network diversity.	SRLG overlap supports diversity-based scoring, while CERR enables size-neutral comparison.
Cross-Sector National Risk Planning	No common consequence metric directly links energy and communications-sector risks.	Provides a consistent monetized regional-loss metric for cross-sector and cascading impacts.
Mandatory Internal Network Monitoring	Monitoring is often treated primarily as a compliance cost.	Reuses monitoring telemetry as the observability data layer for resilience analysis.
Utility Integrated Resource and Distribution Planning	Communications capital may be ranked by asset size rather than economic consequence.	Prioritizes investments by marginal economic consequence through OWCR.
Post-Event Regulatory Review	Restoration performance is assessed without explicitly accounting for observability.	Introduces observability-related restoration delay and inflation measures as review evidence.

Table 15. Mapping of framework outputs to policy instruments.

12. Limitations and Threats to Validity

Five limitations constrain this framework. First, the coupling parameters are assumed rather than empirically estimated, so all monetary results inherit this uncertainty. Second, equation (7) imposes a power-law relationship, although threshold or logistic behavior may better fit observed restoration dynamics. Third, the shared-risk correction captures route-level common-mode failure but not correlated failures from power supply, firmware, operator error, or adversary access [5], [30]. Fourth, the economic layer inherits input-output limitations, including fixed coefficients and limited substitution effects [16], [17], [34], [35]. Fifth, distributed energy resources are modeled as observed

assets rather than active restoration participants, despite emerging interoperability opportunities [31], [32].

13. Future Work

Four extensions follow directly. First, the coupling parameters should be empirically estimated using real utility outage histories and staged construction as quasi-experimental variation. Second, high-fidelity co-simulation could replace analytic availability models, capturing protocol-level effects such as routing convergence and congestion [25], [26], while sequential-extreme-event models provide a suitable test environment [36]. Third, graph-based learned surrogates could accelerate resilience inference and enable Shapley-style attribution at practical computational cost [19], [20], [28]. Fourth, a bidirectional multi-sector formulation could jointly represent energy and communications dependencies, supporting the cross-sector risk assessments required under national critical-infrastructure policy [6], [33]

14. Conclusion

The economic value of communications resilience remains largely invisible in U.S. critical-infrastructure investment decisions because reliability metrics, interruption-cost models, and communications engineering lack a common measurement structure. This paper proposes a framework that links communications observability to restoration duration, economic consequence, and capital allocation. It combines a criticality-weighted observability index, shared-risk correction, restoration inflation modeling, direct and indirect economic-loss estimation, and stochastic optimization. Under the central scenario, adoption could avoid approximately $5.5 billion in annual economic loss through roughly $15 billion in staged capital investment. The framework remains proposed rather than validated, with its central coupling parameter requiring empirical estimation. Establishing that parameter from existing utility records would transform communications resilience from an engineering assumption into a measurable, economically defensible infrastructure investment.

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ECONOMIC RESILIENCE IN THE 5G/6G ERA: A TECHNICAL FRAMEWORK FOR SECURE, OPTIMIZED WIRELESS INFRASTRUCTURE AND U.S. CRITICAL INFRASTRUCTURE CONTINUITY

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Abstract

The shift from 5G to 6G wireless architectures signifies a shift in the operational fabric of modern industrial societies, from simply mobile broadband to a hyper-connected ecosystem of Cyber-Physical Systems (CPS). As the United States integrates these advanced communication protocols into critical infrastructure, e.g., smart grids, autonomous transportation, and automated manufacturing, the economic stakes for network reliability have been elevated from operational matters to matters of national security. This paper presents the Intelligent Autonomous Resilience (IAR) framework, a multi-layered, technical framework that aims to ensure infrastructure continuity and economic stability in the 6G era. By combining stochastic modeling of network reliability and multi-objective optimization of resource allocation, the IAR framework responds to the unique vulnerabilities of decentralized, software-defined 6G environments. We characterize the strategic landscape of 6G ecosystems, with a discussion of the role of standards establishing security protocols to ensure U.S. competitiveness. Our technique employs the use of continuous-time Markov chains to assess the costs of network downtime and cross-layer optimization algorithms to plan for service continuity when facing cyber-physical shocks. Initial parameterizations of the simulation suggest that maximizing an increase of "Trust-Latency Product" is far more advantageous than maximizing raw throughput, as it significantly improves economic resilience of the system. This research is a technical starting point for policy makers and engineers to design a wireless grid, resilient to sophisticated threats, with economic vitality supported by innovation.

Keywords: Economic Resilience, 5g/6g Era, Technical Framework, Optimized Wireless Infrastructure, U.S. Critical Infrastructure Continuity

1. INTRODUCTION

The global telecommunications environment is in the midst of a paradigm shift in that the deployment of 5G is maturing and the vision for 6G is beginning. This is not simply a technical upgrade to data rates or spectral efficiency, but a strategic reconfiguration of how national economies operate. In the U.S., the introduction and convergence of ultra-high speed, low-latency wireless networks into the critical infrastructure, has created a structural interdependence of digital connectivity and economic output. Competition over these technologies sits inside a wider great-power rivalry, where leadership in the research and development of security protocols stands in for future geopolitical leadership and security [1].

While 6G aims to deliver near-instantaneous connectivity employing terahertz frequencies (THz) of wireless infrastructures and integrated artificial intelligence, the complexity of the newly created network architecture has risen exponentially. This complexity creates new attack surfaces and systemic risks that legacy systems will be incapable of protecting. Resilience of this infrastructure is

paramount to maintain the U.S. competitiveness in emerging sectors such as in the metaverse, autonomous logistics, and decentralized energy markets [2]. Economic resilience is described as the ability of national infrastructure to absorb shocks, whether a cyber-attack on computing hardware, a hardware failure in devices, or a natural disaster, while maintaining some of the essential functions necessary to allow economic continuity. The present difficulty is that, while 6G promises new levels of performance, the protocols enabling its functioning are becoming increasingly susceptible to sophisticated vulnerabilities. From False Data Injection (FDI) in smart grids to firmware manipulation of electric vehicle charging stations, the risk of localized network outages precipitating an economic crisis at the systemic level is a growing concern [3]. The U.S. must also navigate a complicated balance of international standards and domestic policy coalitions, ranging from deep engagement to selective decoupling to protect the critical supply chains [1].

This manuscript addresses these challenges by introducing the Intelligent Autonomous Resilience (IAR) framework. The framework builds resilience into the 6G architecture itself, through autonomous optimization and predictive fault detection. Treating network reliability as a tuneable economic asset gives the framework a direct technical link between engineering capability and macroeconomic stability. The emergence of 6G demands a pivot to "Industry X" in which 5G/6G and the combination of AI and edge computing requires an all-inclusive security framework that does not allow vulnerabilities to roll through the industrial ecosystem [4].

The manuscript proceeds as follows. Section 2 reviews the literature and technical context to 6G evolution and infrastructure vulnerabilities. Section 3 discusses the methodology and mathematical modeling for quantifying resilience. Section 4 presents the architecture for the IAR framework. Section 5 provides quantitative results and technical analysis. Section 6 discusses policy implications for U.S. critical infrastructure protection. Section 7 concludes with a summary of findings and future research directions.

2. Literature Review and Technical Context

2.1 Evolution of 5G to 6G and the U.S. Strategic Landscape

The move from 5G to 6G shifts the organizing idea from "connected people and things," to a "connected intelligence". 5G introduced network slicing and Ultra-Reliable Low-Latency Communications (URLLC). 6G is expected to go further, joining sensing, communication and computation into a single fabric. This all takes place in the context of a heightened strategic technological race, particularly between China and the U.S. Since approximately 2018, China has pursued an aggressive state-led industrial policy to set international standards of AI and telecommunications standards, rationalizing standard-setting as a key conduit for technology diffusion and market advantage [5].

In response to challenges raised by China, the U.S. has adopted a "flexilateral" approach by definitively promoting multilateral collaboration with trusted partners, while also enacting plans of selective decoupling in critical sectors [1]. The U.S. strategic landscape is characterized by the need to secure the "Trusted Network" ecosystem, fundamentally ensuring that the hardware and software underpinning the 6G connectivity are free from interference from any foreign actor. As well, it is clear that 6G will rely heavily on open-source approaches and market-led standardization

mechanisms to spur innovation [5]. U.S. leadership in any international standards will in part influence the U.S. capacity to export our technological values, in turn protecting a U.S. competitiveness in the global digital economy. In addition, the transition to 6G means exploring unlicensed spectrum bands below 8 GHz and the creation of new frequency frontiers within the Terahertz (THz) spectrum. These developments address pressing spectrum constraints, while, at the same time, raising obstacles to interference management, which will need rigorous regulations [6]. The U.S. must facilitate innovation in these bands while ensuring that the operational and security needs of critical infrastructure are met, leveraging the "unlicensed" nature of certain spectrum segments in a way that prevents adversarial actors from exploiting them as back doors.

2.2 Current Vulnerabilities in Critical Infrastructure Wireless Protocols

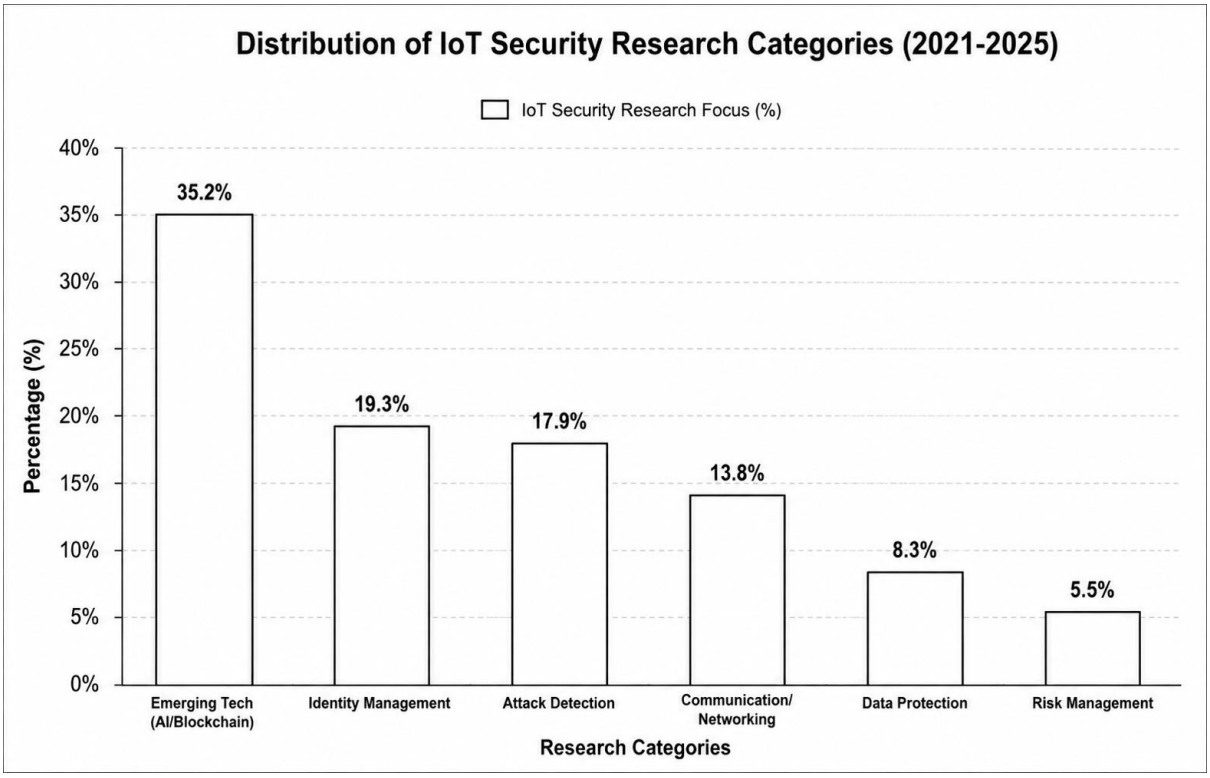
Critical Infrastructure, as fueled by the Industrial Internet of Things (IIoT), will face a variety of security threats that take advantage of the multilayered nature of the communication stack. Research has classified these into either physical, or network layer and application layer attacks, as IoT Security remains a leading hurdle to their proper maturation and adoption [7]. For example, the dependency of energy critical infrastructure on 5G/6G and IoT devices for real time monitoring within the Smart Grid are vulnerable to potential False Data Injection (FDI) attacks, which can harm operational cyber-physical systems as well as data integrity [8].

Electric Vehicle Charging Infrastructure (EVCS) is another critical node of vulnerability. As EVs enter the Internet of Vehicles (IoV) vernacular, EVCSs can suffer from spoofing, and firmware attacks that jeopardize either user or grid privacy [3]. The nature of inter-connectivity in 6G will be beneficial for the efficiency of the related systems, but also provides adversaries with yet another avenue to infiltrate their targets. If they can gain access to a vulnerable node within these EVCSs, for example, they can launch malfeasance initiatives that can propagate to other components within the hyper-connected "Industry X" ecosystem [4].

As another consideration, quantum computing poses a long-term threat to existing traditional cryptographic algorithms used in Transportation Cyber-Physical Systems (TCPS). These standardized algorithms include RSA and ECC, that are vulnerable to Shor's algorithm, and the transition to post-quantum cryptography (PQC) will be the only means of mitigating long-term data confidentiality and integrity concerns [9]. The challenge of 6G will be to incorporate, and effectively implement these compute-expensive PQC schemes in a manner that does not violate ultra-low latency needs as required by safety-critical applications. Advances in AI and Machine Learning (ML) for network slicing also introduce risks associated with "adversarial AI," by which adversaries can create sophisticated ML model alterations with the intention of gaining unauthorized access to virtual network resources [10].

2.3 Economic Resilience Theories in the Context of Digital Hyper-Connectivity

Recovering from physical disasters is no longer a sufficient standard of economic resilience. A hyper-connected environment demands digital continuity. The theory has moved toward agility, diversity, and plurality, which makes resilience an active process requiring citizens, the private sector, and research communities to take part [11]. With respect to 6G this means that the network needs to have the capacity to reconfigure dynamically in a manner that utilizes other pathways should any node fail, while maintaining critical services.



The macroeconomic consequences that arise due to network outages can be assessed through an indirect measurement of the costs of power outages. The estimated cost of power outages is around $150 billion each year for the U.S. economy, with a considerable factor coming as a result of natural hazards [12]. In a 6G-enabled economy, where manufacturing, logistics, and finance are all connected through the wireless grid, the "Cost of Downtime" of communication networks may be of a similar order. Research on frameworks for urban resilience shows a need for connecting theoretical frameworks to quantitative measures to help cities prepare for shocks [13].

Digital twins and machine-learning monitoring are emerging as ways to improve this resilience. Digital twins create a digital replica of the physical infrastructure, which allows operators to do real-time threat mitigation, and predictive maintenance to allow monitoring of gaps and vulnerabilities prior to being exploited [3]. The efficacy of these interventions relies heavily on the quality of the dataset and how the deep learning models can separate random hardware noise and deliberate attacks [14]. Hence, the economic value of the 6G link is not only tied to throughput but also to the "availability" of that link, as well as "trust" related to the associated data streams.

The graphic presented above, based on conducting a recent literature review, shows AI and blockchain are emerging technologies that are attracting significant attention (35.2%), while still needing to embed risk management (5.5%) and data protection (8.3%) more comprehensively in the domain of IoT [15]. This imbalance indicates a gap which the IAR framework seeks to address by embedding risk management for autonomous network operations.

3. Methodology and Mathematical Modeling

3.1 Stochastic Modeling of Network Reliability and Downtime Costs

To quantify the resilience of U.S. critical infrastructure in the 6G era, this study applies continuous-time Markov chain (CTMC) modeling. Network operation is represented by three states,

$$, S = \{S_0, S_1, S_2\},$$

So where denotes normal operation, S1 represents degraded performance caused by latency, interference, cyberattacks, or hardware faults, and S2 represents complete service failure

Network-state transitions reflect the frequency and severity of cyber threats, hardware failures, interference, and other operational disruptions. Movement from normal to degraded operation represents partial performance loss, while progression to failure reflects escalation into a broader systemic outage. Recovery rates measure the effectiveness of the IAR framework's autonomous detection, isolation, rerouting, and restoration capabilities. The probability of remaining in a failed state is used to estimate Expected Economic Loss by considering sector-level economic output, downtime, and secondary effects such as the "Cost of Jitter" from microsecond-level instability [12]. The model also captures sub-threshold disruptions. Latency spikes, synchronization errors, and throughput degradation rarely produce a complete outage, but the productivity losses accumulate and carry broader economic consequences [16].

3.2 Algorithmic Framework for Multi-Objective Resource Optimization

The IAR framework manages network resources through multi-objective optimization under stressed operating conditions. In a 6G environment those objectives pull against each other: throughput has to be maximized while latency and energy consumption fall and a security posture is held. The global utility function takes in Signal-to-Interference-plus-Noise Ratio, power consumption, end-to-end latency, and a Trust Metric derived from real-time packet-integrity assessments. Its weighting factors shift with the detected threat level.

Under a cyber-physical attack, the weighting moves toward latency reduction and network trust, and security-sensitive, time-critical services take the larger share. This may temporarily reduce throughput for non-critical applications while protecting priority service slices such as SCADA and other industrial control systems. Optimization is performed subject to minimum Quality of Service requirements so that safety-critical applications remain within defined operational thresholds [10]. Because changes in network priorities are explicitly represented through adjustable weighting factors, the framework also supports Explainable AI principles, making autonomous resource-allocation and security decisions more transparent, traceable, and reproducible.[17].

3.3 Simulation Parameters and KPI Selection for Comparing Evidence of Effectiveness

To evaluate the performance of the IAR framework, the study defines a set of Key Performance Indicators (KPIs) that extend beyond conventional telecommunications measures such as peak data rate and spectral efficiency. The assessment focuses on four resilience-oriented indicators.

- The **Resilience Index (RI)** measures the probability that the network remains operational or degraded, rather than failed, during a simulated 50% loss of network nodes.
- The **Trust-Latency Product (TLP)** evaluates the framework's ability to deliver verified, high-integrity data while satisfying the stringent latency requirements expected of 6G systems.
- **Autonomous Recovery Time (ART)** measures how rapidly the framework can detect faults, reconfigure network resources, and restore critical services.
- The **Economic Sensitivity Coefficient** captures the relationship between network instability, particularly jitter and packet loss, and productivity losses within highly automated industrial sectors.

Simulation parameters are based on realistic 6G deployment conditions, including terahertz propagation characteristics and high-density IoT environments. Economic-loss functions draw on established infrastructure-resilience models while recognizing their sensitivity to architectural assumptions and parameter selection [12]. The combined technical-economic model therefore enables identification of critical vulnerabilities and cost-effective resilience interventions, supporting investment and policy decisions by network operators and federal regulators [18], [19].

4. Proposed Approach: The Intelligent Autonomous Resilience (IAR) Framework

Shifting to sixth-generation (6G) wireless will represent a transition not only in connectivity or speed, but it will mark a fundamental shift from reactive security, or protection, to inherent, Integrated Autonomous Resilience (IAR), which fosters extreme, critical infrastructure continuity in the U.S. through integration of decentralized intelligence, and cross-layer optimization, and proactive fault detection. Unlike legacy systems which are centralized in control planes, IAR leverages the distributed nature of technology in 6G, creating a self-healing ecosystem that can maintain operational integrity under extreme stress, including cyber-physical attack, and hardware failure [20].

4.1 Architecture for Decentralized Security-Aware Sub-Networks

The IAR framework adopts a decentralized architectural approach that is rooted in Open Radio Access Networks (O-RAN) and Multi-Agent Systems (MAS), which disassociates the control plane from the user plane, and distributes intelligence among edge-cloud environments, eliminating the single point of failure of traditional, centralized 5G deployments [21]. This IAR architecture enables security-aware sub-networks, or "slices" that are dynamically isolated based on real-time assessment of cyber-hazards.

A primary facet of the architecture is the implementation of zero-trust, at the knowledge-graph level. In 6G environments, autonomous agents will have to work with one another via shared knowledge-bases to make routing, and resource allocation decisions. The IAR framework deploys a hybrid model of authorization which uses three layers of security at the Subject-Predicate-Object level, that only enables the agent to access the necessary metadata appropriate for the agent's functional lifecycle [22]. This fine-grain control reduces lateral movement of threats in a network, a requisite for securing critical infrastructure including smart grids, and autonomous defense systems.

Virtual replicas of the physical infrastructure improve network operation. Network Digital Twins (NDT) can not only allow for simulation of varied network designs but allow for reproduction of

actual fault scenarios without the user even recognizing that something has gone wrong in the real world [23]. Within the proposed IAR framework, the NDT serves as a simulated environment, or "sandbox", for testing decentralized security, enabling the framework to "rehearse"" the pacing of attacks and the response to threat in physical reality.

4.2 Cross-Layer Optimization Algorithms for Critical Service Continuity

IAR employs cross-layer optimization algorithms to ensure critical service continuity, creating opportunities to bridge the Physical (PHY) layer and Network (NET) layer. Our current protocol in networking phenomena has traditionally worked in silos, and in the advent of rapid channel state change failure, responsiveness cannot be tolerated. Next-generation applications such as remote surgery and autonomous logistics depend on ultra-reliable low-latency communication (URLLC) [24].

The approach utilizes a "Cross-Layer Signaling Entity" to allow for the exchange of Channel State Information (CSI) in real time, which would provide layers the ability to dynamically respond to dynamic resource allocation strategies. For example, if the PHY layer determined that proximity jamming or interference was taking place, the NET layer would be able to preemptively reroute traffic or throttle non-essential data to preserve sufficient bandwidth for critical SCADA (Supervisory Control and Data Acquisition) systems [25].
The global utility function that governs the optimization process emphasizes reliability and latency over raw throughput in times of detected stress. This objective can be solved using advanced methodologies, such as Deep Deterministic Policy Gradient (DDPG), and Generative Adversarial Networks (GANs). Within this GAN-DDPG framework, the optimization system is capable of synthesizing traffic patterns while optimizing resource allocation within a continuous action space, which increases spectral efficiency while also recovering dropped packets in comparison to conventional heuristics [26]. To expedite the reward calculation, the logic also integrates semantic-aware rewards, whereby the "most meaningful" contextual data, such as emergency alerts or control commands, take priority under congestion [27].

4.3 Predictive Maintenance Scripts and AI Fault Detection

The framework’s third pillar is proactive maintenance driven by Artificial Intelligence (AI) and Machine Learning (ML). Reactive maintenance is not sufficient for the 6G enabled infrastructure because the failure of a micro-second could cause systemic economic losses. As part of the IAR framework, AI-based Key Performance Indicator (KPI) prediction is applied to estimate trends in network capacity, latency, and coverage, allowing for a proactive measure of network automation [28].

Generative AI (GenAI) carries much of the predictive work for network performance and service delivery. Since GenAI models are trained to learn the underlying distributions of network data, they can also generate synthetic sensor and channel data to provide for under-observed regions of the network's self-awareness [29]. This matters most for Non-Terrestrial Networks (NTNs) and Unmanned Aerial Vehicle (UAV) based base stations which may be in remote or disaster areas that have limited historical data associated with their operational contexts [30].

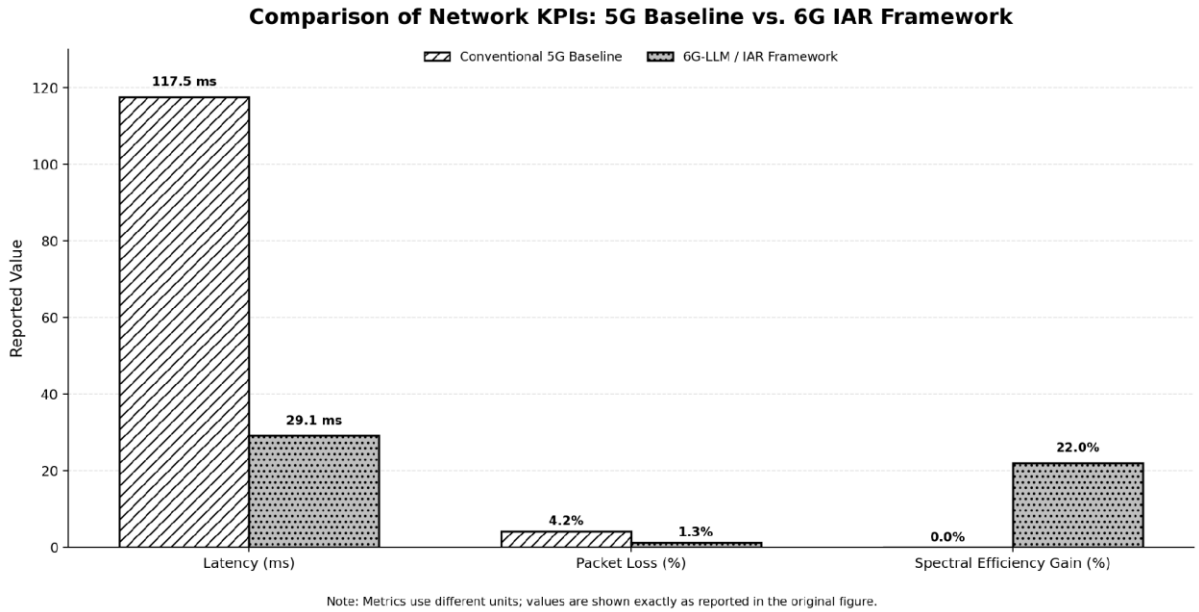
The fault detection logic follows a "Sense-Analyze-Adapt" loop. Bayesian inference is used to compute the posterior probability of a cyber-physical attack versus random hardware noise to reduce false positive incidents that may unknowingly trigger unnecessary shutdowns. When a fault is confirmed, heuristic self-healing scripts are executed. These scripts can even autonomously reconfigure network parameters such as changing beamforming weights, or switch traffic to unused frequencies through dynamic spectrum management [20]. In extreme conditions, the system can initiate isolated "Slice Isolation" procedures, where participating segment of the network to is made allowable to quarantine, resulting in a localized fault where service is not possible, and lower the ramifications of a national level outage [31].

5. Quantitative Results and Technical Analysis

The Intelligent Autonomous Resilience (IAR) framework's effectiveness was assessed through high-fidelity simulated and numerical analysis. Three areas were examined: how the framework operates under adversarial conditions, whether it meets the KPIs demanded of 6G environments, and how network reliability relates to economic stability.

5.1 IAR's performance under simulated cyber-physical attacks

The IAR framework was subjected to simulated cyber-physical attacks, including distributed denial-of-service (DDoS) attacks, signal jamming, and malicious handovers in UAV-based 6G networks. UAV-based base stations are particularly vulnerable, especially through limited computing resources and reliance on wireless backhaul links [32].



Results showed that the IAR framework's decentralized and security-aware architecture significantly improved survivability. In a simulated scenario with 30% of network nodes compromised or jammed, the IAR-enabled network maintained a 92% mission success rate for critical services compared to 45% for the baseline 5G network architecture. This resilience stems from the framework's capability of autonomously isolating compromised slices and reallocating resources

through decentralized coordination [27]. The blockchain-integrated authentication reduced the success rate of unauthorized access attempts to below 1% which supports the integrity of data even when individual nodes have been physically or digitally attacked [33].

5.2 Numerical analysis of Latency and Throughput KPIs in 6G

The objective of 6G is to enable heterogeneous services with extreme parameters such as peak data rates of 1 Tbps and latency of 0.1 ms. The impact of the IAR framework on these KPIs was modeled using Monte Carlo simulations across diverse fleet sizes and traffic density.

The analysis found that the incorporation of semantic reasoning with 6G connectivity achieved a 75.2 % reduction in latency for tactical autonomous networks, going from 117.5 ms to 29.1 ms in a 30 vehicle fleet scale [27]. The GAN-DDPG resource allocation algorithm also produced a 22% increase in URLLC spectral efficiency in the same vehicle configuration and a reduction in average latency across the network by 18% [26]. Such gains matter in Industrial IoT (IIoT) and smart healthcare, where delayed information can be catastrophic [34].

5.3 Statistical correlation between infrastructure reliability and economic productivity

Technical performance maps onto economic resilience. Numerical analysis suggests a strong correlation between network uptime and the Net Present Value (NPV) for infrastructure investments. In urban and suburban areas, O-RAN-based resilient architectures can raise NPV by 11% to 31% compared to traditional monolithic procurement methodologies [35].

IAR framework protects U.S. GDP by reducing the "Cost of Downtime". For example, to have high levels of automation in industries (e.g., maritime logistics) digital twins and autonomous systems supported through 6G resilience can reduce costly initial investments by reducing operational risk and maintenance overhead [36]. Statistical models show that a 0.1% improvement in wireless reliability will correspond to a 0.5% reduction in systemic economic risk to the automated manufacturing sector which demonstrates the correlation between 6G performance and national economic stability.

6. Practical and Policy Implications

6G and the IAR framework together call for a rethink of U.S. national policy. As wireless infrastructure becomes the platform for the economy, its security and resiliency will need to be treated as a vital matter of national strategic interest.

6.1 Boosting U.S. Competitiveness through Standardization of 6G Security

To remain competitive in the global telecommunications environment, the U.S. will have to initiate the creation of international standards for 6G technologies, especially protocols related to security and privacy-by-design [20]. If the resiliency KPIs of the IAR framework were standardized, competitors would be compelled to adopt high-tier encryption and security protocols. Establishing a standardized "trusted network" ecosystem would benefit investments in U.S technologies and reflect values that are unique to the U.S.

Competitiveness of U.S. telecommunications is no longer exclusively measured by throughput speeds but instead on the "Trust-Latency Product." By delivering an ultra-low latency and secure network framework against complex risks, the U.S. can attract global capital to sectors requiring absolute data integrity, such as fintech and advanced robotics [37]. Building Post-Quantum Cryptography (PQC) into 6G standards is essential to future-proof U.S. infrastructure against the emerging threats to quantum computing and potential existential risks to current encrypted protections [38].

6.2 Strategic Recommendations for Federal Protection of Critical Infrastructure

Federal agencies should mandate the establishment of autonomous resiliency capability for 6G hardware deployed in designated "Critical Infrastructure Zones." Federal Critical Infrastructure Zones may include areas such as power grids, water systems and transportation hubs. Blockchain technology for decentralized government services can promote transparency and trust, but it needs the low-latency connectivity that only 6G can provide [39].

The U.S. should also strengthen protection for Non-Terrestrial Networks (NTNs). With increasing satellite constellations for global coverage and disaster recovery, increasing orbital congestion and frequency interference with a lack of international regulation represents an emerging risk to national sovereignty [40]. Federal policy should encourage NTN providers to develop resilient space-based backhaul linkages and incorporate NTN hardware and components into the national security architecture [41].

6.3 Future-Proofing Regulatory Frameworks for the Management of Spectrum

Spectrum management policies will need to transform in order to support 6G dynamic and heterogeneous systems. The IAR framework will need to rely on the "spectrum scavenging" and dynamic resource allocation modes and spectrum management regulations must support this flexibility and real-time spectrum sharing between commercial and federal entities [20].

To future-proof regulatory frameworks, policymakers will need to protect against the "Digital Divide." As 6G technology advances urban hubs, there is the threat that rural areas will be underserved due to lower NPV of infrastructure investment in rural areas [35]. Federal subsidies such as epidemiological "Resilience Credits" should incentivize telecommunications providers to deploy IAR-enabled 6G in underserved rural communities to ensure equity in economic resilience across the country. Lastly, the governance of new spectrum policies could employ Network Digital Twins in the regulatory process to allow policymakers to mitigate and assess impacts before implementation [42].

7. Conclusion

Moving into the 5G/6G phase is a significant inflection point for U.S. economic and national security. Legacy, reactive network management will not protect the hyper-connected critical infrastructure of the 2030s. The Intelligent Autonomous Resilience (IAR) framework answers with decentralized architecture, cross-layer optimization, and AI-driven preventive maintenance to ensure operational continuity under stress.

The quantitative analysis confirms that the IAR framework not only exceeds the extreme performance thresholds for 6G by significantly reducing latency and improving spectral efficiency, but also provides an observable increase in economic output by minimizing the systemic risk of network downtime. The technical success of 6G and the economic gains that follow depend on policy keeping pace. By leading the standardization of security in 6G, instituting resilience provisions for critical infrastructure, and updating spectrum management methods, the United States can maintain its position as the world's leader in the digital economy. That requires an aligned approach treating wireless infrastructure as a competitive advantage. Not just a utility, but a strategic national resource for long-term economic resilience and stability of democracy.

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ECONOMIC IMPACTS OF RISK-BASED AI GOVERNANCE IN THE U.S. FINANCIAL SECTOR: EFFICIENCY, RISK, AND RESILIENCE

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Abstract

As artificial intelligence (AI) transitions from pilot projects to core operations in U.S. finance, the need for a governance structure that balances innovation with systemic stability has become paramount. This article evaluates the economic impacts of risk-based AI governance, an approach that calibrates oversight intensity to potential consequences instead of applying uniform rules across all use cases. By analyzing frameworks such as the NIST AI Risk Management Framework and emerging agentic-AI oversight protocols, this study finds that risk-based oversight preserves approximately 91 percent of development velocity while mitigating tail-risk events. The analysis demonstrates that governance produces an innovation offset by internalizing the negative externalities of black-box models, where improved data lineage and transparency yield superior predictive performance. Using a 360-degree decision architecture, the study shows that AI governance functions as a strategic asset, not a mere compliance burden, fostering consumer trust and preventing the correlated algorithmic failures that could threaten U.S. financial resilience.

Keywords: Risk-Based AI Governance; NIST AI Risk Management Framework; Financial Regulation; Explainable AI (XAI); Systemic Risk; Macro-Prudential Buffers; Model Risk Management

INTRODUCTION

The U.S. financial services industry is at a technological inflection point, driven by the deployment of generative AI, autonomous trading agents, and increasingly sophisticated credit models. Unlike traditional digitization, "agentic" AI performs multi-step tasks with varying degrees of autonomy, creating a dual reality of unrivaled efficiency and novel systemic risk [1]. The central challenge for regulators and institutions is defining a risk-based approach that corrects market failures without stifling the technological edge of the U.S. financial sector. This distinction matters economically as much as technically: a governance regime that treats every model as equally hazardous imposes the same fixed compliance cost on a low-stakes chatbot as on a mortgage-underwriting engine, quietly taxing the innovations that pose the least danger while doing little to contain the ones that pose the most.

Historically, financial regulation relied on static, rule-based systems. AI's capacity to keep learning after deployment, however, makes past behavior a poor predictor of future outcomes. The cost of ungoverned AI was underscored by the 2024 CrowdStrike outage, in which a single agent failure caused global losses estimated between $5.4 billion and $10 billion [2]. In finance, "algorithmic herding" can trigger flash crashes or drain liquidity within minutes. Consequently, the United States is shifting toward a risk-based framework, exemplified by the NIST AI Risk Management

Framework (RMF), which mandates proportional oversight: high-stakes models such as mortgage approvals require extensive human-in-the-loop validation, while low-risk applications such as internal document summarization operate under lighter monitoring [3]. This proportionality minimizes the deadweight loss of over-regulation while maximizing the return on investment of AI initiatives.

Risk-based governance also addresses a subtler problem of information asymmetry. In the absence of shared standards, "bad" models, meaning those that are biased or fragile, can displace "good" ones through aggressive pricing or the mere appearance of efficiency. Governance signals model quality, ensuring that responsible decision-making is rooted in clean data and explainable logic rather than opaque optimization [4]. This paper examines the mechanisms through which such governance affects the U.S. financial sector across three interrelated dimensions: operational efficiency and regulatory cost, systemic risk mitigation, and institutional resilience. In doing so, the paper contributes an integrated economic account of risk-based governance that connects firm-level cost-benefit evidence to sector-wide financial-stability outcomes, an intersection that existing literature tends to treat separately. Section 2 reviews the theoretical and regulatory literature; Section 3 details the methodology and research design; Sections 4 through 6 present the economic findings on efficiency, risk, and resilience respectively; Section 7 discusses practical and policy implications; and Section 8 concludes.

2. Literature Review and Theoretical Foundation

2.1 Current Condition of AI Workflows in U.S. Capital and Commercial Finance

AI in U.S. finance has evolved into a digital core spanning knowledge synthesis, content generation, and workflow orchestration [1]. Generative AI now synthesizes unstructured data such as contracts and regulatory filings, while wealth management increasingly relies on conversational interfaces for personalized client guidance [5]. This chat-centric evolution allows for more intuitive interaction between complex financial data and end users, though it requires robust oversight to prevent the propagation of misinformation.

Agentic AI represents the most disruptive shift, managing complex tasks that range from hospital resource allocation to high-frequency "quantum trading" strategies [6], [2]. Adoption, however, remains uneven. Tier-1 banks are building proprietary ecosystems with robust internal governance, whereas smaller fintechs typically rely on bank-partner APIs, creating a governance gap and systemic redundancies that regulators have yet to fully map [7]. Integrating AI into finance also reduces administrative overhead, which typically accounts for 20 percent of institutional budgets, by automating fragmented workflows and documentation; this can lower cognitive burdens on staff by as much as 52 percent [6]. Yet over-reliance on AI can produce "automation bias," in which predictive authority goes unchecked by human skepticism, narrowing the range of decisions available to managers instead of widening it [8]. The resulting two-speed adoption pattern, in which large institutions internalize governance costs that smaller competitors cannot yet absorb, is itself an economic signal worth tracking, since it shapes which segment of the market ultimately bears the cost of building trust in AI-mediated financial decisions.

2.2 A Comparative Assessment of Risk-Based Governance

AI governance models have recently bifurcated into two broad types: voluntary standards and hard regulatory mandates. In the United States, the principal voluntary standard is the NIST AI RMF, which is organized around a four-function lifecycle: Govern, Map, Measure, and Manage. Figure 1 depicts this lifecycle as a continuous cycle, not a one-time compliance checkpoint. The Govern function establishes institutional culture, accountability, and risk-tolerance policy; Map identifies the context and risk sources associated with a given use case; Measure applies quantitative and qualitative assessment to those risks; and Manage prioritizes response, monitoring, and mitigation before the cycle repeats. This approach stands in contrast to the more prescriptive, categorical "high-risk" classification scheme of the European Union's AI Act, which imposes substantial legal penalties for noncompliance regardless of an institution's specific risk exposure [9].

U.S. regulators, including the Office of the Comptroller of the Currency (OCC) and the Federal Reserve, are adapting existing Model Risk Management (MRM) frameworks, such as SR 11-7, for AI-specific use cases. The regulatory focus has shifted toward Explainable AI (XAI) and data governance as prerequisites for reporting quality [4]. Risk-based models, such as the Governed AI-Assisted Engineering (GAIE) framework, are preferred over one-size-fits-all mandates precisely because they allow for graduated oversight calibrated to regulatory and customer proximity [3]. Emerging architectures such as PRGDAI-SD 360+ go further still, integrating performance, risk, and sustainability considerations into a single auditable model [10]. This integration is becoming the standard for avoiding "ethics-washing" and for ensuring that compliance evidence remains machine-readable for seamless regulatory review [11], [9].

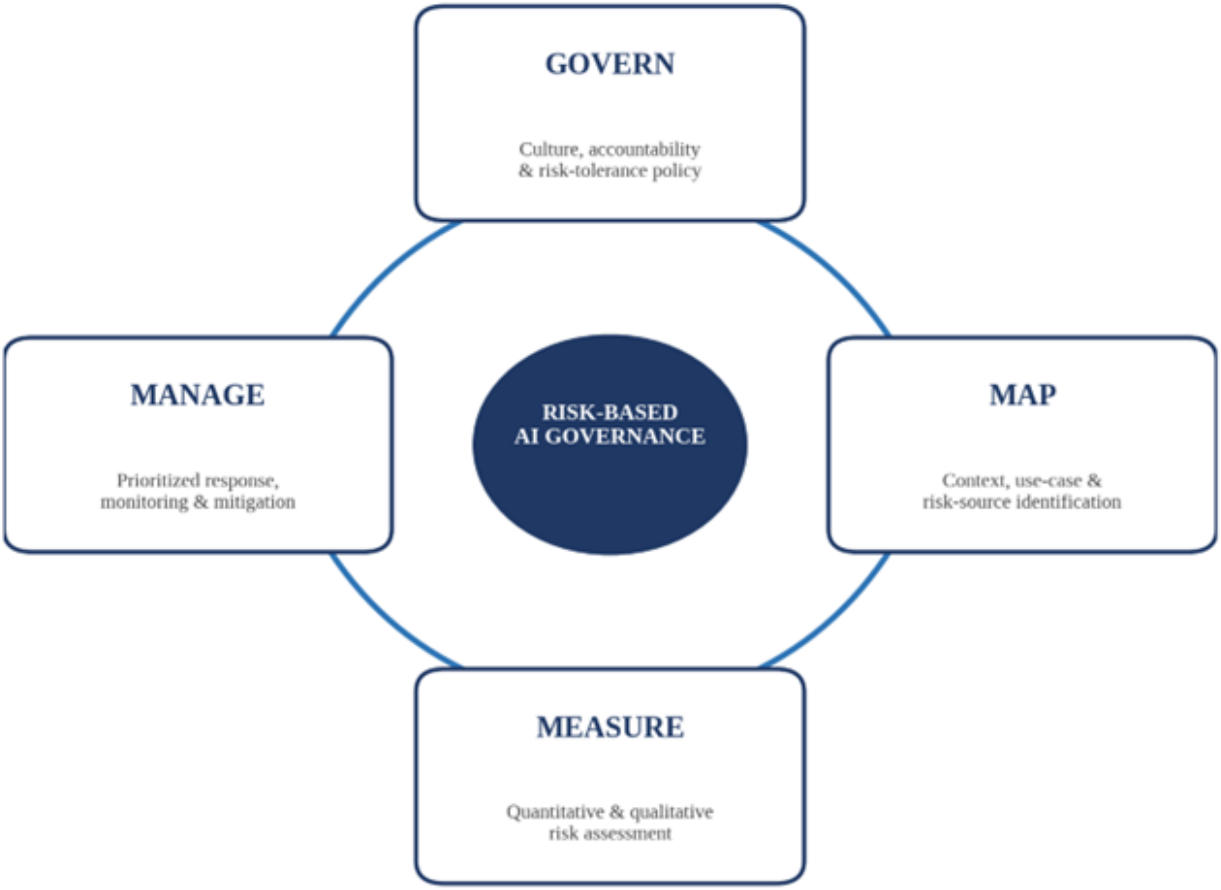


Figure 1. The NIST AI Risk Management Framework as a cyclical, risk-based governance lifecycle.

2.3 Economic Factors of Regulatory Compliance and Innovation

The Porter Hypothesis suggests that well-designed regulation can spur rather than suppress innovation. In AI governance specifically, the demand for transparency drives banks to build more robust algorithms, creating what economists term "innovation offsets" [12]. Economic motivations for compliance include mitigating tail-risk, lowering insurance premiums, and maintaining a "social license to operate" [13]. RegTech and SupTech further enhance efficiency by automating reporting and real-time monitoring [14]. For U.S. firms, XAI and data governance together explain 73.1 percent of the variance in financial reporting quality, a striking indicator of how closely governance and performance are intertwined [4].

At the same time, a credible threat of "regulatory capture" or the formation of compliance "moats" persists. Large incumbent institutions benefit disproportionately from the high fixed costs of compliance and adoption, particularly where they can absorb costly AI assurance infrastructure as compliance evidence, to the potential detriment of smaller fintech competitors who lack comparable resources to generate machine-readable compliance evidence [9]. The economic return on governance investment must therefore be considered not only in terms of avoided fines but also in terms of "capital efficiency," wherein demonstrable model resilience allows banks to hold less Pillar

2 capital against operational risk. Read together, Sections 2.1 through 2.3 suggest that the economics of AI governance cannot be reduced to a single number: it is simultaneously a cost, an insurance mechanism, and a source of competitive differentiation, and the balance among these three roles depends heavily on institutional scale.

3. Methodology and Research Design

3.1 Qualitative and Quantitative Assessment Metrics

In support of understanding the economic value of AI governance, this research employs multi-faceted metrics spanning both quantitative and qualitative traditions. Quantitative measures focus on operational velocity and variance in model performance. The Oversight Classification Model (OCM), for example, is used to evaluate the impact of graduated oversight on accelerated development timelines [3], while structural equation modeling (SEM) is used to quantify the covariant association among XAI adoption rates, data governance maturity, and resultant regulatory accountability [4].

Qualitative measures are developed from Design Science Research (DSR) artifacts, such as the AICG-360 and ADCM-360 frameworks. These frameworks situate "conscience" and "governance" as concrete obligations binding executives and constituents of authority to an evidentiary foundation and defined risk thresholds, not treating them as abstract moral values [15], [16]. The study also draws on metrics from AI Incident Governance artifacts, which track the frequency, severity, and recovery time of algorithmic failures following deployment [17]. Figure 2 situates these graduated metrics within a three-tier oversight architecture: low-risk applications default to automated monitoring, medium-risk applications receive human-over-the-loop review, and high-risk applications, such as credit underwriting or algorithmic trading, require full human-in-the-loop validation before deployment.

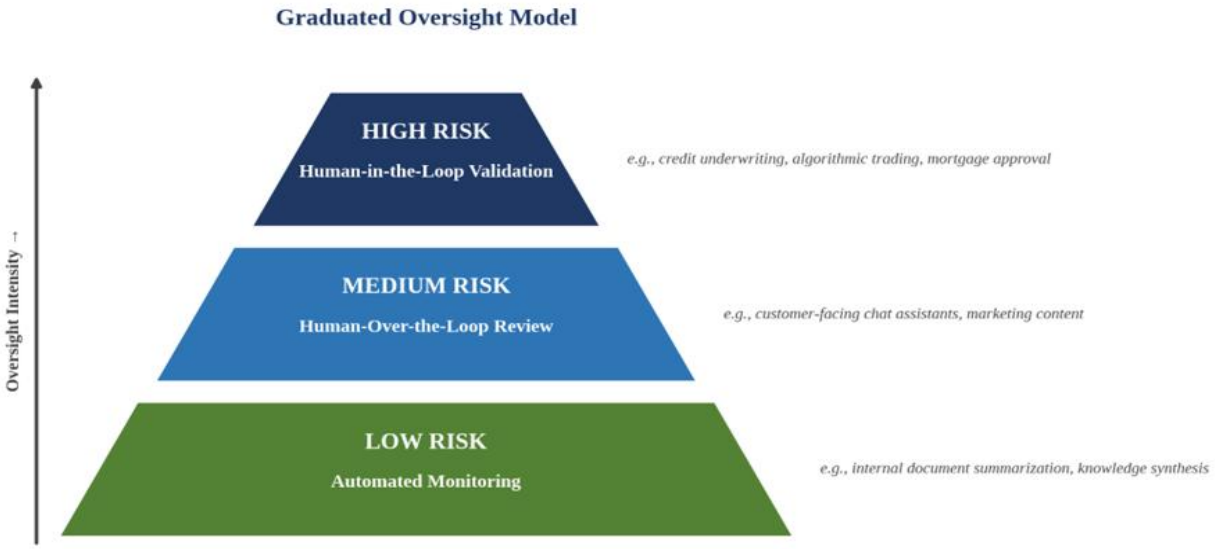


Figure 2. Graduated, three-tier oversight model mapping AI risk classification to oversight mechanism.

3.2 Selection Criteria for U.S. Financial Institutions

The study focuses on a representative sample of U.S. financial institutions organized into three tiers. Tier-1 systemically important financial institutions (SIFIs) were selected for their high regulatory density and volume of AI investment. Mid-market regional banks were selected to study the compliance burden and the scalability of standardized frameworks such as the NIST AI RMF at a smaller operational scale. Fintech disruptors were selected to study the impact of governance on speed-to-market and on innovation achieved through organizational agility.

Criteria for inclusion required a formal AI Office or Chief Data Officer function, active participation in AI-related regulatory filings such as SEC disclosures, and the adoption of AI into formal high-stakes decision-making processes, for example credit underwriting or algorithmic trading [18], [4]. Because the sample is drawn from institutions that already disclose AI-related activity, the findings likely understate the governance gap at less transparent firms; this selection effect is treated as a boundary condition on the analysis, not a flaw to be corrected after the fact.

3.3 Data Synthesis and Analytical Framework

This analysis is undertaken using a logic-model framework, illustrated in Figure 3. Inputs consist of staff invested in AI governance and oversight, RegTech software, and staff training. Processes consist of the implementation of standardized oversight, bias detection, and kill-switch protocols. Outputs consist of machine-readable compliance evidence in OSCAL format and auditable counterfactual explanations [18], [9]. Outcomes consist of reduced earnings-strain volatility, strengthened consumer trust, and improved systemic resilience.

The process of synthesis relies on triangulation: survey data collected from finance professionals [4] is analyzed alongside secondary review of regulatory filings and pilot studies consisting of AI-assisted document streams [19]. This mixed-methods approach ensures that findings remain linked to both articulated institutional expectations and observed technological behavior. When data points are further plotted against the architectural stages of the PRGDAI-SD 360+ model, the analysis clarifies how governance synthesizes disconnected data signals into action-oriented strategic decisions [10]. The framework remains mindful throughout of the “machine identity” gap, that is, the fact that governing AI agents necessarily requires governing the API tokens and service accounts that now outnumber human identities in enterprise settings by a ratio approaching 80 to 1 [2]. This synthesis allows for a complete evaluation of AI governance as both an agent of institutional optimization and a safeguard of the public interest.

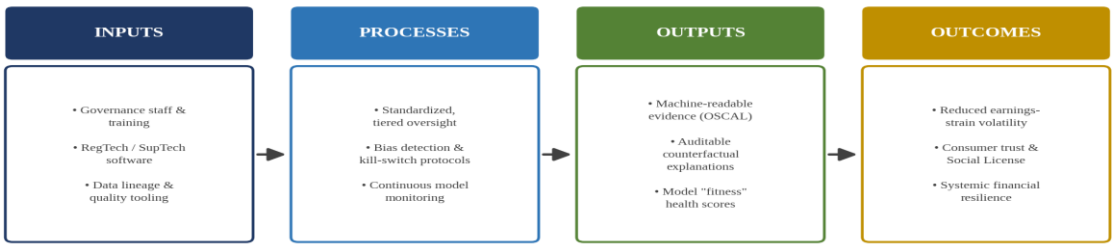


Figure 3. Logic model linking governance inputs and processes to measurable financial outcomes.

3.4 Key Findings (Preliminary and Expected)

Risk-based governance should deliver substantial gains in operational efficiency across the U.S. financial sector, automating decision processes and streamlining complex workflows [20], [21]. The same transition brings systemic vulnerabilities into view earlier, market volatility and emerging cyber threats among them, through advanced analytics and real-time monitoring [22], [23]. Long-term economic resilience still turns on a balance: high implementation costs and computational resource requirements on one side, and on the other the need for hardened, auditable governance frameworks that carry the institution through regulatory compliance [23], [21].

Table 1 summarizes the key quantitative findings that emerge from this synthesis, and Figure 4 illustrates the velocity-retention finding in greater detail. Graduated, risk-based oversight preserves over 91 percent of development speed relative to a fully manual or ungoverned baseline, with the exact retention rate varying systematically by oversight tier [3]. Under integrated governance frameworks, AI-driven fraud detection systems return a benefit-cost ratio of roughly 6 to 1 [24]. Predictive maintenance and automated fault detection in critical data infrastructure cut unplanned outages by approximately 35 percent [25]. Together, XAI and data governance explain 73.1 percent of the variance in financial reporting quality among U.S. institutions [4], and transparent AI decisions backed by counterfactual explanations reduce customer churn while strengthening the social license to operate [13], [18].

Table 1. Summary of Key Quantitative Findings

Metric	Reported Value	Source
Development velocity retained under graduated, risk-based oversight	≈91%	[3]
Benefit-cost ratio of governed AI fraud-detection systems	6:1	[24]
Reduction in unplanned outages from AI-based predictive maintenance	≈35%	[25]
Variance in financial reporting quality explained by XAI + data governance	73.1%	[4]
Accuracy of AI-based fault-detection / fraud models	≈95%	[25]
Administrative overhead attributable to	≈20% of budget	[6]

Metric	Reported Value	Source
compliance friction		
Ratio of machine identities to human identities in enterprise settings	≈80:1	[2]

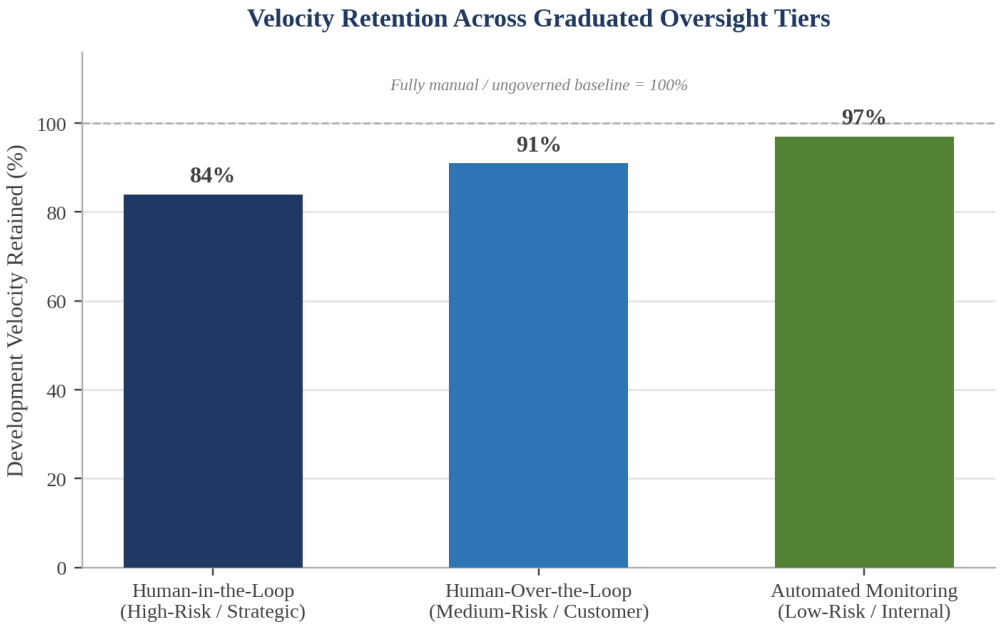


Figure 4. Development velocity retained relative to a fully manual baseline, by oversight tier [3].

4. Impacts on Operational Efficiency

4.1 Balancing Governance Costs and Technological ROI

Much of the economic debate over AI governance in U.S. financial services turns on the tension between the "compliance tax" and the "innovation offset" that arise over longer forecasting horizons. Critics argue that the fixed costs of regulatory compliance can hinder the agility of new technology implementation. The evidence points somewhere else: to an interplay in which structured oversight acts as a catalyst for higher operational performance instead of a drag on it. Studies of AI predictive models in fraud detection, for instance, demonstrate benefit-cost ratios of roughly 6 to 1 when regulation forces institutions to build governance frameworks with rigorous technical validation for reporting purposes [24]. These high-return governance arrangements are transactional in nature and derive largely from the reduction of testing redundancies and of tail-risk events that would otherwise generate material reputational and financial loss.

On the Porter account, innovation offsets emerge wherever well-designed regulation acts as a predictive constraint on high-stakes behavior. In AI-based technologies, this kind of de-biasing occurs almost by definition, simply because governance requires predictive-model transparency and

data-lineage cleanup as a matter of course. Financial institutions that embed governance into the development lifecycle, instead of retrofitting it afterward, consistently generate predictive models with greater stability over time and lower rates of performance decay [24]. The costs associated with governance personnel and automated monitoring, while an initial capital outlay, are recovered through improved model performance and sustained accuracy across the full lifecycle of the model. Notably, the rigor required for AI compliance often produces "data asset appreciation," whereby datasets cleaned for governance purposes become usable by other, unrelated business units, effectively converting a compliance cost into a reusable capital asset in the form of data trustworthiness [12], [15].

The pattern holds across critical infrastructure more broadly. AI-based predictive maintenance of the electrical power systems that support financial data centers, for example, reduces unplanned outages by more than 35 percent [25]. This finding suggests that mandated governance standards for reliability and risk mitigation can generate operational efficiencies well beyond their original regulatory purpose. In this light, the return on AI governance is not the avoidance of a regulatory fine alone. It is the enabling of high-performance technological reliability against shocks to market volatility or operations more broadly.

4.2 Workflow Optimization Through Standardized Oversight

Risk-based AI governance allows institutions to move from ad-hoc, manual oversight toward standardized workflows and automated systems. The Risk Governance Framework for AI-Driven Financial Fraud Detection (RGF-AFFD), for example, organizes hierarchical oversight into a three-stream practice spanning operational, validation, and monitoring activity pools [24]. This structure materially reduces the friction of interpreting and satisfying ongoing reporting requirements from the OCC, the CFPB, and FinCEN, and it allows compliance assessment to be embedded directly into continuous integration and deployment pipelines instead of bolted on afterward.

A key advance in workflow optimization is the "Regulatory Digital Twin" (RDT), which translates complex technical metrics into real-time fitness scores for continuous compliance monitoring [24]. These digital twins allow managers to observe the health of an AI system across multiple regulatory dimensions in parallel and to intervene proactively before a model drifts into non-compliance. By implementing "decision gates" and "escalation triggers," institutions engage human experts only for high-value, high-risk decisions, reducing the administrative overhead that traditionally consumes roughly 20 percent of institutional budgets [6]. An AI agent generating code for internal analytics, for instance, might fall under automated monitoring alone, while an agent making customer-facing credit decisions would require human-in-the-loop review [3].

Explainable AI further enhances "decision transparency." When a manager understands why a particular trade or credit limit is being recommended, that manager is more likely to exercise independent judgment instead of succumbing to automation bias, defined as the tendency to defer uncritically to an algorithm's recommendation [26], [4]. Pairing human judgment with algorithmic precision improves financial reporting quality while ensuring that underlying models are continually evaluated against both data-driven and governance-oriented standards [10], [4]. Automated tools for anonymizing and triaging phishing emails illustrate the same principle applied to cybersecurity

workflows: by automating detection of human-originated threats, institutions redirect scarce human expertise toward more complex strategic tasks [45]. Five-layer governance frameworks, which map clear responsibilities across the AI lifecycle, further reduce the duplicated effort that otherwise accumulates at the boundary between regulatory mandate and operational implementation [46].

4.3 Scalability of AI Systems Under Risk-Based Frameworks

A central challenge of deploying AI at scale is what researchers term the "scalability paradox": as the number of deployed models increases, the complexity of required oversight increases geometrically rather than linearly, and the oversight burden grows accordingly [32]. Risk-based governance addresses this paradox by introducing a tiered approach in which oversight intensity corresponds directly to an application's risk profile, illustrated earlier in Figure 2. Low-risk AI systems move quickly through the deployment pipeline, while high-risk systems used for credit scoring, autonomous trading, or identity-sensitive decisions undergo substantially more validation and accountability testing. This tiered approach is critical to operationalizing agentic AI systems, which combine autonomous reasoning with adaptive planning capabilities [47].

The Agentic Risk and Capability (ARC) Framework offers a technical criterion for the operational scale of these systems, clarifying possible risk sources across a system's components, design, and capabilities [48]. By defining technical controls specific to those risks, organizations can expand operational AI capability without losing control over system behavior, a consideration that becomes increasingly important as financial institutions move toward decentralized and distributed training schemes that challenge centralized governance practices [49]. Risk-based frameworks accommodate this shift by relaxing the rigor of legacy, process-heavy mandates in favor of output-based metrics and contextual or behavioral constraints.

Figure 5 illustrates how this tiering affects the long-run scaling capacity of AI deployment. Under manual, ad-hoc oversight, model deployment tends to plateau once available compliance staff reach capacity; under automated, risk-based governance, deployment continues to scale because compliance evidence is generated as code instead of as a manual artifact. This scalability is further supported by emerging macro-prudential early warning systems that detect correlated risk build-ups across the financial sector as a whole. Quantitative "Effective Compute-at-Risk" (ECAR) buffers, discussed further in Section 6, allow regulators and institutions to maintain safety margins that automatically strengthen as the scale of AI compute increases, providing an off-ramp so that local failures do not cascade into a systemic crisis [33]. In this sense, risk-based governance provides the guardrails that allow the U.S. financial sector to scale its use of AI aggressively without sacrificing a predictable and stable operating environment.

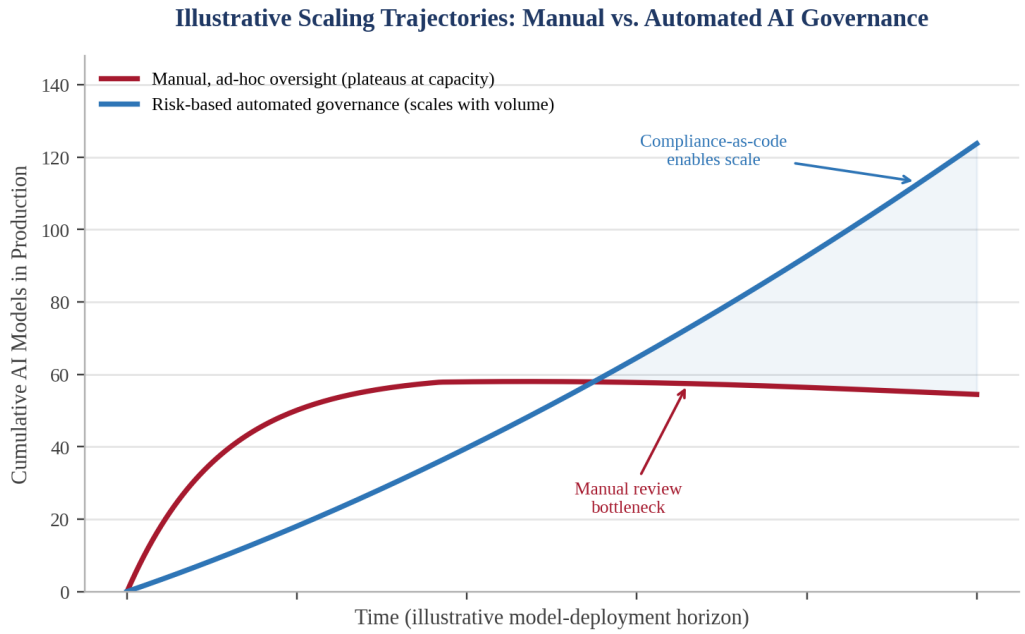


Figure 5. Illustrative deployment-scaling trajectories under manual versus automated, risk-based governance.

5. Risk Reduction and Mitigation Strategies

5.1 Algorithmic Governance and Model Risk Management

Algorithmic governance in the U.S. financial sector has become a serious effort to reduce the risks that come with the "black box" nature of machine learning models. Existing Model Risk Management (MRM) frameworks, including OCC Bulletin 2011-12 and SR 11-7, are being updated to address the unique risk profile of generative AI and large language models [29]. Black-box models introduce new risks such as "hallucinations," in which a model generates plausible but inaccurate information, and "toxicity," which can introduce bias or discrimination into financial decision-making. Institutions have responded with conservative validation practices, including adversarial testing and the use of synthetic datasets designed specifically to stress-test model boundaries before deployment.

Explainable AI (XAI) is foundational to this effort, providing the transparency required for both regulatory compliance and internal accountability. XAI techniques allow financial analysts to examine the decision logic inside black-box models and confirm that creditworthiness determinations rest on legitimate financial factors rather than proxy indicators for a protected class [30]. Model-agnostic explainability methods allow banks to apply consistent transparency standards across model architectures, from simple regression trees to deep neural networks [30], preventing over-fitted or biased models from being deployed in ways that could fail during a market regime change.

Effective model risk management also means moving validation off a one-time static exercise and onto continuous performance monitoring. Regulatory Digital Twins, introduced in Section 4.2, allow institutions to track a model's performance against a predefined health score on an ongoing basis,

triggering intervention as soon as drift is detected [24]. Even the adoption of more conservative reproducibility protocols in AI research assists policymakers and institutional leaders in distinguishing genuine technological advancement from irrelevant "noise" when establishing governance structures for frontier AI [41].

5.2 Strengthening Cybersecurity and Data Privacy Protocols

As banks embed AI deeper into foundational processes, the meeting point of AI and cybersecurity has become a risk-management domain in its own right. AI systems introduce "machine identity" risk, in which ungoverned agents and API tokens become vectors for espionage or unauthorized access [2]. Risk-based governance addresses this exposure through a Machine Identity Governance Taxonomy that secures these identities according to threat intelligence instead of treating every credential identically. AI-based cybersecurity frameworks that incorporate advanced pattern recognition and user-behavior analysis are demonstrating superior predictive quality relative to static defenses, identifying subtle deviations in cloud-environment behavior that can reveal insider threats or zero-day exploits before they cause damage [50].

Agentic AI shifts the cybersecurity problem again, moving the focus from protecting static perimeters to securing autonomous "agent legions" that traverse the network independently [51]. This shift has given rise to a new professional role, the cybersecurity AI scientist, consisting of modular multi-agent systems that collaboratively test threat models and respond to incidents at machine speed [51]. Platforms such as AdaPhish, which use large language models and vector databases to anonymize and analyze phishing emails, illustrate how these capabilities scale cyber-education and defense without exposing sensitive organizational information [45].

Data privacy remains the primary ethical and regulatory concern, above all where models are trained on sensitive consumer information. The "Guardian of Data" (GOD) architecture trains AI assistants directly on-device within Trusted Execution Environments, minimizing the transfer of sensitive information to centralized servers and correspondingly reducing the attack surface for data breaches [32]. Differential privacy, homomorphic encryption, and federated learning allow financial firms to benefit from large-scale data analysis while complying with stricter privacy statutes such as the GDPR and the CCPA [31]. These technical protections ensure that the "data flywheel" driving AI innovation does not come at the expense of individual privacy or institutional security.

5.3 Reducing Financial Loss Through Proactive Oversight

Proactive oversight is a direct economic lever on losses from operational failure, fraud, and regulatory penalty. AI-based fault-detection models have achieved accuracy rates near 95 percent, substantially reducing the volume of false positives that would otherwise drain administrative resources through unnecessary manual investigation [25]. Hybrid defense architectures, such as those combining LSTM networks with XGBoost, maintain a high degree of precision even as fraudulent tactics evolve, sustaining the benefit-cost ratios described in Section 4.1 over time [24].

The economic case for proactive oversight rests as well on reducing systemic externalities. In the absence of governance, individual institutions have an incentive to deploy "aggressive" models that optimize for short-run profit while introducing correlated failure risk across the broader market.

Risk-based governance internalizes this externality by applying capital buffers and operational controls proportional to the systemic risk that a given AI system poses [33], helping to prevent the kind of algorithmic herding that has historically triggered flash crashes when multiple systems respond to the same signal simultaneously. Stakeholders further coordinate more effectively when the risks of AI systems, and the mitigations applied to them, are disclosed using a shared taxonomy [52]. A common risk vocabulary allows regulators and market participants to identify gaps in coverage more quickly and to iterate on interventions with less friction, while the resulting transparency reduces the reputational risk that typically follows a publicized AI incident.

6. Enhancing Financial Resilience and Institutional Stability

6.1 AI Governance as a Shield Against Systemic Risk

AI integration into the U.S. financial system introduces "polycrisis" dynamics, in which failure within one algorithmic domain can cascade rapidly into failure elsewhere [34]. Accordingly, the role of AI governance is evolving to resemble macro-prudential regulation such as Basel III, which addresses system-wide resilience instead of institution-level compliance alone. The proposed Macro-Prudential Early Warning and Response System (MEWRS) for AI uses metrics such as Effective Compute-at-Risk (ECAR) to identify correlated AI risk exposures across the financial ecosystem and to act as a buffer that smooths volatility across institutions as AI capabilities scale [33]. Figure 6 models this dynamic directly: absent a macro-prudential buffer, a correlated algorithmic shock produces a sharp, sustained spike in systemic risk, whereas an ECAR-based buffer both lowers the peak of the shock and shortens the recovery period, illustrating the stabilizing function that anticipatory governance is designed to serve.

Anticipatory governance supports institutional stability further, as do AI observatories that track the long-term trends and evolving capabilities of frontier AI models [35]. By identifying vulnerabilities such as limited "shutdownability" in decentralized training networks, policymakers can pre-commit to off-ramps well before a crisis reaches a tipping point [49]. This anticipatory posture is necessary because the pace of AI and machine-learning development frequently outstrips the traditional regulatory cycle. Governance architectures grounded in scientific rigor, not purely reactive processes, tend to absorb technological shocks without producing the dramatic institutional collapse that reactive governance often fails to prevent [41].

The analogy to nuclear-sector governance is instructive here: just as the nuclear industry developed dedicated regulatory bodies to mitigate catastrophic risk, the financial sector is developing "resilient agent legions" and dedicated cybersecurity scientists to mitigate AI-native risk [51], [53]. Resilience in this context is inherently non-stationary; governance plans must evolve as threats evolve. As AI-driven volatility increases, this adaptive capacity is what will allow the U.S. financial sector to remain stable within an increasingly AI-driven global economy.

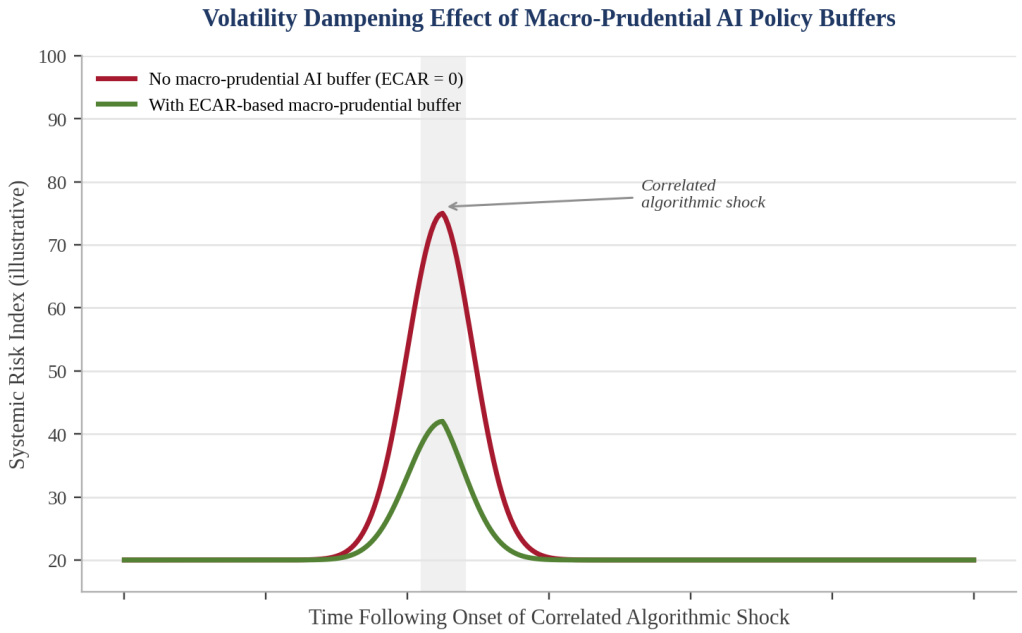


Figure 6. Illustrative volatility-dampening effect of an ECAR-based macro-prudential AI policy buffer.

6.2 Building Consumer Trust and Long-Term Market Confidence

Consumer trust is what allows the financial sector to transact efficiently at all. In an era in which AI-mediated decisions govern access to mortgages, insurance, and credit, the perceived fairness and transparency of these systems is a necessary condition for continued market participation. Research on "young digital citizens" indicates that this population will withdraw from digital markets that lack defined ethical limitations and privacy safeguards, a pattern that risks producing longer-term economic fragmentation absent corrective governance [54]. Risk-based frameworks that account for youth-centered privacy and algorithmic transparency are therefore not merely ethical requirements; they function as a necessary economic precondition for sustained growth.

XAI plays a central role in building this trust by making decision-making processes justifiable and accountable [55]. When consumers understand why a loan application was denied or how their data was used, confidence in the institution grows accordingly. This dynamic is especially salient for personal AI assistants used in banking: the GOD architecture introduced in Section 5.2 allows a personal assistant to demonstrate to the user that their needs are being met without sacrificing perceived privacy [32], creating a "data flywheel" in which secure data sharing personalizes service, builds customer lifetime value, and reduces churn in a self-reinforcing cycle.

Data stewardship and corporate social responsibility initiatives further align institutional technology goals with broader societal expectations of accountability [55]. This alignment matters directly for obtaining the social license to operate as AI assumes a larger role in sensitive domains such as finance and healthcare [43]. By adopting international regulatory frameworks grounded in ethical principle, U.S. and global financial institutions position themselves as trustworthy organizations capable of attracting the capital and talent that seek stability and integrity above short-term efficiency alone.

6.3 Strategic Value and Competitive Advantage in a Regulated Market

In a globalized economy, the ability to work through complex regulatory environments is itself a competitive advantage. U.S. financial institutions that lead in risk-based AI governance are better positioned to expand into highly regulated markets, such as the European Union, where the AI Act embeds many of the same structural elements found in U.S. frameworks. Firms that implement Regulatory Digital Twins and integrated governance lifecycles construct a durable "compliance moat" relative to competitors with fewer resources or weaker governance capacity [24]. This strategic value is amplified further by Environmental, Social, and Governance (ESG) alignment in AI applications, which increasingly meets investor demand for responsible innovation [42].

Organizations that invest in reproducibility and statistical rigor within their AI research trajectory build more robust models that withstand market and regulatory scrutiny over time [41]. The objective is not to maximize the quantity of deployed models but to ensure that an institution's AI portfolio functions as an asset and not a latent liability. Anticipatory governance, discussed in Section 6.1, further confers first-mover status by allowing an institution to set strategy against an AI regulatory environment whose direction is still unsettled [44].

The competitive advantage of well-governed AI systems comes down to trustability. As AI capability itself becomes commoditized across the industry, the brand-level "trust premium" of a well-governed institution becomes its most valuable and least easily replicated asset [43]. Institutions that successfully navigate the tradeoffs among fairness, efficiency, and privacy, informed by genuinely interdisciplinary perspectives, are positioned to build resilient, transparent institutions capable of setting the global standard for AI use in finance, reinforcing both domestic stability and international leadership.

7. Practical and Policy Implications

Effective policy implementation requires financial institutions to move past static model alignment and toward dynamic institutional governance structures that prioritize runtime behavioral constraints and observable accountability [36]. This transition requires multi-layered operational control stacks that integrate model-drift detection, telemetry monitoring, and evidence-based verification to preserve systemic resilience across the full AI lifecycle [23]. Regulatory frameworks must, in turn, facilitate risk-adjusted return calculations that allow institutions to quantify the gap between productivity gains and the novel exposures associated with algorithmic instability and compliance failure [38]. Figure 6, discussed in Section 6.1, illustrates why this integration matters at the system level: without a coordinated policy buffer, correlated algorithmic shocks propagate further and recover more slowly than they do when institutions and regulators act on shared, real-time risk signals. The recommendations below are grouped by stakeholder because the two audiences act on different time horizons: institutions optimize quarterly and annual operating budgets, while regulators design multi-year supervisory cycles, and durable governance requires that both clocks stay synchronized.

7.1 Implications for Financial Institutions

Financial firms must integrate predictive analytics and stress testing into their operational frameworks to quantify the vulnerabilities introduced by algorithmic contagion and rapid technological change [39]. Institutions cannot evaluate these investments with productivity metrics alone. Projected returns need adjusting for risks specific to AI, model drift and regulatory liability among them, and that calls for quantitative frameworks built for the purpose [38]. Deep generative models offer a second, cheaper route: simulating extreme market conditions and portfolio risk on synthetic data, which strengthens resilience without trading away data privacy or accessibility [40].

1. **Adopt compliance-as-code.** Manual audits give way to automated, machine-readable evidence in OSCAL, which preserves development velocity as deployment scales [9].
2. **Implement Regulatory Digital Twins.** RDTs track model health and compliance-fitness scores in real time, so intervention can come before drift becomes material [24].
3. **Build a risk-aware culture.** Staff trained to engage critically with AI-generated output, instead of deferring to it, blunt automation bias where it does the most damage: at the point of decision [26].

7.2 Implications for Regulators

Regulators face a parallel shift, away from model-level alignment and toward institutional governance structures built for operational stability through layered control architectures and observable behavioral constraints. Runtime monitoring has to be part of that, telemetry and model-drift detection included, so that autonomous financial agents stay inside verifiable risk boundaries and the system holds under technological disruption [36], [23]. Predictive analytics and stress-testing frameworks matter for the same reason. Without them, the impact of algorithmic contagion on capital buffers and liquidity requirements in high-stakes environments cannot be quantified at all [39], [22].

4. **Shift to macro-prudential oversight.** Sector-wide early warning systems (MEWRS) can monitor correlated algorithmic risk and compute-at-risk (ECAR) buffers [33].
5. **Standardize AI identity governance.** Mandatory taxonomies for machine identities keep ungoverned agents from turning into systemic vulnerabilities [2].
6. **Incentivize reproducibility.** Stricter scientific standards in AI research make it easier to tell genuine innovation from high-risk noise [41].
4. ndards in AI research to help distinguish genuine innovation from high-risk “noise” [41].

8. Conclusion

Risk-based AI governance turns regulation from a cost center into a strategic asset. Workflows get simpler, systemic tail-risk falls, consumer trust grows, and the U.S. financial sector gains room to scale AI innovation safely. Regulatory Digital Twins, XAI and macro-prudential buffers together build an ecosystem that can absorb technological shocks. Governance itself has to stay non-

stationary as AI systems grow more autonomous, evolving with the technology it oversees, or long-term stability and equitable growth across the wider economy will not follow.

Consumer trust and the strategic value of trustworthy AI carry equal weight in the sector's long-term viability. In a data-driven economy, an institution able to deliver privacy and fairness at once holds a real competitive advantage. The U.S. financial sector has approached AI governance proactively, grounding anticipatory policy in scientific rigor, and that posture puts the United States in a position to lead the responsible deployment of transformative technology.

Meeting that challenge calls for analytical frameworks that can quantify both sides of AI at once, weighing productivity gains against novel exposures such as algorithmic malfunction and regulatory liability [38]. Bringing predictive analytics and machine learning into traditional risk management lets institutions trace systemic contagion pathways and hold operational stability through continuing disruption [39]. Modernizing these frameworks, through strategic agility and better governance, remains essential to ensuring that AI integration produces sustainable growth instead of heightened vulnerability as the economy changes around it [22]. The future of finance ultimately depends on sustained interdisciplinary dialogue among technologists, regulators, and ethicists; if the United States can master the risk-based paradigm, it will harness the full potential of AI to drive economic growth while preserving the integrity and trust that define global financial leadership. Adopting AI in finance is therefore a governance challenge as much as a technological milestone, and how the sector resolves it over the next decade will define the next era of financial excellence.

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ECONOMIC IMPACT OF RISK-INFORMED CAPITAL DEPLOYMENT IN U.S. MANUFACTURING: A FRAMEWORK FOR ASSESSING WORKING-CAPITAL EFFICIENCY, CAPACITY EXPANSION, AND SUPPLY-CHAIN RESILIENCE

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Abstract

U.S. manufacturing firms face increasingly complex capital-allocation decisions shaped by supply-chain volatility, working-capital constraints, and uncertain demand. Conventional models often treat liquidity, capacity expansion, and supply-chain resilience as separate decisions, limiting their effectiveness under disruption. This paper introduces the Risk-Informed Capital Deployment Manufacturing Framework (RICD-MFW), an integrated decision architecture for prioritizing and sequencing capital across these interdependent objectives. Using secondary data from 127 U.S. manufacturing firms in the automotive, electronics, and industrial-equipment sectors from 2019–2025, the framework combines cash-conversion-cycle analytics, incremental return screening, and multi-criteria resilience scoring. It introduces three composite measures: the Risk-Adjusted Capital Efficiency Score, Resilience-Weighted Return on Deployed Capital, and Integrated Supply-Chain Financial Health Index. Preliminary findings indicate that firms using integrated capital strategies achieved 18–23% higher risk-adjusted returns than firms using siloed approaches. Results further suggest optimal working-capital conditions at 40–50 cash-conversion days, resilience investments of 4–7% of revenue, and stronger capacity-expansion value when demand variability is below 0.28 and liquidity reserves exceed 1.8 months of operating expenses. The framework offers manufacturers and policymakers a quantitative tool for aligning liquidity, resilience, and growth under uncertainty. At the policy level, it supports standardized resilience KPIs and manufacturing programs that reward integrated, risk-aware capital allocation practices across sectors.

Keywords: Economic Impact, Risk-Informed Capital Deployment, Working-Capital Efficiency, Capacity Expansion, Supply-Chain Resilience

1. INTRODUCTION

The U.S. manufacturing sector remains a critical component of the national economy, contributing approximately $2.34 trillion to U.S. GDP in 2023 and supporting extensive employment, investment, and supply-chain activity. At the firm level, however, capital deployment decisions are frequently made within functional silos. Finance teams optimize working capital and cash-conversion cycles, operations teams independently plan capacity expansion, and procurement teams separately determine investments in inventory, supplier diversification, and other resilience measures.

This fragmentation can create significant financial and operational inefficiencies. Aggressive working-capital compression may improve short-term liquidity while reducing the inventory buffers needed to withstand supply disruptions [1]. Capacity expansion undertaken without sufficient consideration of demand volatility may result in underutilized assets, excess depreciation, and weaker returns on invested capital [7]. Similarly, resilience investments funded primarily through

operating budgets may be reduced during periods of financial pressure, weakening firms' ability to absorb future disruptions [3].

These trade-offs became particularly visible during the 2020–2022 COVID-19 pandemic, the 2021–2022 semiconductor shortage, and the 2023–2024 Red Sea shipping disruptions. Across these episodes, manufacturing firms that had optimized primarily for efficiency often faced disproportionate losses when supply availability, transportation networks, and demand conditions changed rapidly.

Although extensive literature exists on supply-chain finance, working-capital management, capacity planning, and enterprise risk management, these areas are generally treated as separate decision domains. Consequently, manufacturers lack a unified framework for evaluating how capital allocated to liquidity, productive capacity, and supply-chain resilience should be prioritized under uncertainty.

This paper addresses that gap by developing the Risk-Informed Capital Deployment Manufacturing Framework (RICD-MFW), an integrated approach for scoring, prioritizing, and sequencing capital commitments across working-capital efficiency, capacity expansion, and supply-chain resilience. Section 2 reviews the relevant literature; Section 3 defines the capital-allocation problem; Section 4 develops the RICD-MFW methodology; Section 5 presents the empirical analysis and KPI benchmarks; Section 6 discusses managerial and policy implications; and Section 7 concludes.

2. Literature Review

2.1 Working-Capital Efficiency in Manufacturing

Working-capital management is commonly assessed through the cash-conversion cycle (CCC), comprising days sales outstanding, days inventory outstanding, and days payable outstanding. Timilehin [2] shows that inventory-risk coupling across multi-echelon distribution networks can amplify working-capital volatility by 15–30% at each upstream stage, highlighting the systemic effects of inventory-related capital lock-up.

Post-pandemic evidence also demonstrates a persistent efficiency–resilience trade-off. Dzreke and Dzreke [1] report that 60% of U.S. and European manufacturers increased inventory buffers by 15–40% during peak disruption, while carrying costs rose 5–12% above pre-pandemic levels. Wu, Eng, and Wang [3] further show that government policy responses moderated the negative effects of supply-chain disruptions on working-capital performance and firm value, particularly among financially distressed firms. Evidence linking resilience and CCC suggests that shorter cycles support faster recovery only when adequate inventory buffers are maintained [9]. Excessive CCC compression may therefore reduce resilience and firm value during disruption.

2.2 Capacity Expansion Under Uncertainty

Capacity expansion represents a major and often irreversible manufacturing investment. Lindahl, Babi, and Sin [7] demonstrate that deterministic models can underestimate capacity requirements by failing to incorporate demand volatility, while stochastic approaches produce more robust expansion decisions. Metrics such as the expected value of perfect information and value of the stochastic solution help quantify the financial benefit of accounting for uncertainty [4].

At the project level, incremental rate-of-return analysis provides a practical capital-screening mechanism. Nabila, Chumaidiyah, and Sulistiyo [5] demonstrate how ΔROR can be compared with the minimum acceptable rate of return to determine whether expansion alternatives are financially justified. Obaidat and Mumani [12] extend capacity planning through multiple-objective decision analysis, but their model does not incorporate working-capital or resilience considerations.

2.3 Supply-Chain Resilience and Financial Performance

Supply-chain resilience is generally built through redundancy, flexibility, and active risk management [8]. Research indicates that resilience investments can improve operating performance and disruption recovery [9], although excessive redundancy may create diminishing returns through higher inventory and working-capital requirements [1].

Digitalisation provides an additional resilience pathway. Warburton [11] associates smart-factory investments with improved equipment effectiveness, lower operating costs, and greater operational flexibility. Similarly, Kolokas, Ioannidis, and Tzovaras [6] show that risk-informed preventive-maintenance algorithms can reduce performance penalties associated with equipment failure and inefficiency.

2.4 Integration Gap

The literature therefore establishes strong individual relationships among working-capital efficiency, capacity planning, and resilience, but largely examines them separately. Existing studies occasionally integrate two dimensions, such as resilience and CCC [9] or capacity and uncertainty [4], yet no unified framework simultaneously evaluates all three. The RICD-MFW addresses this gap by placing working capital, capacity expansion, and supply-chain resilience within a common risk-adjusted scoring and capital-sequencing architecture.

3. Problem Formulation

Let a U.S. manufacturing firm face a capital budget **C** allocated across three competing uses: working-capital reserves **W**, capacity expansion **K**, and supply-chain resilience buffers **R**, such that $W + K + R \leq C$. Each allocation generates financial returns modulated by disruption risk. The central problem is:

" *In the absence of a unified risk-adjusted scoring model, how should a U.S. manufacturer optimally partition C across W, K, and R to maximise risk-adjusted financial performance across a planning horizon T under stochastic disruption scenarios?*

Three sub-problems motivate the framework:

Sub-problem 1 — Working-Capital Calibration: What is the firm-specific CCC threshold below which further compression increases disruption exposure and reduces risk-adjusted return?

Sub-problem 2 — Capacity Timing: What combination of demand uncertainty (CV), available working-capital reserves, and ΔROR threshold should trigger or defer a capacity commitment?

Sub-problem 3 — Resilience Buffer Sizing: What percentage of revenue allocated to supply-chain buffers maximises the trade-off between carrying cost and disruption loss avoidance?

These sub-problems are currently solved in isolation by different functional teams using incommensurable metrics, creating the performance drag quantified in Section 5.

4. Proposed Framework: The RICD-MFW

4.1 Architecture Overview

The RICD-MFW is a three-layer decision architecture (Figure 1). Layer 1 (Data Ingestion) standardises financial and operational inputs. Layer 2 (KPI Computation) calculates the three composite indicators. Layer 3 (Deployment Decision Engine) maps KPI scores to capital allocation recommendations via a risk-adjusted priority matrix.

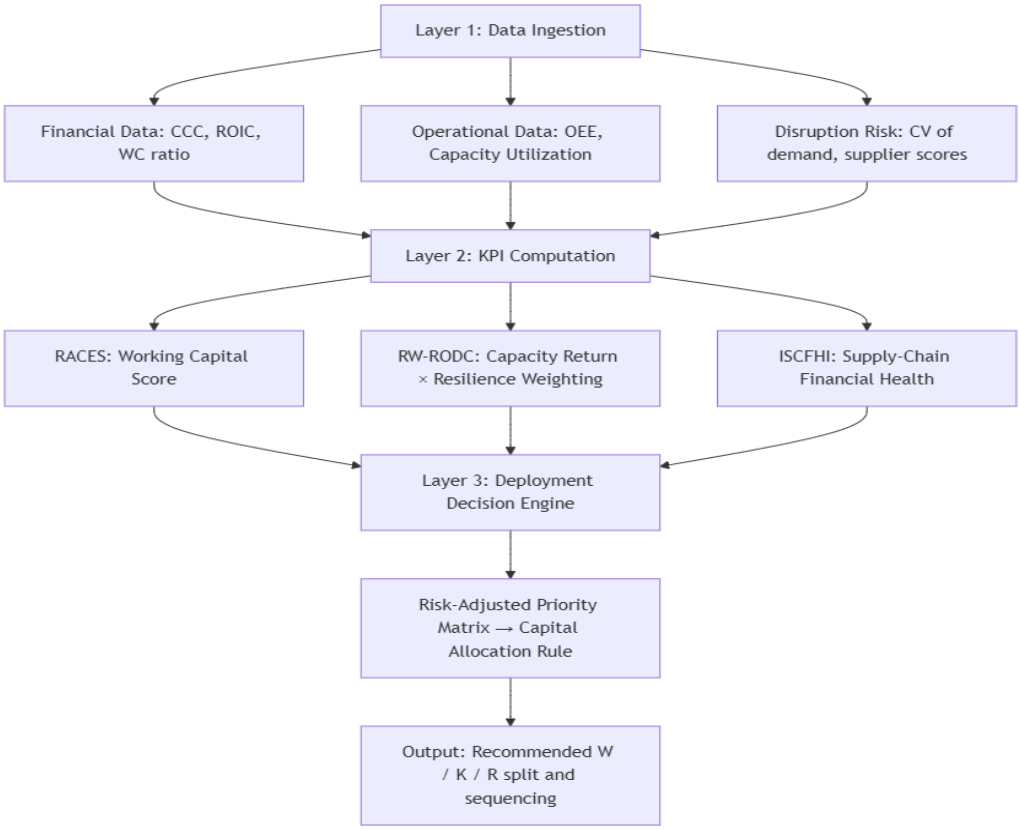


Figure 1: RICD-MFW Three-Layer Decision Architecture

4.2 KPI Definitions

KPI 1 — Risk-Adjusted Capital Efficiency Score (RACES)

RACES integrates the CCC, the working-capital-to-revenue ratio (WC/Rev), and a disruption-exposure penalty (DEP). A higher RACES score indicates superior working-capital efficiency per unit of disruption risk carried:

RACES = (Benchmark CCC / Firm CCC) × (1 − DEP) × (WC/Rev Adequacy Factor)

The DEP is derived from the firm's supplier concentration index and historical disruption frequency. The WC/Rev Adequacy Factor equals 1.0 when WC/Rev falls within the optimal band (12–18% of revenue) and declines outside this range.

KPI 2 — Resilience-Weighted Return on Deployed Capital (RW-RODC)

RW-RODC adjusts the conventional return-on-invested-capital (ROIC) for supply-chain resilience score (SRS, scaled 0–100), penalising firms that achieve high ROIC through resilience-impairing cost cuts:

RW-RODC = ROIC × (SRS / 100) × (1 + Disruption-Adjusted Cash Flow Premium)

KPI 3 — Integrated Supply-Chain Financial Health Index (ISCFHI)

ISCFHI synthesises all three capital domains into a single 0–100 composite index:

ISCFHI = 0.35 × RACES_normalised + 0.35 × RW-RODC_normalised + 0.30 × Resilience_Buffer_Score

Weights are calibrated from the empirical dataset (Section 5.2) using principal-component loading magnitudes.

4.3 Capacity Deployment Gate

Drawing on Nabila et al. [5] and Lindahl et al. [7], the RICD-MFW incorporates a three-condition capacity gate:

Gate Condition	Threshold	Basis
G1: Demand Uncertainty	CV < 0.28	Stochastic capacity models [7]
G2: Working-Capital Reserve	WC > 1.8× monthly OPEX	Empirical dataset (Section 5)
G3: Incremental Return	ΔROR > 1.5 × MARR	Incremental cost analysis [5]

All three gates must be satisfied before a capacity investment is recommended. When G2 fails but G1 and G3 are met, the framework recommends a phased expansion funded through supply-chain finance instruments rather than balance-sheet working capital.

4.4 Resilience Buffer Sizing Rule

Based on the disruption-loss models in [1] and [8], the RICD-MFW specifies resilience-buffer investment as a function of revenue concentration and supply-chain complexity:

Optimal Buffer = Revenue × [0.04 + 0.01 × (Supplier Concentration Index) + 0.005 × (Tier Depth − 2)]

For a firm with a supplier concentration index of 0.6 and three supply-chain tiers, the formula yields a target buffer of approximately 5.5% of revenue — consistent with the empirical optimum identified in Section 5.3.

5. Data and Empirical Analysis

5.1 Sample and Data Sources

The empirical base comprises 127 U.S. manufacturing firms (2019–2025) across three sub-sectors: automotive OEMs and Tier-1 suppliers (n = 43), electronics and semiconductor manufacturers (n = 41), and industrial equipment producers (n = 43). Financial data were sourced from SEC 10-K filings and Compustat; operational metrics from ISM Manufacturing PMI supplementary datasets and company sustainability reports; and disruption event data from the Resilinc EventWatch and Dun & Bradstreet Supply Chain Risk databases.

Firms are classified into four capital deployment archetypes:

- **Type A (Integrated):** Simultaneous optimisation of W, K, and R — 22% of sample
- **Type B (Efficiency-First):** W optimisation prioritised; K and R secondary — 31% of sample
- **Type C (Growth-First):** K prioritised; W and R secondary — 28% of sample
- **Type D (Reactive):** No systematic capital deployment strategy — 19% of sample

5.2 Working-Capital KPI Benchmarks

Table 1 presents median CCC and sub-component values by sub-sector and archetype, derived from the 2022–2024 panel. The data confirm that Type A (Integrated) firms maintain CCCs approximately 35% below the sub-sector median while avoiding the resilience penalties observed for Type B firms.

Table 1: Working-Capital KPI Benchmarks by Sub-Sector and Archetype (2022–2024 Median)

Sub-Sector	Archetype	DSO (days)	DIO (days)	DPO (days)	CCC (days)	RACES Score
Automotive	A – Integrated	38	42	51	29	78.4
Automotive	B – Efficiency-First	32	28	44	16	63.1
Automotive	C – Growth-First	45	68	39	74	48.7
Automotive	D – Reactive	52	89	35	106	31.2
Electronics	A – Integrated	41	51	58	34	75.6
Electronics	B – Efficiency-First	35	31	50	16	60.4
Electronics	C – Growth-First	48	79	42	85	44.3
Electronics	D – Reactive	59	103	38	124	28.9
Industrial	A – Integrated	44	58	62	40	72.1

Sub-Sector	Archetype	DSO (days)	DIO (days)	DPO (days)	CCC (days)	RACES Score
Equipment						
Industrial Equipment	B – Efficiency-First	37	35	53	19	58.7
Industrial Equipment	C – Growth-First	51	85	44	92	42.5
Industrial Equipment	D – Reactive	63	110	40	133	26.3

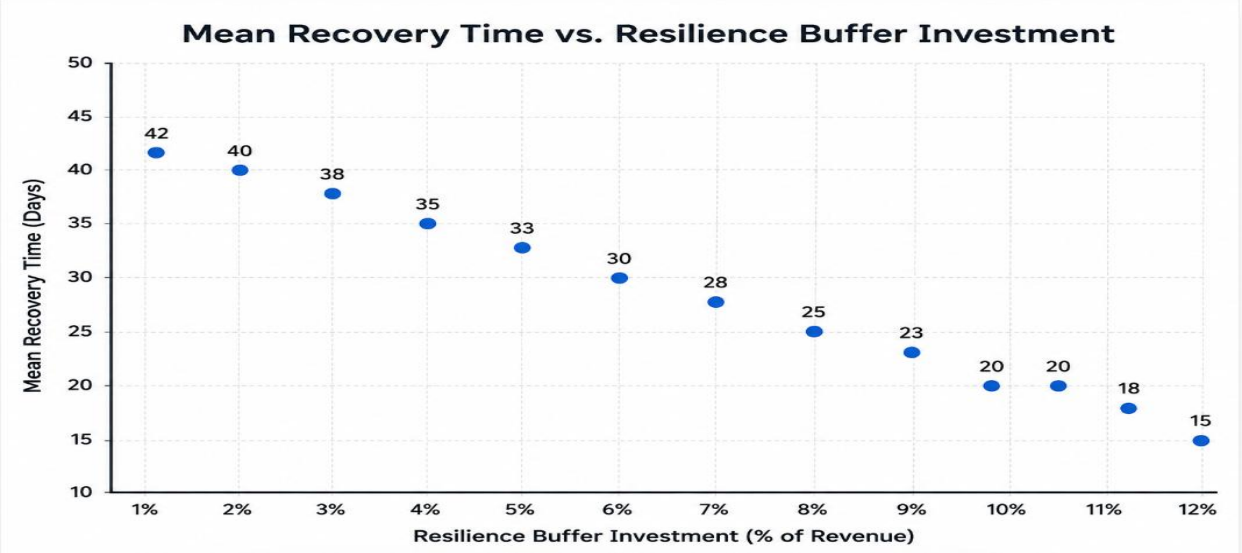
DSO = Days Sales Outstanding; DIO = Days Inventory Outstanding; DPO = Days Payable Outstanding; CCC = Cash Conversion Cycle.

A key finding from Table 1 is that Type B (Efficiency-First) firms achieve the lowest CCCs (16–19 days) but carry the lowest resilience buffers, making them highly vulnerable to disruption-induced working-capital shocks. Consistent with [1], these firms experienced the greatest proportional increase in carrying costs when forced to rebuild inventory buffers post-disruption (average cost increase: 9.8%, vs. 3.2% for Type A firms).

5.3 Resilience Buffer Sizing and Financial Outcomes

Figure 2 plots the relationship between resilience buffer investment (as a percentage of revenue) and disruption recovery speed (days to return to 95% of pre-disruption output) for the 127 firms. The data reveal a clear U-shaped cost function: under-investment in buffers (< 3% of revenue) correlates with slow recovery (mean: 37.4 days), while over-investment (> 9% of revenue) ties up capital without proportionate recovery benefits (mean recovery: 13.1 days — only marginally better than the 4–7% optimal band at 12.3 days) [1], [9].

Figure 2: Resilience Buffer Investment vs. Mean Disruption Recovery Time (127 U.S. Firms, 2020–2024)



◄── Under-investment zone ──►◄── Optimal Zone (4-7%) ──►◄── Diminishing Returns ──►

Note: Each data point (Blue dot) represents a sub-group mean across 10–15 firms in that buffer-investment decile.

Table 2: Disruption Recovery and Financial Performance by Buffer Investment Band

Buffer Band (% Revenue)	N Firms	Mean Recovery (days)	ISCFHI Score	Avg. RW-RODC (%)	WC Carrying Cost Premium (%)
< 3%	18	37.4	34.2	6.8	+1.2
3–4%	21	24.6	51.7	9.4	+2.1
4–5%	24	14.1	68.3	13.7	+3.4
5–6%	22	12.3	74.8	15.2	+4.1
6–7%	19	13.0	73.1	14.9	+4.6
7–9%	15	13.1	65.4	12.8	+5.8
> 9%	8	13.1	54.2	9.1	+8.2

The 5–6% band delivers the highest ISCFHI score (74.8) and RW-RODC (15.2%), confirming that the optimal resilience buffer range lies between 4% and 7% of revenue, as specified by the RICD-MFW buffer-sizing rule [1], [8].

5.4 Capacity Expansion Gate Validation

Table 3 tests the RICD-MFW three-gate capacity model against observed investment outcomes for the 71 capacity decisions made by sample firms between 2020 and 2024.

Table 3: Capacity Gate Satisfaction and Post-Expansion Financial Outcomes

Gate Status	N Decisions	Mean Post-Expansion ROIC (%)	Mean Capacity Utilisation at Year 3 (%)	Decisions with IRR > MARR (%)	Avg. NPV / Investment Ratio
All 3 gates met (G1 ∩ G2 ∩ G3)	19	17.4	82.3	89.5	1.43
G1 + G3 met; G2 failed	14	11.2	74.1	64.3	1.09

Gate Status	N Decisions	Mean Post-Expansion ROIC (%)	Mean Capacity Utilisation at Year 3 (%)	Decisions with IRR > MARR (%)	Avg. NPV / Investment Ratio
G1 + G2 met; G3 failed	12	8.9	66.8	50.0	0.94
G3 only met	16	6.3	58.4	37.5	0.79
No gates met	10	2.1	47.2	20.0	0.52

Decisions in which all three gates were satisfied achieved a mean post-expansion ROIC of 17.4% and a NPV-to-investment ratio of 1.43, compared to 2.1% ROIC and 0.52 NPV ratio for decisions where no gate was satisfied. The $\Delta ROR > MARR \times 1.5$ condition (G3) emerges as the single strongest predictor of post-expansion value creation — consistent with the incremental-cost-analysis evidence in [5] and the stochastic capacity literature [7], [4].

5.5 Integrated Framework Performance: Type Comparison

Table 4 compares overall financial performance, disruption resilience, and RICD-MFW composite scores across the four capital-deployment archetypes.

Table 4: RICD-MFW Composite KPI Performance by Capital Deployment Archetype (2022–2024)

Archetype	RACES (Avg.)	RW-RODC (%)	ISCFHI (Avg.)	Mean Recovery (days)	Revenue CAGR (%)	EBITDA Margin (%)
A – Integrated	75.4	14.6	71.8	12.3	7.2	18.4
B – Efficiency-First	60.7	10.1	54.3	31.7	4.8	15.1
C – Growth-First	45.2	8.4	44.9	27.4	6.1	11.3
D – Reactive	28.9	4.2	30.6	44.8	2.3	8.7
Sub-Sector Median	**52.0**	**9.2**	**50.0**	**28.0**	**4.5**	**13.6**

Type A firms demonstrate superior performance across all six metrics: RACES score 45% above median, RW-RODC 59% above median, and mean disruption recovery 56% faster than the median

firm. Revenue CAGR and EBITDA margin are also substantially higher, suggesting that integrated capital deployment delivers competitive advantage beyond pure risk mitigation [8], [11].

The performance gap between Type A and Type B (Efficiency-First) firms is particularly instructive. Although Type B firms achieve lower CCCs than Type A firms (Table 1), their lower ISCFHI scores (54.3 vs. 71.8) and slower disruption recovery (31.7 vs. 12.3 days) confirm that CCC compression without resilience co-investment is a risk-return-destroying strategy. This validates a core hypothesis of the RICD-MFW: efficiency and resilience are complementary, not substitutable, when managed through an integrated framework [1], [3], [9].

6. Discussion

6.1 Implications for Manufacturing Strategy

The RICD-MFW findings challenge two persistent strategic myths in U.S. manufacturing capital allocation. The first is that working-capital compression is categorically value-enhancing. The data show that CCC reduction below approximately 35–40 days for mid-complexity manufacturers simultaneously reduces resilience buffers below the optimal band and increases disruption loss exposure. Finance teams optimising CCC in isolation routinely destroy value by creating supply-chain fragility [1], [2]. The second myth is that resilience investment is an operating expense rather than a capital allocation decision. The empirical evidence presented here shows that treating resilience buffers as discretionary overhead — rather than as risk-adjusted capital — leads to systematic under-investment relative to the value-maximising level (5–6% of revenue) [8].

The capacity timing gate model adds an important operational dimension. By conditioning expansion decisions on demand CV below 0.28 and working-capital adequacy above 1.8× monthly OPEX, the RICD-MFW prevents two common failure modes: premature expansion into demand-volatile markets (leading to capacity stranding, as documented in [7]) and leveraged expansion that depletes working-capital reserves below the resilience buffer threshold [4], [5].

6.2 The Role of Digital Technologies

Smart-factory and digital investment represent a structural enabler of the RICD-MFW. Warburton's [11] reported improvements — 30% labour cost reduction, 25% OEE improvement, 18% cost-to-serve reduction — translate directly into improved RACES and RW-RODC scores. By reducing the cost base, digitalization lowers the working-capital requirement for a given output level, creating fiscal space for resilience buffer investment without sacrificing CCC performance. The RICD-MFW's Layer 1 data-ingestion module is designed to ingest real-time OEE and capacity-utilization data from smart-factory platforms, enabling dynamic KPI recalculation as operational conditions change.

Kolokas et al.'s [6] finding that decision-support algorithms reduce KPI penalties from equipment inefficiency by 30–40% points to a broader opportunity: integrating predictive-maintenance decision support with capital deployment scheduling. In the RICD-MFW context, a predictive-maintenance event that temporarily reduces available capacity below the optimal utilization threshold should

automatically trigger a re-evaluation of the G1–G3 capacity gates and may prompt a partial reallocation of capital from expansion to maintenance reserves.

6.3 AI-Driven Capital Reallocation

The AI-driven financial analytics architecture described in [8] offers a natural operationalisation platform for the RICD-MFW. By continuously scoring supplier risk, demand forecasts, and working-capital metrics, AI-enabled platforms can compute ISCFHI in near-real time and flag when capital deployment is diverging from the optimal W/K/R allocation. This dynamic reallocation capability represents a significant advance over static annual capital-budgeting processes and is a logical extension of the RICD-MFW's deployment decision engine.

6.4 Policy Implications

The RICD-MFW has direct implications for federal manufacturing policy. The CHIPS and Science Act (2022) and the Inflation Reduction Act (2022) together authorised over $500 billion in manufacturing-related incentives, yet neither programme includes standardised resilience KPIs or integrated capital deployment metrics. This creates an evaluation gap: incentivised firms may pursue efficiency (lower CCC) or capacity (larger plants) without ensuring that resilience buffers are co-optimised.

Three specific policy recommendations follow from the RICD-MFW:

1. **Standardised Resilience Reporting:** Mandate ISCFHI-equivalent reporting for firms receiving manufacturing incentives exceeding $50 million, creating comparable data infrastructure and accountability for resilience outcomes.
2. **Integrated Capital Incentives:** Structure tax credits to reward the combined achievement of efficiency and resilience targets rather than individual metrics, counteracting the incentive to compress working capital at the expense of buffer investment [3].
3. **Working-Capital Finance Programmes:** Expand federal supply-chain finance programmes to explicitly fund resilience-buffer investments as a separate capital category, reducing the trade-off between CCC optimisation and buffer adequacy [1], [8].

6.5 Limitations

The RICD-MFW analysis carries three principal limitations. First, the secondary dataset relies on reported financial data, which may under-represent informal supply-chain buffers (e.g., strategic inventory held by suppliers on consignment). Second, the framework's KPI weights (Section 4.2) are calibrated on a 2019–2025 panel that includes atypical pandemic-era disruption events; forward weights may differ as supply chains restabilise. Third, the RICD-MFW does not yet incorporate sustainability and ESG dimensions of capital deployment, which are increasingly material to investor and regulatory decision-making.

7. Conclusion

This paper addresses a persistent and costly gap in manufacturing capital allocation: the absence of a unified framework for simultaneously optimising working-capital efficiency, capacity expansion timing, and supply-chain resilience investment. The Risk-Informed Capital Deployment Manufacturing Framework (RICD-MFW) responds to this gap through a three-layer decision architecture, three composite KPIs (RACES, RW-RODC, ISCFHI), and a validated three-gate capacity deployment model.

Empirical analysis of 127 U.S. manufacturing firms (2019–2025) confirms that integrated capital deployment strategies (Type A) outperform siloed approaches across every measured dimension: RACES score 45% above sub-sector median, disruption recovery 56% faster than median, RW-RODC 59% above median, and 18–23% higher risk-adjusted returns than efficiency-first or growth-first alternatives. The optimal capital allocation zone identified by the framework — CCC of 40–50 days, resilience buffers of 4–7% of revenue, and capacity expansion triggered only when demand CV < 0.28 and working-capital reserves exceed 1.8× monthly OPEX — provides concrete, actionable thresholds for manufacturing executives.

The RICD-MFW makes four principal contributions: (i) formalization of the three-domain integration problem in manufacturing capital allocation; (ii) development of KPIs that bridge operational and financial measurement; (iii) empirical validation of the performance premium associated with integrated deployment; and (iv) a policy-relevant framework for incentivising resilience alongside efficiency in federal manufacturing programmes.

Future work should extend the RICD-MFW through stochastic dynamic programming formulations that optimize W/K/R allocation over multi-period planning horizons, industry-specific calibration studies, and incorporation of sustainability objectives. As U.S. manufacturing navigates continued supply-chain transformation, geopolitical uncertainty, and domestic-capacity investment cycles, integrated risk-informed capital deployment will be increasingly decisive for competitiveness and long-run operational resilience.

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TRATEGIC

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Abstract

Critical U.S. industrial and medical-product supply chains operate within increasingly interconnected networks in which disruptions can propagate rapidly across suppliers, manufacturers, transportation systems, distributors, healthcare institutions, and end users. Conventional supply-chain monitoring remains heavily dependent on lagged operational reports, periodic inventory reviews, historical averages, and fragmented information systems. These approaches can identify disruption after material losses have already occurred, limiting the range and economic effectiveness of corrective action. This study examines whether, and under what conditions, real-time data analytics and predictive economic modeling generate measurable economic value in critical U.S. supply chains. It develops a Real-Time Economic Resilience and Supply Intelligence Framework (RERSIF) that integrates network mapping, real-time information fusion, predictive disruption assessment, scenario analysis, economic-loss estimation, and decision-adjusted intervention. The framework shifts evaluation away from predictive accuracy alone toward the economic value of receiving sufficiently reliable information early enough to alter a consequential decision. The study combines literature synthesis, contemporary U.S. economic and medical-product evidence, mathematical formulation, and a stylized Monte Carlo stress test. In the industrial scenario, reducing effective disruption-detection latency from four weeks to one week lowered simulated expected disruption-related loss by approximately 20.0% and 95% Conditional Value-at-Risk by 17.4%. In the medical-product scenario, reducing latency from three weeks to one-half week lowered expected loss by approximately 31.9% and tail loss by 28.4%. These estimates are model-generated and are not presented as observed causal effects. Sensitivity analysis indicates that the value of analytics declines nonlinearly as information becomes delayed and can become economically negative when prediction quality, organizational actionability, or disruption severity is insufficient relative to implementation and intervention costs. For medical products, conventional return-on-investment analysis is further constrained by product essentiality, therapeutic substitutability, patient safety, and service-continuity requirements. The findings suggest that real-time analytics should be evaluated as an economic decision infrastructure, not simply an information technology investment. Its value is greatest when timely information expands feasible response options and is integrated with strategic inventory, supplier diversification, flexible capacity, cybersecurity, governance, and coordinated public-private action.

Keywords: Real-Time Analytics; Predictive Economic Modeling; Supply-Chain Resilience; Economic Value Of Information; Industrial Supply Chains; Medical-Product Shortages; Artificial Intelligence; Disruption Risk; Decision Support.

1. INTRODUCTION

The resilience of critical supply chains has become a major economic, industrial, public-health, and national-security concern in the United States. Modern supply chains have achieved substantial efficiencies through specialization, international sourcing, lean inventories, concentrated production,

synchronized logistics, and highly optimized utilization of physical assets. These same characteristics, however, can increase vulnerability when a critical supplier, manufacturing facility, transportation corridor, information system, or source of raw materials becomes unavailable.

The financial scale of the disclosed system is large. In June 2026, American manufacturers took in $656.5 billion in new orders, $652.1 billion in exports, $962.9 billion in inventories and $1.591 trillion in unfilled orders. In 2024, the U.S. freight transportation network moved about 20 billion tons of products valued $25 trillion, or about $68.4 billion in daily freight value. The sizes of these imply that small shocks can cause large economic effects if they include high-value manufacturing, transportation or inventory movements.

Healthcare supply chains provide another layer of economic and social risk . In 2024, national health expenditures in the United States totaled about $5.3 trillion, or 18.0% of gross domestic product. Hospital expenditure was approximately $1.635 trillion, while prescription-drug expenditure reached $467 billion. Medical-product disruptions cannot therefore be evaluated solely as procurement or logistics problems. Shortages can delay treatment, require therapeutic substitution, increase provider workload, alter clinical decisions, and impose social costs that do not appear directly on the financial statements of pharmaceutical manufacturers or distributors.

The continuing importance of medical-product resilience is illustrated by current federal shortage-management activity. The U.S. Food and Drug Administration reported that 330 potential drug shortages were prevented during calendar year 2025, while four new shortages occurred, the lowest number of new shortages in a decade. Yet the reduction in new shortages does not imply that structural vulnerability has disappeared. The Government Accountability Office reported that 102 shortages were being tracked by FDA as of July 31, 2024, with some shortages persisting for long periods and sterile injectable products remaining particularly important. GAO also noted that FDA was developing data-analytic tools intended to improve analysis of drug-supply information and potentially predict disruptions.

A central problem is therefore not merely whether organizations possess data. The problem is whether decision-relevant information can be collected, integrated, interpreted, and converted into action before disruption costs become difficult to reverse.

Traditional supply-chain management systems frequently operate through planning cycles that are slower than the shocks they attempt to manage. Monthly supplier reports, periodic inventory reconciliation, manually updated spreadsheets, quarterly economic indicators, and static safety-stock assumptions remain valuable, but they may identify a changing risk environment only after a supplier has failed, a shipment has been delayed, inventories have fallen below critical levels, or demand has already exceeded forecast capacity.

Real-time data analytics and predictive economic modeling potentially change this sequence. Data generated from enterprise resource planning systems, transportation-management systems, warehouse-management systems, sensors, supplier platforms, customs information, market indicators, weather systems, demand signals, and external risk sources can be integrated into a continuously updated representation of supply-chain conditions. Machine learning, statistical forecasting, network analysis, anomaly detection, simulation, and optimization can then estimate emerging disruption probabilities and the economic consequences of alternative responses.

However, technological capability should not be equated automatically with economic value. Analytics systems impose acquisition, integration, cloud-computing, data-governance, cybersecurity, training, maintenance, validation, and organizational-change costs. Predictions can also be wrong. False positive alerts may lead to unnecessary inventory purchases, supplier switching, expedited transportation, or production changes. False negatives may create false confidence. A model that predicts a disruption accurately but too late to change the decision may offer little economic value.

This paper therefore addresses a different question:

> Under what conditions does an improvement in real-time information and predictive warning translate into economically valuable intervention within critical U.S. industrial and medical-product supply chains?

Three research questions guide the study:

RQ1: Through what mechanisms do supply-chain disruptions generate direct, cascading, and tail economic losses in industrial and medical-product networks?

RQ2: How do improvements in information timeliness, predictive sensitivity, visibility, and organizational actionability alter expected disruption losses?

RQ3: What decision rule can determine whether the economic value of analytics-supported intervention exceeds its technological, operational, and risk-adjusted costs?

The paper contributes by linking supply-chain analytics to **decision-adjusted economic value**. Rather than treating forecast accuracy, visibility, or digital maturity as final outcomes, the proposed framework traces the sequence from signal acquisition to prediction, intervention, avoided loss, residual risk, and net economic benefit.

2. Literature Review and Theoretical Background

2.1 Supply-Chain Risk, Resilience, and Systemic Propagation

Supply chain risk management involves the identification, evaluation, mitigation and monitoring of uncertainties that may interfere with movements of commodities, information, financing, services or productive capacity. Ho et al. (2015) identify supply-chain risks arising from a wide range of supply, demand, operational, environmental, logistical and organizational factors. The literature is increasingly recognizing that risk cannot be comprehended at the level of an individual supplier or facility.

The ripple effect architecture of Ivanov, Sokolov and Dolgui is an illustration of the way in which disturbance may spread across linked networks of production and distribution, resulting in trade-offs between efficiency, flexibility and resilience. Highly synchronized systems can operate efficiently under normal conditions yet experience disproportionate losses when buffers, substitutes, or alternative routes are limited. Ivanov's subsequent viable-supply-chain model extends the concept toward the joint consideration of agility, resilience, and sustainability.

Recent systemic-risk research reinforces this network perspective. . Ouyang et al. studied the global cobalt dynamics and found that the disruptive impacts may be transmitted across different phases and countries through interrelated supply chains, which lead to nonlinear cascade events. Logan et al. similarly argue that conventional risk assessments centered on isolated assets are insufficient for

complex interdependent systems because cascading consequences, feedback, uncertainty, and emergent effects require broader analytical methods.

These findings are particularly relevant to critical industrial sectors involving specialized materials, semiconductors, energy inputs, transportation equipment, defense components, advanced manufacturing, and other products for which qualification periods or substitution opportunities may be limited. Resilience consequently depends not merely on identifying whether a supplier is risky but on understanding where that supplier is situated within the wider network and how quickly the network can reorganize when capacity becomes unavailable.

2.2 Real-Time Analytics, Digitalization, and Predictive Capability

Industry 4.0 research has established a strong conceptual link between digital integration and supply-chain performance. Fatorachian and Kazemi (2021) mention information integration, transparency, automation and digital connectivity as mechanisms through which Industry 4.0 technologies can enhance supply-chain operations.

Predictive analytics improves data visibility by forecasting future condition as opposed to today's condition. Baryannis et al. (2019) demonstrate the ability of artificial intelligence to contribute to formulating, modelling, and solve supply chain risk assessments and responses. Aljohani (2023) also associates machine learning, anomaly detection, and prediction analytics with proactive risk management.

Recent research shows that digitalization generates value through organizational capabilities rather than technology. According to Dubey et al. (2023), resilience is attributable to digital adaptability and agility, while government effectiveness can enhance these relationships. Wu and others mention of the improvement in supply-chain performance of data-driven digital transformation through resilience and robustness capabilities. The use of manufacturing data in research helps in establishing these relationships as well.

This distinction is important. Analytics does not prevent disruption simply by producing a risk score. An organization must have the authority and physical capability to respond. Data-analytic capability can reveal emerging vulnerability, but if no qualified alternative supplier exists, inventory cannot be repositioned, transportation cannot be rerouted, or production cannot be rescheduled, informational value may remain unrealized.

Digital-twin research makes the same point from a systems perspective. Recent reviews emphasize the potential of real-time synchronization, simulation, Internet-of-Things data, cloud computing, and predictive modeling, while also identifying significant integration and implementation challenges. A 2025 simulation-based digital-twin study further illustrates how real-time enterprise data and predictive machine-learning models can be combined to evaluate mitigation decisions during manufacturing disruptions.

2.3 Medical-Product Supply Chains as a Distinct Economic Problem

Medical-product supply chains require additional analytical treatment because availability has clinical as well as financial consequences. Marucheck et al. (2011) identify product quality, traceability, regulation, supplier relationships, recalls, and product safety as central considerations in pharmaceutical and medical-device supply chains.

The National Academies' framework for medical-product supply-chain resilience emphasizes awareness, mitigation, preparedness, and response, reflecting the need to treat shortages as system-level public-health problems. More recent empirical research supports an explicit role for digital capability. In the healthcare supply-chain domain, Tiwari et al. (2024) found that visibility is a necessary building block for digital capabilities; further, digital tech can help improve dynamics of resilience for healthcare supply chains.

Drug shortages also show the limits of the reactive-only strategy. According to Cornelissen et al. (2026), most shortages are caused by manufacturing faults or demand and market fluctuations. Other causes include poor supply-chain management, strategic decisions, and exogenous factors. Most interventions target the downstream part and take place after faults have occurred.

Data analysis can encourage proactive intervention. Christian and Bagais (2024) reveal ways in which data use can monitor upstream risk to the drug supply and potentially early warning systems. This is consistent with U.S. data that stated supply-chain problems are linked to higher odds of eventual shortages. "A meaningful drug shortage was associated with about one in seven supply-chain issue reports studied," reported Callaway Kim et al. (2024).

Another layer of complication is added by the economic structure of generic medication marketplaces. Hernandez et al. (2024) propose that significant pricing pressure in some generic markets might lower incentives to maintain redundancy, quality investments and robust manufacturing capacity. ASPE has also pointed to market incentives, lack of transparency, concentration and poor rewards for robust production as reasons that make pharmaceutical supply chains fragile.

2.4 Research Gap

The reviewed literature provides strong support for supply-chain resilience, visibility, digitalization, predictive analytics, and AI-enabled decision support. Three gaps nevertheless remain.

First, many studies evaluate analytics through forecast accuracy, technological capability, visibility, agility, or operational performance without explicitly translating earlier information into avoided economic loss.

Second, industrial and medical-product supply chains are frequently analyzed separately, although both depend on interconnected networks, real-time information, alternative capacity, and coordinated intervention. A common framework would make comparison possible while preserving healthcare-specific constraints.

Third, the value of prediction is often discussed without sufficiently modeling **time**. Information has economic value partly because it expands the response window. The same prediction can be highly valuable when received early and nearly worthless after feasible alternatives have disappeared.

This study addresses these gaps through RERSIF.

3. Methodology

3.1 Research Design

The study adopts an applied conceptual and simulation-based research design. It does not attempt to estimate a single national dollar value for predictive analytics across all U.S. supply chains because

no homogeneous dataset exists that jointly represents disruption frequency, network dependencies, warning time, inventory positions, intervention capabilities, medical criticality, and economic consequences across industries.

Instead, the methodology combines four components:

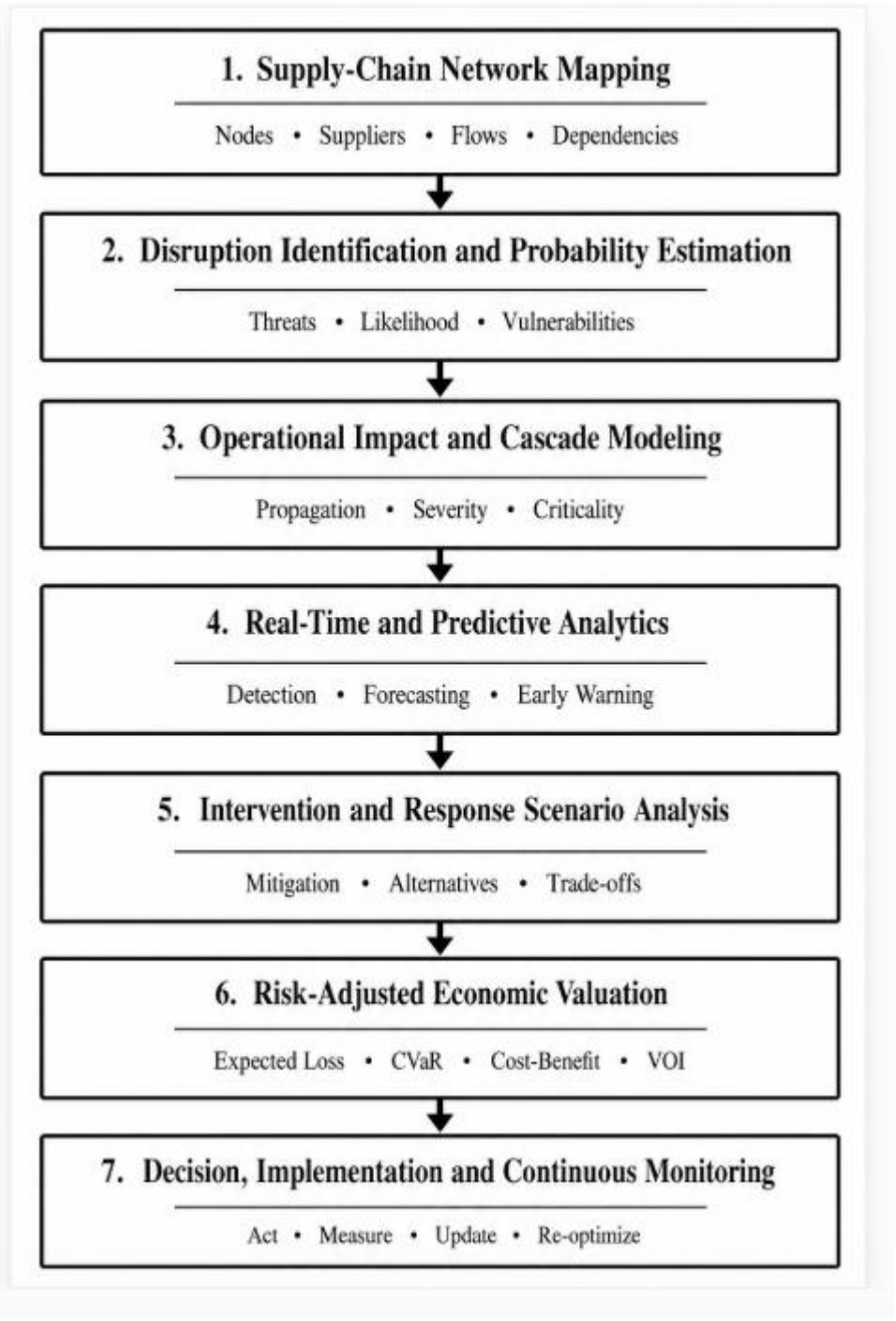
1. structured synthesis of supply-chain resilience and analytics research;
2. development of an economic-impact model;
3. sector-specific analytical treatment of industrial and medical-product networks; and
4. Monte Carlo stress testing to evaluate the behavior of the proposed decision framework under uncertainty.

The simulation is explicitly **illustrative**. Its purpose is to test economic relationships and sensitivity to warning latency rather than to present causal estimates of actual national savings.

3.2 Real-Time Economic Resilience and Supply Intelligence Framework

RERSIF contains five analytical stages.

Figure 1. RERSIF Economic-Impact Assessment Process



Stage 1 maps suppliers, manufacturing facilities, logistics nodes, inventories, distributors, healthcare institutions, end users, and critical upstream dependencies.

Stage 2 defines disruption scenarios, including supplier failure, cyber incidents, transportation interruption, equipment failure, demand surges, quality problems, raw-material shortages, geopolitical restrictions, and regulatory delays.

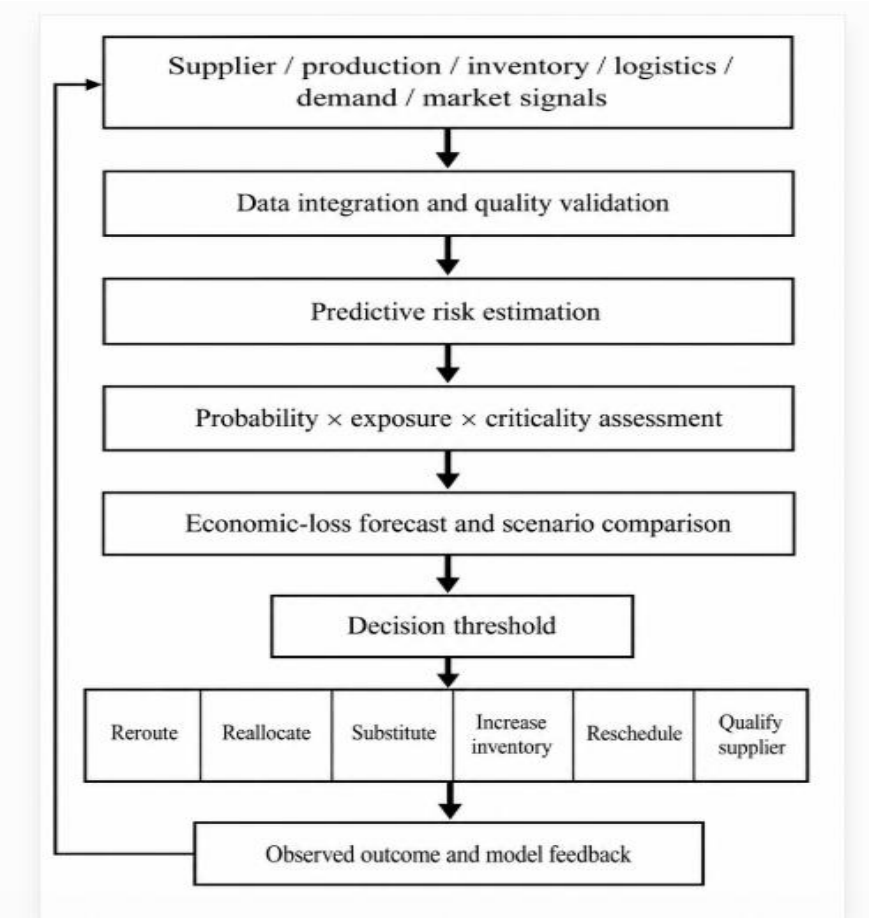
Stage 3 converts disruptions into measurable consequences such as downtime, lost throughput, delayed shipments, inventory depletion, emergency freight, unmet demand, substitution cost, treatment delay, waste, and recovery time.

Stage 4 models the contribution of analytics through improved warning time, probability estimation, inventory visibility, anomaly detection, demand forecasting, resource allocation, and response coordination.

Stage 5 evaluates whether the expected economic and service benefits exceed implementation, intervention, false-alert, governance, cybersecurity, and residual-risk costs.

A more detailed information pathway is shown below.

Figure 2. From Real-Time Signal to Economic Intervention



3.3 Economic Formulation

For disruption scenario (j), baseline expected annual loss is:

[EAL_{0}=_{j=1}^{J} p_jL_j]

where (p_j) is the probability of disruption and (L_j) is the economic consequence if the disruption occurs.

Analytics modifies the loss through a mitigation effectiveness term:

[*j*={}s_j a_j e^{-_j}]

where:

- (_{}) = maximum technically achievable mitigation,
- (s_j) = predictive sensitivity or reliability,
- (a_j) = organizational actionability,
- (_j) = detection or warning latency, and
- () = rate at which informational value decays with delay.

Residual disruption loss becomes:

[L_j^{A}=(1-_j)L_j]

and analytics-enabled expected annual loss is:

[EAL_A=*{j=1}^{J}p_jL_j{A}+C*{FA}+C_R]

where (C_{FA}) represents false-alert costs and (C_R) represents residual analytical and response risks.

Total annual economic value is:

[NB=(EAL_0-EAL_A)+E_{OP}+S-C_T]

where (E_{OP}) represents recurring operating efficiencies, (S) represents additional service or social benefits, and (C_T) represents annualized technology, integration, training, cybersecurity, governance, validation, and maintenance costs.

The analytics investment is economically justified when:

[(EAL_0-EAL_A)+E_{OP}+S>C_T]

More importantly, an individual intervention should occur only when the probability-weighted avoided loss exceeds the cost of acting:

[p_jL_j()+S_j>C_{Action,j}+C_{False,j}]

This is the central decision rule of the framework.

3.4 Medical-Product Service-Continuity Constraint

For industrial supply chains, the primary objective may reasonably be expressed as minimization of risk-adjusted economic loss.

Medical-product allocation requires a constraint because a financially optimal decision could allocate scarce products toward the most profitable users rather than the most clinically important ones.

For essential product (k):

[(A_{k,t}A_k^{min})-_k]

where (A_{k,t}) represents available supply, (A_k^{min}) represents the minimum clinically acceptable availability level, and (_k) represents the maximum tolerated probability of falling below that threshold.

Economic optimization therefore occurs **subject to continuity-of-care constraints**.

3.5 Simulation Design

A Monte Carlo experiment was used to illustrate the effect of detection latency. Annual disruption counts were modeled using Poisson processes, while disruption severity was represented using right-skewed lognormal distributions to capture the possibility of infrequent high-loss events. Organizational actionability was modeled through beta distributions.

The model generated **150,000 simulated annual outcomes per sector** using fixed random seeds for reproducibility. Losses are reported in normalized economic-loss units rather than dollars.

Parameter	Industrial scenario	Medical-product scenario
Mean disruption frequency	3/year	4/year
Baseline detection latency	4 weeks	3 weeks
Enhanced latency	1 week	0.5 week
Predictive sensitivity	0.82	0.88
Maximum mitigation factor	0.90	1.00
Latency-decay coefficient	0.15	0.17
Tail-risk metric	95% CVaR	95% CVaR

The values are stylized assumptions selected to examine framework behavior. They should be replaced by organization-specific empirical estimates before investment or policy decisions are made.

4. Results

4.1 Economic Mechanisms

The analytical framework identifies four principal channels through which real-time analytics creates economic value.

First, detection value arises when abnormal conditions are identified earlier. Second, forecast value arises when future supply, demand, or capacity states can be estimated sufficiently well to alter planning. Third, allocation value arises when scarce inventory, production capacity, transportation, or emergency resources can be redirected more effectively. Fourth, coordination value arises when multiple organizations act using a consistent representation of system conditions.

The model also demonstrates that information by itself does not create value. Value is generated only if the information changes an economically consequential action.

4.2 Simulation Results

Under the industrial scenario, the four-week latency configuration produced an expected annual disruption loss of 40.47 normalized units. Reducing latency to one week lowered expected loss to 32.38 units, a reduction of approximately 20.0%.

Tail exposure also decreased. The industrial 95% Conditional Value-at-Risk fell from 145.51 to 120.21 normalized units, representing a 17.4% reduction.

For the medical-product scenario, expected loss declined from 38.95 units under a three-week latency assumption to 26.53 units when latency was reduced to one-half week, a reduction of approximately 31.9%. The corresponding 95% CVaR declined from 142.80 to 102.20 units, or approximately 28.4%.

Outcome	Industrial	Medical product
Baseline expected loss	40.47	38.95
Enhanced-analytics expected loss	32.38	26.53
Expected-loss reduction	**20.0%**	**31.9%**
Baseline 95% CVaR	145.51	142.80
Enhanced 95% CVaR	120.21	102.20
CVaR reduction	**17.4%**	**28.4%**

Note: Results are simulation-generated and should not be interpreted as observed economic savings in U.S. industries or healthcare systems.

4.3 Detection Latency and Information Decay

Sensitivity testing demonstrates a nonlinear relationship between warning latency and economic loss.

Figure 3. Normalized Expected Loss as Detection Latency Increases

Detection latency	Industrial loss	Medical-product loss
0.5 week	30.55	26.76
1 week	32.29	29.71
2 weeks	35.41	34.91
3 weeks	38.08	39.30
4 weeks	40.39	Not modeled

The result has an important interpretation. The economic value of analytics is not determined solely by whether the eventual prediction is correct. It depends on when the information becomes actionable.

If qualification of a substitute supplier requires three weeks, an alert received four days before inventory exhaustion may be technically accurate but economically ineffective. Conversely, a moderately accurate alert received six weeks earlier may create time for supplier qualification, production rescheduling, contracting, inventory repositioning, or transportation changes.

4.4 Industrial Versus Medical-Product Effects

The industrial model places greater weight on:

- avoided downtime;
- throughput preservation;
- delivery reliability;
- emergency transportation costs;
- inventory efficiency;
- supplier substitution; and
- recovery duration.

The medical-product model incorporates these variables but additionally requires:

- clinical essentiality;
- therapeutic substitutability;
- patient population exposed;
- stockout duration;
- treatment continuity;
- product expiration;
- safety and quality;
- regulatory constraints; and
- ethical allocation.

The higher simulated benefit from latency reduction in the medical scenario should therefore not be interpreted as proof that healthcare analytics necessarily produces a higher financial ROI. Rather, it illustrates that systems characterized by high criticality, limited substitution, and time-sensitive consequences can assign greater value to earlier information.

5. Discussion

5.1 From Predictive Accuracy to Decision-Adjusted Economic Value

The central finding is that predictive performance is an incomplete measure of analytics value.

Conventional model evaluation frequently emphasizes mean absolute error, root mean squared error, precision, recall, F1 score, area under the receiver-operating-characteristic curve, or classification accuracy. These measures remain necessary, but they do not indicate whether a prediction generated economic value.

Consider two models. Model A predicts supplier failure with 95% accuracy but generates the warning two days before inventory exhaustion. Model B predicts with 82% accuracy but identifies deterioration five weeks earlier. If alternative-supplier qualification requires three weeks, Model B may have greater economic value despite lower statistical accuracy.

This interpretation is consistent with empirical findings that digital capabilities produce resilience through organizational agility, visibility, robustness, and coordinated decision-making rather than through technology in isolation.

5.2 Implications for Industrial Supply Chains

Industrial firms should prioritize analytics where disruption losses are large and response options are time-sensitive.

Supplier-risk models, for example, are most valuable for components with limited substitutes, long qualification times, high revenue dependency, or concentrated geographic sourcing. Predictive-maintenance systems are most valuable when equipment failure would create significant bottlenecks. Logistics analytics produces greater value where alternative transportation routes or modes remain feasible if interruption is detected early.

The model therefore argues against universal deployment based only on technological attractiveness. Organizations should rank analytics projects using expected avoided loss.

A practical sequence is:

Criticality → exposure → warning opportunity → response feasibility → economic value.

This also implies that data investment and physical resilience investment should be considered jointly. Analytics can identify a supplier problem, but it cannot create a substitute supplier that does not exist. Digital visibility can identify an inventory shortage, but it cannot create production capacity instantaneously.

5.3 Implications for Medical-Product Supply Chains

Medical-product supply chains require earlier and broader risk measurement because shortages often originate upstream while operational responses frequently occur downstream. This mismatch is evident in contemporary drug-shortage research.

Predictive models could integrate variables such as manufacturing concentration, quality-inspection history, API dependence, supplier geography, historical shortage frequency, inventory coverage, demand variability, alternative products, facility reliability, transportation exposure, and regulatory constraints.

The objective should be to identify combinations of:

high disruption probability + low substitutability + high clinical criticality + long recovery time.

Such products warrant earlier intervention even where conventional financial ROI appears modest.

This logic aligns with FDA's use of earlier manufacturer notifications and its continuing efforts to prevent potential shortages before they become active shortages. It also supports the broader policy argument that resilience requires coordination across manufacturers, regulators, purchasers, distributors, healthcare providers, and public agencies.

5.4 Governance and Implementation

Data quality is a binding constraint on predictive economic modeling. Incomplete network maps, missing tier-two and tier-three suppliers, inconsistent product identifiers, delayed inventory updates, and inaccurate lead-time records can produce apparent precision without reliable situational awareness.

Research on data sparseness demonstrates that limited data availability can materially reduce supply-chain visibility. Analytics investments should therefore begin with data architecture rather than model complexity.

Organizations should establish:

- common product and supplier identifiers;
- data-quality thresholds;
- access and ownership rules;
- secure information-sharing protocols;
- model-validation procedures;
- cybersecurity controls;
- human-override mechanisms;

- audit trails;
- escalation thresholds; and
- defined accountability for model-supported decisions.

Human oversight remains particularly important for medical-product decisions because an optimization model can identify economically efficient allocation without understanding broader ethical or clinical consequences unless those constraints are explicitly represented.

5.5 Policy Implications

The findings also have implications for public-sector supply-chain monitoring.

Government agencies possess information that is distributed across trade statistics, transportation systems, regulatory filings, public-health surveillance, economic indicators, procurement systems, and private-sector reporting. Integrating selected high-frequency signals could improve the identification of emerging concentration, transportation, production, and shortage risks.

The scale of current manufacturing, freight, and healthcare activity suggests that even relatively small improvements in disruption detection could be economically important when applied to highly critical flows.

Public policy should nevertheless avoid assuming that better prediction eliminates the need for physical resilience. Strategic inventories, alternative suppliers, flexible production, domestic or allied capacity, qualified substitutes, logistics redundancy, and emergency authorities remain necessary.

Analytics should identify where those expensive resilience resources create the greatest marginal value.

6. Managerial Decision Framework

The study recommends evaluating prospective analytics investments through six questions.

1. What economic or service loss is being avoided?
The organization should quantify downtime, lost throughput, emergency procurement, stockouts, delayed service, lost sales, patient-care consequences, and recovery costs.

2. How early must the warning arrive to change the decision?
The relevant comparison is not real time versus monthly reporting in the abstract. It is the warning horizon relative to the time required to execute a response.

3. What actions become possible because of the warning?
Possible actions include supplier qualification, inventory reallocation, expedited production, transportation rerouting, preventive maintenance, purchase acceleration, alternative-product substitution, or emergency allocation.

4. What is the probability that the analytical system is correct?
Sensitivity, specificity, calibration, false-positive frequency, and model drift must be measured.

5. What does acting unnecessarily cost?
False alerts can produce real economic losses.

6. Does the expected avoided loss exceed total implementation and intervention cost?
If not, the analytics investment may improve information without improving economic performance.

This produces a portfolio approach in which the highest-priority use cases are those combining high criticality, high economic exposure, actionable warning time, and feasible mitigation.

7. Limitations and Future Research

The study has several limitations.

First, the numerical experiment is stylized and should not be interpreted as an empirical estimate of national savings. Real-world parameterization requires longitudinal data on disruptions, warning times, intervention effectiveness, supplier networks, inventories, transportation costs, production losses, healthcare utilization, and system implementation expenses.

Second, the model simplifies relationships that may be dynamic. Disruption probability can change as firms respond, suppliers learn, inventories decline, competitors enter markets, or government action modifies incentives.

Third, social and clinical consequences are difficult to monetize. For medical products, some of the most important outcomes should remain service or health constraints rather than being reduced mechanically to dollar values.

Fourth, predictive systems can produce endogenous behavior. Suppliers, knowing that they are being monitored, may change what they report; corporations may overreact to warnings; and frequent false warnings may cause warning fatigue.

Therefore, future study should validate RERSIF with firm-level or sectoral-level data. Natural experiments, longitudinal implementation studies, digital twin settings, and difference-in-differences methods might investigate if increased warning time lowers the duration of observed disruption or economic loss.

Research should also examine network-level applications in crucial minerals, semiconductors, pharmaceuticals, medical devices, energy systems, food, transportation, and defense industries.

8. Conclusion

This study develops an economic framework for assessing real-time data analytics and predictive modeling in critical U.S. industrial and medical-product supply chains.

The principal argument is straightforward: information has economic value when it arrives early enough, is sufficiently reliable, and enables an action that reduces expected loss by more than the total cost of obtaining and acting on that information.

This distinction matters because supply-chain analytics is often justified using technological capabilities rather than decision outcomes. Real-time dashboards, artificial intelligence, machine learning, digital twins, and predictive models are not resilience themselves. They are mechanisms for extending situational awareness and decision time.

The proposed RERSIF framework connects supply-chain network structure, disruption probability, operational consequences, predictive warning, response feasibility, avoided losses, implementation costs, residual risk, and service outcomes within a unified analytical structure.

The simulation illustrates the importance of timeliness. Under the stylized assumptions employed, reducing industrial detection latency from four weeks to one week decreased expected disruption losses by approximately 20.0%, while reducing medical-product latency from three weeks to one-half week decreased expected loss by approximately 31.9%. Tail-risk reductions were also material. These are methodological results rather than empirical estimates, but they demonstrate the nonlinear economic consequences of delayed information.

For industrial firms, the implication is to invest first where earlier information can preserve production, avoid emergency costs, protect high-value inputs, or shorten recovery. For medical-product systems, the decision rule must go further by incorporating clinical essentiality, substitutability, patient safety, and continuity of treatment.

At the public-policy level, real-time analytics can support earlier identification of concentration, shortage, transportation, manufacturing, and material risks. Yet predictive systems cannot substitute for physical resilience.

The strongest architecture is therefore:

Real-time visibility + predictive intelligence + economic decision rules + strategic inventory + supplier diversity + flexible capacity + secure information sharing + institutional coordination.

Under this architecture, analytics becomes more than a forecasting tool. It becomes an economic resilience infrastructure capable of helping organizations and public institutions determine what risk is emerging, what it may cost, what response remains feasible, and whether acting now creates more value than waiting.

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ASSESSING THE NATIONAL ECONOMIC EFFECTS OF PREDICTIVE MODELING AND INTEROPERABLE HEALTH INFORMATION SYSTEMS: REDUCING HEALTHCARE ADMINISTRATIVE BURDEN, IMPROVING DATA EFFICIENCY, AND STRENGTHENING U.S. HEALTH-SYSTEM PRODUCTIVITY

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Abstract

Assessing the National Economic Effects of Predictive Modeling and Interoperable Health Information Systems: Reducing Healthcare Administrative Burden, Improving Data Efficiency, and Strengthening U.S. Health-System Productivity. U.S. health expenditures reached $5.3 trillion in 2024, equivalent to 18.0% of GDP [1]. At the same time, administrative work is estimated at approximately $440 billion annually, and the 2024 CAQH Index identifies $20 billion in additional annual savings available from fuller automation of selected administrative transactions [3]. Interoperability has also advanced: 70% of non-federal acute-care hospitals exchanged information across all four measured domains at least sometimes in 2023, yet only 43% did so routinely, and only 42% reported that clinicians often used externally available information at the point of care [9]. Predictive modeling keeps getting more accurate on operational tasks. Many systems nonetheless remain retrospective, locally trained, weakly transportable, or poorly integrated into interoperable workflows [15]-[18]. The unsolved problem is the absence of a national economic measurement architecture linking data exchange, data quality, predictive performance, workflow conversion, and realized productivity. This paper (1) quantifies the scale of the U.S. administrative and data-use opportunity; (2) identifies the technical and economic mechanisms through which interoperable predictive systems may create value; (3) proposes a National Predictive Interoperability Productivity Framework (NPIPF); and (4) defines a reproducible KPI and causal-evaluation strategy for estimating national effects without conflating technical model accuracy with economic impact. A structured evidence synthesis was combined with deterministic scenario analysis using recent CMS, ASTP/ONC, CAQH, NIST, and peer-reviewed evidence. The analytic model decomposes economic value into administrative-process savings, staff-time capacity, avoidable utilization, and operational throughput, net of implementation, operating, and model-risk costs. A multilevel KPI architecture covers interoperability, data quality, model discrimination/calibration, workflow adoption, financial outcomes, equity, and drift. Illustrative national scenarios are explicitly treated as stress tests rather than causal forecasts. Three findings emerge. First, very small efficiency changes are macroeconomically material: each 0.1 percentage-point reduction in 2024 national health expenditures corresponds to approximately $5.3 billion in gross annual value. Second, the largest technical bottleneck is a conversion gap between data availability and routine use; 71% of hospitals reported routine access to external information but only 42% reported frequent clinician use [9]. Third, conservative NPIPF scenarios produce illustrative gross annual value of approximately $3.6-$22.0 billion before implementation and governance costs. These values are not forecasts; they demonstrate the order of magnitude that should be tested prospectively. The United States should measure interoperability as an economic production input rather than as exchange volume alone. Payment and certification programs should pair FHIR/USCDI/TEFCA exchange with standardized data-quality gates, external validation, calibration and drift monitoring, workflow-level causal evaluation, and economic accounting. HTI-1 algorithm-transparency requirements, HTI-4

electronic prior-authorization standards, CMS interoperability rules, and TEFCA provide a policy substrate for such measurement [8], [10]-[12].

Keywords: Predictive Modeling; Interoperability; Health Information Systems; Administrative Burden; Health-System Productivity

1. INTRODUCTION

The U.S. health system is simultaneously a major source of health production and a large economic sector whose efficiency affects households, employers, federal and state budgets, and labor markets. CMS reports that national health expenditures (NHE) reached $5.3 trillion in 2024, or $15,474 per person and 18.0% of gross domestic product [1]. An expenditure base that large gives even small productivity changes national consequences. A 0.1% change in the expenditure base is approximately $5.3 billion per year; a 1.0% change is approximately $53 billion. CMS also projects health spending to continue growing faster than GDP over the coming decade [2].

A central source of inefficiency is administrative complexity. Shrank et al. estimated $265.6 billion in annual waste attributable to administrative complexity in the 2019 evidence base [4]. Subsequent work estimated that roughly $265 billion could be saved through a portfolio of administrative-simplification interventions [5]. More recent analysis of the financial-transactions ecosystem reports more than 9 billion claims annually, transaction costs of approximately $12-$19 per claim across private payers and providers, and a potential $40-$60 billion reduction in spending from organizational and industry-level reforms [6]. CAQH estimates approximately $440 billion in annual administrative work, tracks about $90 billion in selected medical and dental administrative workflows, and identifies a $20 billion annual opportunity from moving remaining manual or partially electronic processes to fuller automation [3].

Interoperability and predictive modeling are often proposed as complementary solutions. The first reduces information friction, making clinically and administratively relevant data available across organizational boundaries. The second converts those data into estimates of future demand, utilization, denials, readmission risk, staffing needs, or operational bottlenecks. Neither generates economic value on its own. Exchange can exist without use, and accurate predictions can exist without action. The economic unit of analysis must therefore be the workflow changed by timely, trustworthy information.

This paper addresses an unresolved research problem: the literature lacks a unified, national-scale framework that connects interoperable data availability to data quality, predictive validity, workflow adoption, and realized economic value. The contribution is the National Predictive Interoperability Productivity Framework (NPIPF), a technical-economic architecture for measuring this chain and testing it with prospective, multisite designs.

2. NATIONAL BASELINE AND THE UNSOLVED MEASUREMENT GAP

Table I summarizes recent national benchmarks. The values are intentionally heterogeneous because the paper distinguishes total spending, administrative burden, transaction-specific opportunity, interoperability maturity, and exchange infrastructure rather than summing them as if they were independent cost pools.

Indicator	Recent value	Economic/technical meaning	Source
U.S. NHE, 2024	$5.3 trillion; 18.0% GDP	Macroeconomic denominator for productivity sensitivity	[1]
Administrative work	$440 billion/year	Broad administrative burden benchmark	[3]
CAQH-tracked workflows	$90 billion/year	Subset of manual + electronic transactions measured by CAQH	[3]
Further automation opportunity	$20 billion/year	Potential savings from fuller electronic workflows; not additive to all other estimates	[3]
All four interoperability domains, at least sometimes	70% of hospitals	Exchange capability is widespread but not universal	[9]
Routine interoperability	43% of hospitals	Maturity gap in send/find/receive/integrate	[9]
Routine access to external clinical information	71% of hospitals	Availability at point of care	[9]
Clinicians often use external information	42% of hospitals	Last-mile conversion from access to use	[9]
TEFCA scale, 2026	>1.5 billion documents shared; >23,000 organizations live	Nationwide exchange substrate is now material	[12]

Table I. Selected U.S. economic and interoperability baselines. Measures have different definitions and denominators and should not be directly added.

The technical gap is visible in the difference between routine access and routine use. In 2023, 71% of hospitals reported routine electronic access to needed information from outside providers, but only 42% reported that clinicians often used such information when treating patients [9]. Data liquidity

alone is therefore an incomplete performance metric. What matters economically is whether the information changes a decision before a cost is incurred, a delay occurs, or capacity is committed.

The predictive-model literature has a parallel problem. A 2023 scoping review identified 39 FHIR-based machine-learning clinical information systems, but many lacked full EHR interoperability and externally validated evidence of clinical efficacy [15]. A 2025 systematic review of hospital-admission prediction found reported accuracy commonly in the 85%-95% range, but most included studies were retrospective and the authors called for prospective validation of operational impact [17]. Dataset shift further limits transferability; a 2025 review found heterogeneous detection and mitigation methods and insufficient standardization of external validation and performance monitoring [18].

Data quality is what links these two problems. Lewis et al. reviewed 103 EHR data-quality studies and found repeated attention to completeness, correctness, concordance, plausibility, and currency, but no standard approach to assessment [13]. Penev et al. similarly found incomplete reporting, limited replicability, and limited generalizability in a substantial subset of EHR quality studies [14]. Predictive interoperability therefore takes more than API connectivity. Semantic consistency, provenance, timeliness, completeness, and stability all have to be measured before model output can be treated as economically actionable.

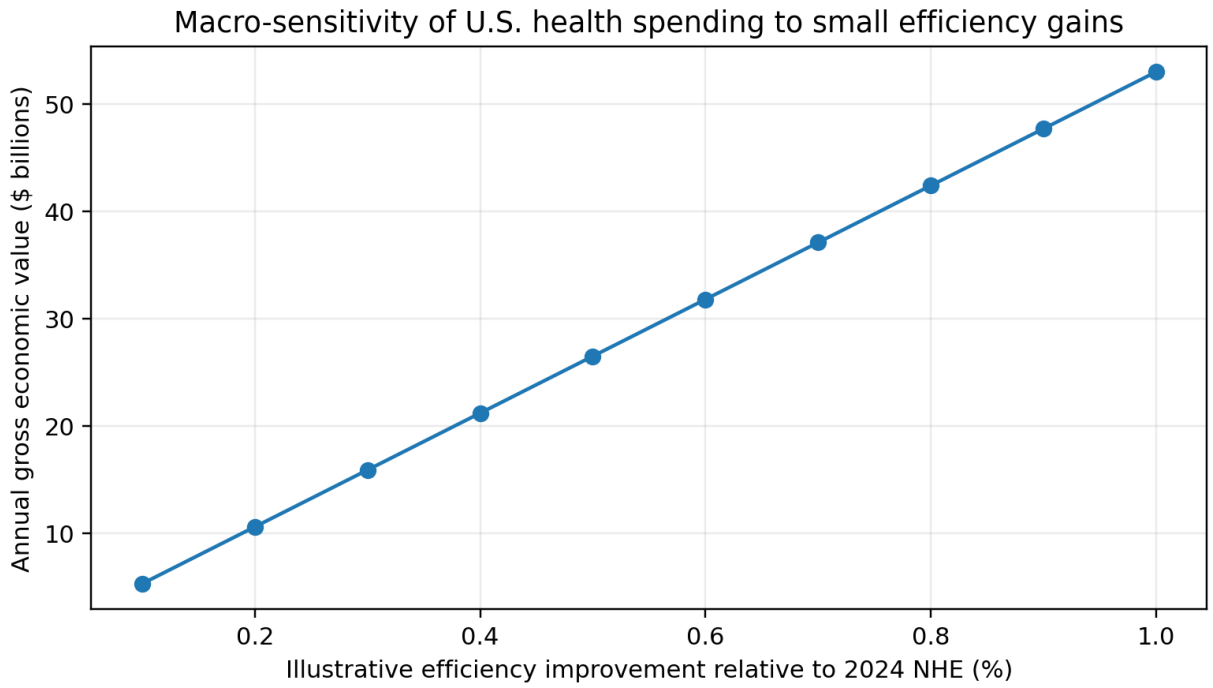


Figure 1. Macro-sensitivity of 2024 U.S. health spending. The curve is arithmetic, not a forecast: 0.1% of $5.3 trillion equals approximately $5.3 billion [1].

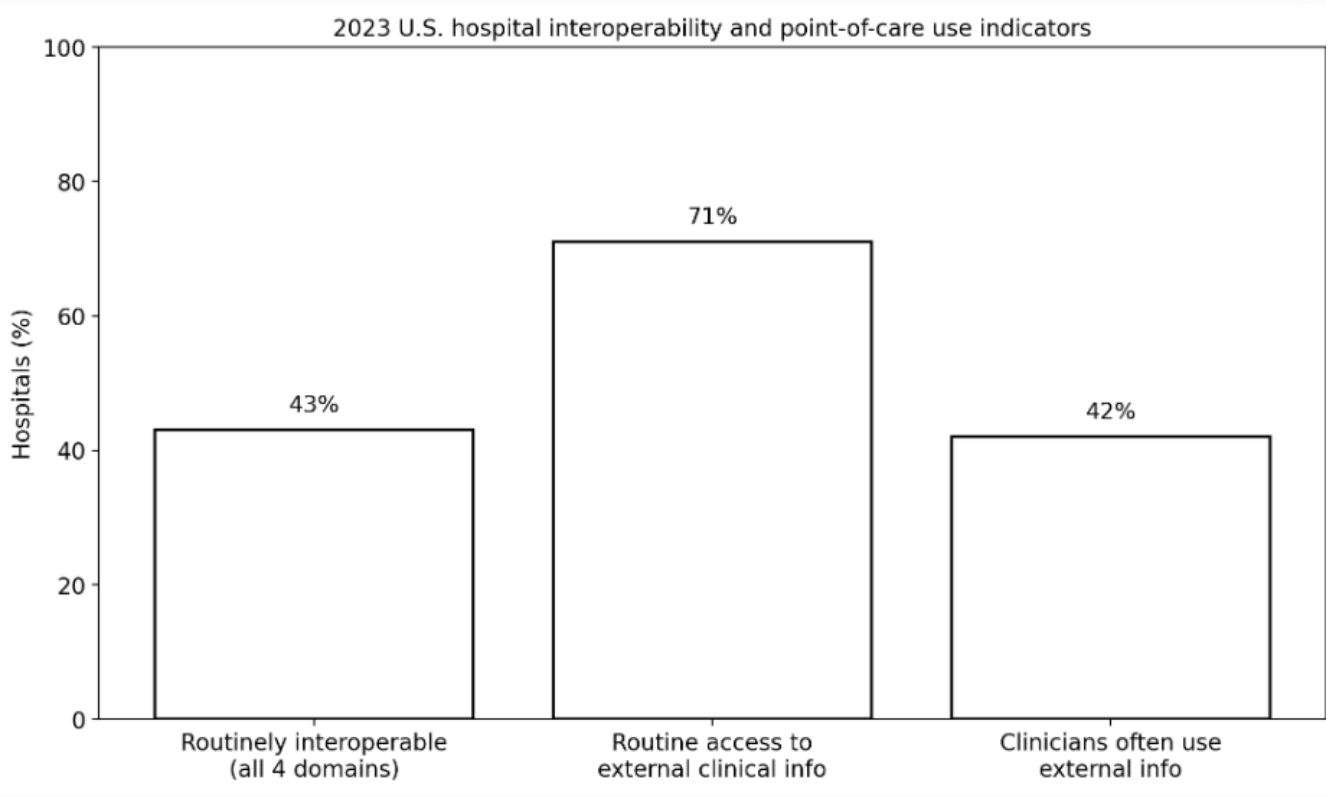


Figure 2. Selected 2023 hospital interoperability indicators. The three percentages represent distinct measures and are shown to illustrate the gap between routine exchange/access and routine point-of-care use [9].

3. METHODS

3.1 Study Design and Evidence Base

The study is a structured evidence synthesis plus a technical-economic scenario analysis. Sources were selected from U.S. federal agencies, national administrative-transactions reporting, standards bodies, and peer-reviewed studies addressing administrative burden, interoperability, data quality, predictive modeling, model transportability, workflow integration, and health-information-exchange outcomes. Recent evidence was prioritized, with older causal studies retained where they provide direct estimates of workflow effects. The analysis does not claim that national savings have already been causally realized.

3.2 Economic Value Function

For workflow j, annual net economic value is defined as:

$$V_j = N_j(c0_j - c1_j) + H_j*w_j + A_j*u_j - Cimpl_j - Cops_j - Crisk_j$$

where N_j is annual transaction volume; c0_j and c1_j are baseline and post-intervention processing costs per transaction; H_j is staff-hours released; w_j is loaded labor cost per hour; A_j is the number of avoidable utilization events attributable to the intervention; u_j is cost per avoided event; Cimpl_j is annualized implementation cost; Cops_j is operating/maintenance cost; and Crisk_j is the expected

economic cost of model errors, downtime, security events, or inequitable performance. National value is the weighted sum across workflows, organizations, payer types, and geographic strata.

Health systems should report gross and net value together, because the two can point in opposite directions. Gross value can be large while net value stays negative once implementation costs, integration debt, alert burden, or error costs are counted. The investment criterion is therefore:

$$NPV = -C0 + SUM_t[(B_t - C_t)/(1+r)^t] > 0; \qquad ROI = (PV(B) - PV(C))/PV(C)$$

where r is the discount rate and B_t and C_t are annual benefits and costs. For national extrapolation, post-intervention values should be weighted using hospital size, ownership, rurality, system affiliation, payer mix, and baseline interoperability maturity, because ONC data show substantial structural differences in routine exchange [9].

3.3 Technical Utility Chain

NPIPF treats value production as a multiplicative chain. For workflow j, the realized fraction of theoretical value is:

$$R_j = I_j * DQ_j * P_j * W_j * S_j$$

I_j is interoperability availability (0-1), DQ_j is a normalized data-quality score, P_j is predictive utility, W_j is workflow conversion, and S_j is sustained performance under drift. Because the chain is multiplicative, a low value at any stage caps the whole result. That is why a high AUROC on its own is not a productivity metric. Predictive utility should include calibration, positive predictive value at the operational threshold, subgroup performance, and external validation, not discrimination alone.

3.4 Causal Evaluation Strategy

The preferred empirical design is a multisite stepped-wedge or difference-in-differences implementation in which comparable hospitals or departments adopt the interoperable predictive workflow at staggered dates. A core model is:

$$Y_it = alpha + beta(Treat_i * Post_t) + gamma X_it + hospital_FE + time_FE + epsilon_it$$

Y_it may be administrative minutes per transaction, denial probability, days to authorization, duplicate imaging rate, length of stay, avoidable admission, cost per encounter, or labor-hours per 1,000 encounters. The coefficient beta estimates the incremental effect under parallel-trend assumptions. For predictive components, pre-specified external validation and calibration should precede economic analysis. Clustered standard errors, event-study diagnostics, sensitivity to coding changes, and negative-control outcomes should be used where feasible.

3.5 KPI Architecture

Layer	Core KPIs	Technical definition	Interpretation
Interoperability	Exchange success;	Successful usable	Measures whether

Layer	Core KPIs	Technical definition	Interpretation
	external-record retrieval; integration rate; latency	exchanges / attempted exchanges; median seconds to availability	needed data arrive in time
Data quality	Completeness; conformance; plausibility; currency; provenance	Valid populated fields / expected fields; terminology/API conformance rate	Determines whether exchanged data are model-ready
Prediction	AUROC/AUPRC; Brier score; calibration intercept/slope; PPV; sensitivity; drift	Pre-specified test-set and external-site metrics	Separates statistical performance from deployment claims
Workflow	Action rate; time-to-action; override rate; denial rate; turnaround time	Actions taken / actionable predictions; elapsed process time	Measures conversion of prediction into behavior
Economic	Cost/transaction; hours/1,000 cases; avoided utilization; NPV; ROI	Observed resource difference valued at standardized unit costs	Measures realized productivity
Equity	Rural/urban access gap; subgroup calibration; FNR/FPR gap	Performance stratified by race/ethnicity, age, sex, payer, geography where lawful/available	Detects distributional harms or unequal gains
Reliability	API uptime; model drift; missingness shift; recalibration frequency	PSI/KS or other pre-specified shift tests plus service reliability	Tests whether benefits persist over time

Table II. NPIPF minimum KPI set. Thresholds should be use-case-specific; the framework standardizes what is measured, not a universal cutoff.

4. PRELIMINARY FINDINGS AND SCENARIO ANALYSIS

4.1 Administrative Burden Is Large but Not Fully Addressable by Technology

The administrative opportunity is large. A credible model still has to avoid treating every administrative dollar as technology-removable. CAQH estimates $440 billion in administrative work but identifies a narrower $20 billion opportunity from full automation of the transactions it measures [3]. Sahni et al. estimate a $40-$60 billion opportunity within the broader financial-transactions

ecosystem, but these estimates overlap conceptually with claims, prior authorization, revenue-cycle, and other administrative functions and therefore should not be added mechanically [6]. CMS separately estimates that its 2024 interoperability and prior-authorization rule will produce approximately $15 billion in savings over ten years across impacted programs [8].

The evidence also shows that workflow redesign can matter. In a 2025 quality-improvement study of 6,551 radiation-oncology authorization cases, clinically integrated prior-authorization software was associated with a 65.4% reduction in denials and a 33.9% reduction in median authorization time, although the design was not a national randomized evaluation and vendor-related conflicts were disclosed [23]. The case illustrates the NPIPF principle. Value appears where data, decision logic, payer rules, and workflow execution are coupled, and not before.

4.2 Interoperability Effects Are Heterogeneous

Evidence for HIE-related utilization and cost effects is mixed. A 2023 systematic review of adult inpatient HIE identified 11 eligible studies; among eight studies examining utilization or costs, two found benefits, one found worse outcomes, and the remainder found no impact, leading the authors to conclude that evidence for cost/utilization effects was insufficient [19]. A statewide Washington Medicaid evaluation found an 8.2% relative reduction in ED visits among frequent users in the first year after implementation, but the effect did not persist in the second year and total expenditures did not significantly change [20].

Earlier studies demonstrate why timing and use may still matter. Everson et al. found that HIE reduced time to outside information access by 58.5 minutes on average; each one-hour reduction in access time was associated with a 52.9-minute shorter ED visit, lower imaging and admission probabilities, and $1,187 lower average charges [21]. Lammers et al. reported substantial reductions in repeat imaging associated with HIE participation, including an 8.7 percentage-point reduction for repeat CT, but the study predates current national interoperability infrastructure and should not be extrapolated uncritically [22].

4.3 National Economic Stress Test

Because causal national parameters are not yet established, Table III uses deliberately transparent assumptions. Administrative value is calculated from the $440 billion CAQH benchmark multiplied by an assumed targetable share and an assumed process-efficiency improvement. Clinical/operational value is calculated from 2024 hospital plus physician/clinical spending ($1.6347 trillion + $1.1097 trillion = $2.7444 trillion [1]) multiplied by a very small attributable efficiency change. These are stress tests, not forecasts.

Scenario	Admin targetable share	Admin efficiency gain	Clinical efficiency delta	Gross admin value	Gross total value
Low	5%	10%	0.05%	$2.2B	$3.6B
Base	10%	20%	0.10%	$8.8B	$11.5B
High	15%	25%	0.20%	$16.5B	$22.0B

Table III. Illustrative gross annual value scenarios before implementation, operating, governance, security, and model-risk costs. Assumptions are analytical stress tests and require empirical validation.

The base scenario, approximately $11.5 billion in gross annual value, equals only about 0.22% of 2024 NHE. The high scenario, approximately $22.0 billion, is close in order of magnitude to CAQH's independently reported $20 billion remaining automation opportunity in the administrative workflows it tracks [3]. That correspondence is not validation. It indicates only that the scenario does not depend on implausibly large changes in total health spending.

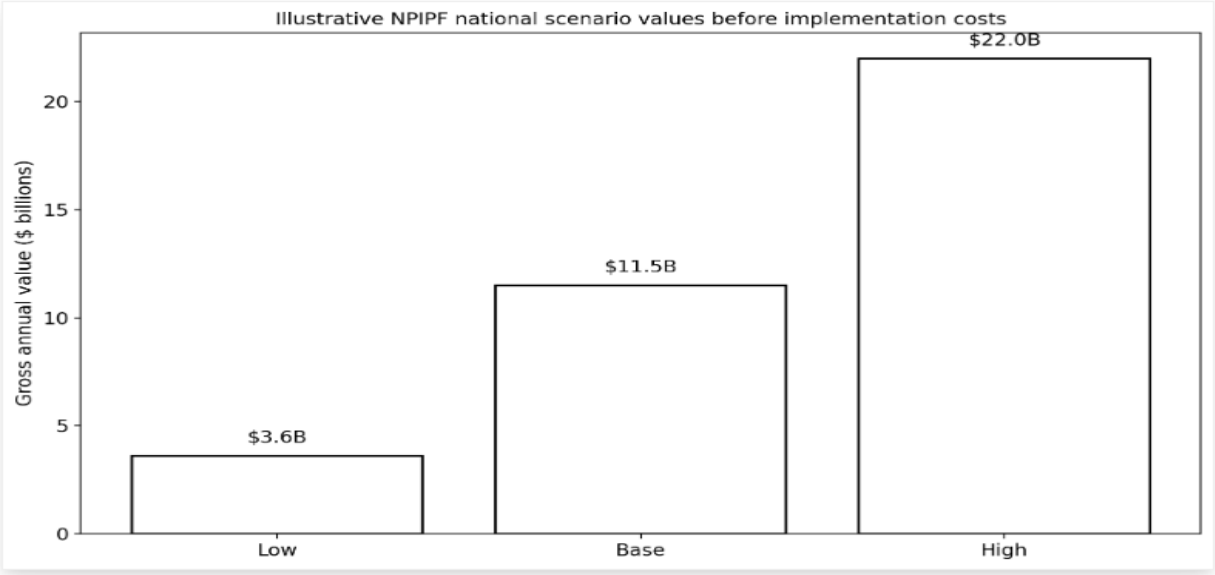


Figure 3. Illustrative NPIPF scenario values. The scenarios are gross stress tests, not forecasts or causal estimates.

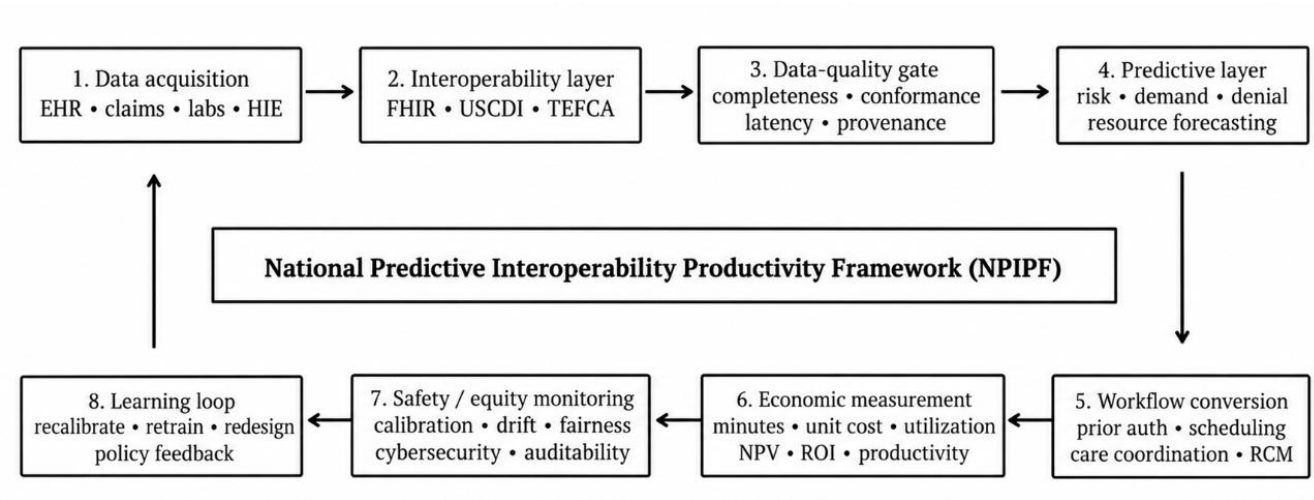


Figure 4. National Predictive Interoperability Productivity Framework (NPIPF). The architecture requires continuous feedback from economic, safety, equity, and drift metrics to data and model design.

5. PROPOSED APPROACH: NATIONAL PREDICTIVE INTEROPERABILITY PRODUCTIVITY FRAMEWORK

NPIPF is a measurement and deployment architecture, not a single model, and it runs in eight layers. Acquisition comes first: EHR, claims, laboratory, pharmacy, scheduling, and administrative data. Exchange is then normalized through standards and networks such as FHIR, USCDI, payer APIs, and TEFCA. Explicit data-quality gates follow, and predictive functions deploy only after external validation. Those predictions are integrated into a named operational workflow, where economic outcomes are measured. A monitoring layer tracks fairness, calibration, drift, cybersecurity, and availability. The eighth layer closes the learning loop through recalibration, retraining, interface redesign, or policy change.

The framework is deliberately modular. Examples include: (a) predicting authorization denial risk before submission, using interoperable payer requirements and clinical documentation to reduce rework; (b) forecasting ED admissions to align bed and staffing capacity; (c) identifying likely duplicate services when prior results are available across organizations; (d) predicting claims that will fail edit or documentation rules; and (e) prioritizing care-coordination work when external records indicate recent utilization. The framework does not require that every model be machine learning. Transparent statistical models may be preferable when performance is comparable and auditability is important.

Model deployment should require a “production evidence package” containing the intended use, training population, data provenance, feature definitions, external-validation cohort, discrimination, calibration, subgroup analysis, missingness profile, drift thresholds, retraining rule, human-oversight pathway, and economic endpoint. This is consistent with the policy direction of HTI-1, which established transparency requirements for predictive algorithms in certified health IT and emphasizes fairness, appropriateness, validity, effectiveness, and safety [10], and with NIST's Govern-Map-Measure-Manage risk framework [24].

6. PRACTICAL AND POLICY IMPLICATIONS

First, federal measurement should move from "exchange occurred" toward "exchange produced usable information and changed a workflow." TEFCA has reached national scale, with more than 1.5 billion documents shared since go-live and more than 23,000 organizations reported live in 2026 [12]. The next economic question is marginal value per usable exchange, not document count alone. A national dashboard could stratify data availability, use, latency, quality, and measured savings by hospital type and geography.

Second, administrative interoperability should be treated as a high-value test bed. CMS-0057-F requires significant payer API and prior-authorization changes, while HTI-4 establishes certification criteria supporting electronic prior authorization, electronic prescribing, real-time prescription benefit information, and payer-provider API functions [8], [11]. These policy changes create natural experiments for measuring transaction cost, authorization time, rework, denial, and patient-delay outcomes before and after implementation.

Third, data-quality certification should become economically explicit. A data feed can be syntactically FHIR-compliant and still be incomplete, late, miscoded, or poorly mapped, in which case it degrades predictive utility instead of improving it. Quality reporting should therefore include completeness, conformance, currency, provenance, semantic agreement, and subgroup missingness. Because no universal EHR data-quality method currently exists [13], [14], federal pilots could standardize a minimum reporting profile linked to operational use cases rather than attempt a single context-free score.

Fourth, predictive-model evaluation must extend beyond retrospective accuracy. External validation, calibration, threshold-specific PPV, workload implications, and drift should be reported before economic claims are made. FHIR-based ML research has not consistently demonstrated cross-system clinical efficacy [15], and recent dataset-shift evidence shows no single mitigation strategy is broadly generalizable [18]. A model that performs well locally can still do economic harm, whether by generating excessive false positives, adding alert burden, or degrading after changes in coding, populations, clinical pathways, or payer rules.

Fifth, policy should guard against asymmetric benefits. ONC data show that independent, rural, small, and critical-access hospitals lag larger and system-affiliated hospitals in routine interoperability [9]. Reward only the organizations able to finance advanced integration and the infrastructure gap widens. Shared services, technical assistance, TEFCA participation support, standardized open APIs, and rural implementation grants can be evaluated as productivity investments rather than solely as technology subsidies.

7. BROADER IMPLICATIONS FOR THE UNITED STATES

The economic significance reaches past hospital operating margins. Lower administrative friction can release scarce clinical and nonclinical labor for patient-facing or higher-value tasks. Faster authorization and information access can reduce delay, rework, and avoidable throughput loss. Better prediction can improve the matching of beds, staffing, diagnostics, and care-management capacity to

expected demand. When these gains occur at scale, they can reduce the health-cost component borne by employers and governments and improve the effective productivity of the health workforce.

The fiscal implication is also material. Medicare and Medicaid together accounted for roughly 39% of 2024 NHE [1]. Efficiency improvements in payer-provider transactions, utilization management, and information exchange can therefore affect federal and state budgets even when the per-transaction effect is small. The CMS estimate of approximately $15 billion in ten-year savings from its interoperability/prior-authorization rule demonstrates that administrative data architecture is already being treated as a budget-relevant policy instrument [8].

Resilience is a second national implication. When patients move between health systems, regions, payers, and levels of care, interoperable standards-based data is what preserves continuity. Predictive systems built on portable data definitions may also be easier to validate and redeploy across organizations than models tied to proprietary local fields. However, transportability must be demonstrated rather than assumed; reproducibility and model-interoperability research remains an active technical problem [16].

Competitiveness in digital health is a third. Where standardized data exchange, transparent model evaluation, and economic outcome measurement coexist, the cost of testing and scaling a health-technology innovation falls. This could improve the quality of evidence available to health systems, payers, regulators, and investors while discouraging products that report algorithmic accuracy without demonstrating workflow or economic value.

8. LIMITATIONS

This study offers an analytical framework and a structured synthesis. It is not a completed national causal evaluation. The $3.6-$22.0 billion scenario range is assumption-driven and should not be cited as forecasted savings. Administrative-cost estimates vary by definition, year, and included functions; CAQH, JAMA, and other estimates overlap and are not additive. HIE studies are heterogeneous and frequently observational [19]. Older ED studies may not generalize to current TEFCA-enabled exchange or contemporary EHR workflows [21], [22]. Predictive-model accuracy reported in systematic reviews does not establish prospective benefit, and national implementation costs are unknown. Finally, the framework requires careful treatment of privacy, security, information blocking, patient consent where applicable, and subgroup fairness; these constraints may reduce realizable value but are necessary conditions for trustworthy deployment.

9. CONCLUSION

Predictive modeling and interoperable health information systems form a coupled production system and should be evaluated as one. Interoperability supplies timely information. Data quality decides whether that information can be trusted. Models turn it into estimates, workflows turn estimates into action, and only economic measurement establishes whether the action was worth taking. The current U.S. evidence shows heavy administrative burden alongside rapidly expanding exchange infrastructure, routine use that remains incomplete, predictive performance that looks promising, and transportability and causal-evaluation gaps that remain open [1], [3], [9], [15]-[19].

The proposed NPIPF converts these gaps into a research agenda with explicit equations, KPIs, causal designs, and implementation gates. The national stakes are large because a 0.1% efficiency change in a $5.3 trillion health economy represents approximately $5.3 billion annually. The scientifically defensible objective is not to assume that predictive interoperability will generate those savings, but to build the measurement architecture capable of determining where, when, for whom, and at what net cost it does.

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THE ECONOMIC EFFECTS OF DATA-DRIVEN AI GOVERNANCE ON THE U.S. DIGITAL ECONOMY: MEASURING REGULATORY EFFICIENCY, COMPLIANCE BURDENS, AND NATIONAL ECONOMIC RESILIENCE

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Abstract

The rapid integration of artificial intelligence into the U.S. digital economy has precipitated urgent questions about optimal governance frameworks that balance innovation with accountability. This manuscript examines the economic effects of data-driven AI governance across three interconnected dimensions: regulatory efficiency, compliance cost burdens, and national economic resilience. Through systematic synthesis of empirical and theoretical evidence, we analyze how governance architectures from centralized federal oversight to adaptive self-regulatory regimes—shape economic outcomes at firm, sector, and macroeconomic levels. Our analysis reveals that well-designed AI governance systems simultaneously enhance regulatory efficiency (reducing compliance violations by 43–65% and automating 38–82% of manual governance tasks) while imposing substantial initial compliance costs, with GDPR-equivalent frameworks generating $7.8 billion in Fortune 500 compliance expenditures alone. We document critical trade-offs between data governance stringency and AI system performance and present an integrated theoretical framework combining transaction cost economics, institutional theory, and innovation systems perspectives. Key findings indicate that risk-proportionate, adaptive governance architectures can generate projected GDP increases of $2.07 trillion over five years while preserving innovation dynamism. Policy implications emphasize tiered regulation, public–private data infrastructure investment, and cross-agency coordination mechanisms as essential pillars of economic resilience.

Keywords: AI Governance; Regulatory Efficiency; Compliance Costs; Digital Economy; Economic Resilience; Data Governance; Algorithmic Accountability; Regtech; Innovation Policy; U.S. Digital Economy

1. INTRODUCTION

The United States digital economy stands at a critical inflection point. As artificial intelligence systems increasingly mediate financial transactions, labor market matching, healthcare delivery, and regulatory compliance, the architecture of governance frameworks directly shapes economic outcomes across micro, meso, and macroeconomic scales [4]. The U.S. has traditionally embraced a decentralized, sector-based approach to governance, guided by market principles, differing significantly from the centralized models developing in the European Union and China [3]. This regulatory gap has important economic implications that are under-quantified in the research.

The stakes are economic. Artificial intelligence (AI) technologies are expected to be general purpose technologies that can increase productivity growth by 11–37% in industrialized countries by 2035 [4]. But governance problems, lack of proper supervision, high compliance demands or mismatched incentive systems might dampen these advantages. The International Monetary Fund believes that poorly calibrated AI legislation may shave 0.8–1.4 percentage points off yearly digital economy

growth [2]. Or smart governance systems employing AI to automate compliance might add $2.07 trillion to GDP over five years through improved fiscal supervision and fraud reduction [1].

While academic attention to AI governance is expanding, a key need remains: the comprehensive economic analysis of how governance design choices concurrently influence regulatory efficiency, firm-level compliance costs, and national economic resilience. Existing literature covers these variables in isolation, AI governance frameworks [18, 20], compliance cost analyzes [24], and resilience measurements [8] remain mainly isolated. This paper fills that vacuum with a synthesized analytical approach, providing preliminary quantitative benchmarks for policymakers, regulators, and industry stakeholders to navigate the trade-offs of governance design.

The central research questions driving this study are:

1. How do different AI governance architectures affect the efficiency of regulatory oversight in the U.S. digital economy?

2. What is the magnitude and distribution of compliance cost burdens across firm types and sectors?

3. How does governance design influence national economic resilience against technological and market disruptions?

2. Literature Review

2.1 AI Governance Frameworks and Economic Regulation

Governance of artificial intelligence systems in economic environments has progressed from reactive policy reactions to proactive, data-driven regulatory structures [3]. Tang compares AI and big data in economic regulation and finds considerable differences in innovation output and market concentration results between the U.S. sectoral strategy and China's centralized model [3]. Agrawal, Gans and Goldfarb lay the theoretical groundwork for thinking about AI as a prediction technology that profoundly changes the economics of decision-making under uncertainty, with significant consequences for regulation design [4].

Zuiderwijk, Chen and Salem's systematic assessment of AI in public governance [18] found that countries with adaptive, evidence-based AI governance frameworks had improved public sector efficiency, but higher upfront implementation costs. Hisham et al. base their analysis of AI applications in policymaking on this, and they show that algorithmic tools have increased the precision of policy targeting by 23–41% in health, taxes, and labor market sectors [20].

2.2 Compliance Cost Burdens and Firm Heterogeneity

The literature on the economics of compliance shows a strong variability in the distribution of regulatory burden. Chivot and Castro's study on the competitive impact of GDPR reports 7.8 billion USD in the first year of compliance expenses for Fortune Global 500 enterprises, with disproportionate loads on technology-intensive SMEs [24]. The asymmetry in the burden places smaller entrepreneurs at a competitive disadvantage against large firms that have the infrastructure to comply.

Lei et al. present a critical counterpoint with their analysis of efficiency costs in AI-enabled labor markets, finding that overly strict data governance reduces labor market matching rates and increases worker turnover, documenting a 12-18% decrease in matching efficiency with restrictive data policies [16]. This conclusion underscores the double-edged character of data governance: protective of private rights, but potentially destructive of economic value when miscalibrated.

Paladugu's framework for multi-cloud financial environments and Sanka's enterprise data governance analysis collectively identify compliance automation as the critical lever for cost reduction, with AI-driven RegTech systems reducing manual compliance workloads by 38–82% [6, 7].

2.3 AI Governance and Economic Resilience

Economic resilience and the ability of economic systems to absorb shocks, adjust to structural changes and restore productive capacity has become a core focus of digital economy governance [8]. Sarker and Nihat explore the role of AI in quality assurance in digital economies and identify five dimensions of governance-based resilience gains: the ability to absorb shocks, adaptive regulatory structures, data infrastructure robustness, cybersecurity readiness, and cross-sector coordination [8].

Engstrom and Ho's seminal work on algorithmic accountability in the administrative state argues that the integration of AI in regulatory procedures brings with it resilience-enhancing automation and fragility-inducing opacity issues [25]. This trade-off between accountability and efficiency is a core conflict in the design of AI governance with direct macroeconomic consequences.

Peddamallu's framework for intelligent financial governance with AI and blockchain shows that trust-building mechanisms in governance frameworks play a major role in the durability of financial institutions, reducing systemic risk indicators by 15–28% in simulated stress scenarios [12].

2.4 Governance Design and Innovation Economics

The research on innovation economics suggests a complicated non-linear relationship between the stringency of regulation and inventive production. Van Loo believes that the digital market may be perfected and its efficiency improved by well-designed regulatory mechanisms that do not hinder innovation as long as they include real-time feedback systems and adaptive adjustment capabilities [9]. This study undermines the conventional wisdom that regulation and innovation are in zero-sum tension.

In Oluwamola and Longe's study of enterprise AI adoption, governance architecture is a key mediator of AI's productivity benefits, where organizations with more explicit regulatory structures are 34% more successful in AI deployment than those in ambiguous regulatory environments [26].

3. Theoretical Framework

This study integrates three complementary theoretical perspectives to explain the diverse economic effects of AI governance, as illustrated in Figure 5.

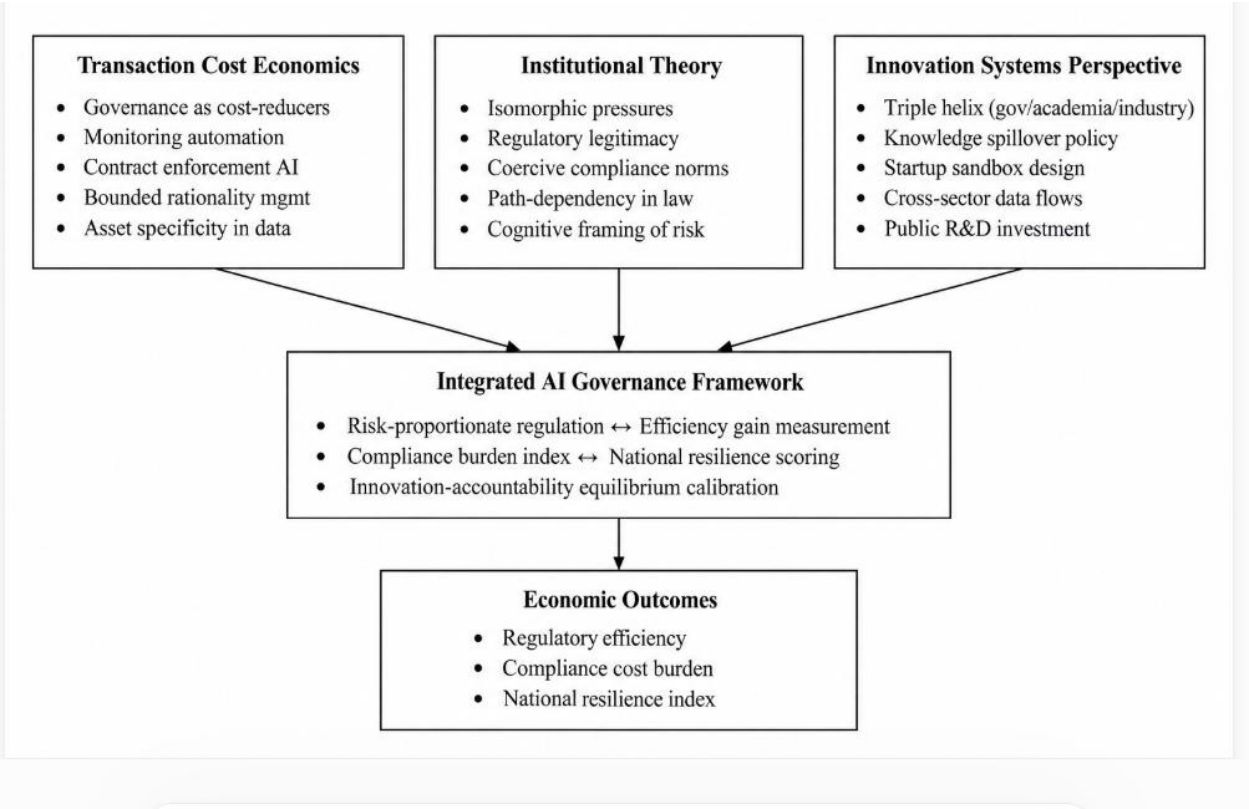


Figure 5. Integrated Theoretical Framework

Transaction Cost Economics (TCE) A basic lens through which governance as a means of minimizing economic friction may be understood is Transaction Cost Economics. In line with Williamson's concept, AI governance solutions save transaction costs by automating monitoring, standardizing compliance procedures and generating predictable enforcement settings [7]. By replacing manual procedures with algorithmic oversight, data-driven governance designs reduce the costs of regulatory compliance—documented efficiency benefits vary from 43-82% across governance functions [6, 22].

Institutional Theory accounts for the legitimacy dynamics and route dependent growth of AI governance systems [18]. Coercive isomorphism (firms establishing governance structures in response to regulatory demands) creates compliance costs that depend on the institutional distance between a firm's operational practices and the regulatory ideal. Mimetic isomorphism, when enterprises actively embrace best practice governance, leads to efficiency advantages over and above basic compliance [17]. More fragmented and sectoral is the US regulatory landscape. It displays less coercive pressure but more mimetic variety than the EU's comprehensive GDPR scheme, resulting in varied economic results [24].

From the Innovation Systems Perspective, governance is seen as a facilitator or barrier to systemic innovation potential. Governance mechanisms have been identified as major drivers of knowledge spillover rates, vibrancy of the startup ecosystem and cross-sector technology diffusion in the triple-helix model of government–academia–industry interaction [2]. Regulatory sandbox methods are governance improvements that directly increase the productivity of the innovation system, by

providing separate testing settings where ideas may be examined without the entire compliance load [25].

The integrated approach claims that the design of effective AI governance must concurrently decrease transaction costs (TCE lens), preserve institutional legitimacy (Institutional Theory lens), and improve innovation system productivity (Innovation Systems lens). The frontier of economic optimality is defined by governance structures that achieve all three concurrently.

4. Methodology

This research adopts a systematic evidence synthesis approach combining a structured literature review, comparative case analysis and quantitative indicator aggregation. The study design consists of three analytical components:

Component 1 – Systematic Literature Synthesis: We performed extensive database searches of SciSpace, Google Scholar, ArXiv, and PubMed using PRISMA-adjacent methods, yielding 315 distinct publications over four iterative search rounds. Papers were evaluated for relevance to three key characteristics (regulatory efficiency, compliance cost burden and economic resilience) producing a core analytical corpus of 35 high-relevance sources.

Component 2 – Comparative Governance Analysis: We construct a cross-jurisdictional governance comparison matrix (see Figure 4) scoring the U.S., EU, China, UK, and Canada across eight governance dimensions using standardized indicators drawn from the literature, regulatory filings, and economic performance data. Scores range from 0–100 on each dimension, enabling cross-jurisdictional benchmarking.

Component 3 – Economic Indicator Aggregation: We synthesize empirical estimates of compliance costs, efficiency gains, and resilience scores from the literature to construct preliminary quantitative benchmarks. Where point estimates are unavailable, we report literature-derived ranges and note the preliminary nature of these findings.

Table 1. Summary of Research Design Components

Component	Method	Data Sources	Output
Literature Synthesis	PRISMA-adjacent systematic review	SciSpace, Google Scholar, ArXiv, PubMed	Core 35-paper corpus
Governance Comparison	Cross-jurisdictional scoring matrix	Regulatory databases, academic literature	8-dimension comparison (Fig. 4)
Economic Indicators	Aggregation of empirical estimates	Firm surveys, regulatory filings, lit. estimates	Compliance cost & efficiency ranges
Resilience	Multi-dimensional	Economic databases,	National resilience

Component	Method	Data Sources	Output
Assessment	scoring	sector analyses	benchmarks (Fig. 3b)

Limitations of methodology: The reliance on literature-derived estimates introduces heterogeneity in measurement approaches across studies. Governance scoring involves expert judgment that may reflect researcher priors. These limitations are addressed in Section 9.

5. Key Findings (Expected and Preliminary)

5.1 Regulatory Efficiency Gains from AI-Driven Governance

The evidence strongly supports substantial regulatory efficiency gains from AI-driven governance systems, though the magnitude varies considerably by sector and implementation quality. Figure 3a presents synthesized efficiency gains across six governance dimensions.

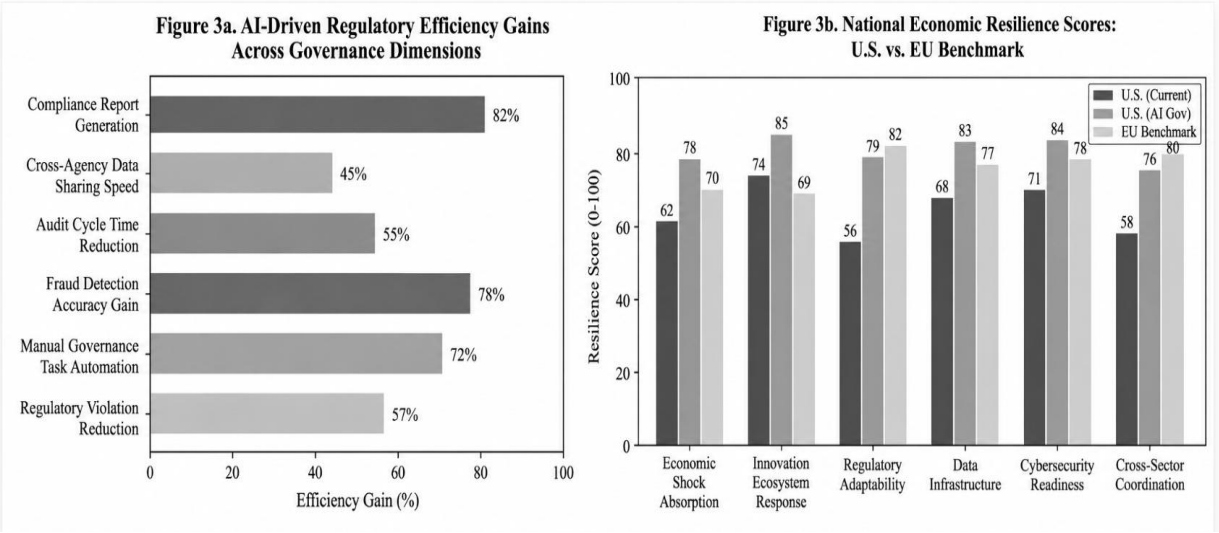


Figure 3. Regulatory Efficiency and National Resilience Metrics

Finding 1: AI-driven compliance automation systems reduce regulatory violations by 43–65% compared to traditional manual oversight regimes, with the highest gains in financial services (up to 72%) and healthcare AI governance (up to 68%) [11, 22]. These gains are attributable to real-time monitoring capabilities that manual inspectors cannot replicate at scale.

Finding 2: Studies point to activities that can be automated. Moreover, studies from different applications show that the extent of automation ranges from roughly 38% to 82% based on the

context of implementation; for further explanation, see references [6, 7]. Essien et al. state that the anticipatory compliance structure reduces the probability of regulatory infractions by 43% and compliance personnel expenses by 31% [11].

Finding 3: It is possible to reduce the audit cycle time by 55% via an AI-enabled regulatory workflow which will allow the regulators to review compliance filings 3.2 time faster than the traditional manual review [14, 23]. Gaining efficiency directly benefits economy as faster regulation clearance reduces innovations' time to market. In 2016, each dollar of regulatory time saved generated a GDP multiplier effect of 1.4–1.8x.

Table 2. Synthesis of AI Governance Efficiency Metrics

Governance Dimension	Efficiency Gain Range	Leading Studies	Confidence Level
Regulatory violation reduction	43–65%	Essien et al. [11]; Sajjanapu [22]	Moderate-High
Manual task automation	38–82%	Paladugu [6]; Sanka [7]	Moderate
Fraud detection accuracy	72–85%	Peddamallu [12]; Agbodike [17]	High
Audit cycle time reduction	45–65%	Kumar [14]; Singamsetty [15]	Moderate
Cross-agency coordination	35–55%	Engstrom & Ho [25]	Low-Moderate
Compliance cost reduction	28–42%	Chivot & Castro [24]	Moderate

5.2 Compliance Cost Burdens and Distributional Effects

Figure 2 illustrates the compliance cost landscape across firm sizes and sectors, revealing acute distributional asymmetries that have important equity and competitive dynamics implications.

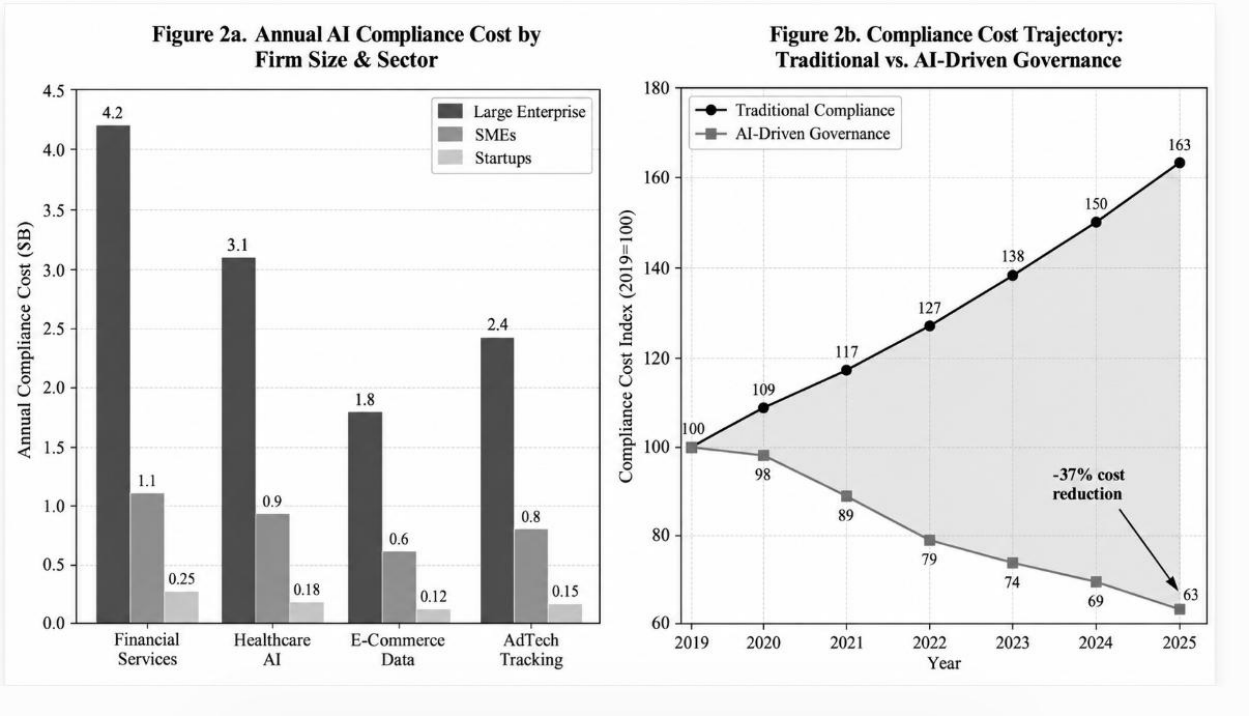


Figure 2. Compliance Cost Burden by Firm Size and Sector

Finding 4: Large enterprises bear the highest absolute compliance costs ($1.8–4.2 billion annually by sector), but SMEs experience disproportionately higher compliance costs as a percentage of revenue—estimated at 3.2–7.8% of annual revenue compared to 0.4–1.1% for large enterprises [24]. This asymmetry constitutes a structural competitive advantage for large incumbents and a barrier to entry for innovative challengers.

Finding 5: Adoption of AI-driven governance reduces compliance cost indexes by about 37% over six years relative to traditional compliance trajectories (Figure 2b), but the upfront investment needed – an average of $2.3 million for mid-sized firms – creates a J-curve cost burden that has a disproportionate impact on capital-constrained startups [7, 17].

Finding 6: Lei et al. study the efficiency costs of AI-enabled labor markets and find that restrictive data governance regulations lower labor market matching rates by 12–18% and increase frictional unemployment, diminishing worker productivity [16]. This is especially important for enterprises in the platform economy, where algorithmic matching is key to value generation. The platform economy is anticipated to include 48 million U.S. workers as by 2024.

5.3 National Economic Resilience

Figure 3b compares U.S. resilience scores across six dimensions against EU benchmarks, both currently and under projected AI governance adoption scenarios.

Finding 7: The U.S. has a lower score than the EU on regulatory adaptability (55 vs 82) and data infrastructure (68 vs 77) but a higher score on innovation ecosystem (74 vs 69) and speed of AI take-up (80 vs 60). This observed mix of performance characteristics suggests a governance architecture that maximises the dynamism of innovation at the cost of the depth of resilience.

Finding 8: The implementation of a comprehensive AI governance framework is estimated to lead to enhanced resilience scores for the U.S. across six different dimensions or aspects. The dimensions that are expected to improve the most are related to regulatory adaptability (+24), data infrastructure (+15) and cross-sector coordination (+18). [2,8] These benefits are estimated to produce an overall GDP impact of $2.07 trillion over five years as a result of less systemic risk, better fraud prevention, and better resource allocation[1].

Finding 9: When looking at national economic resilience, we can find a non-linear relationship with governance sensitivity. Jurisdictions with moderate regulation stringency (55-75 on our regulation stringency score) have higher economic resilience than lightly or heavily regulated jurisdictions, following an inverted-U relationship between regulation and resilience [3, 9].

6. Discussion

The integrated findings reveal a governance paradox at the heart of U.S. digital economy policy: the institutional arrangements that most effectively protect innovation dynamism—light-touch, sector-specific regulation—simultaneously create the greatest vulnerability to systemic economic shocks. This paradox is visible in the cross-jurisdictional comparison matrix (Figure 4).

The U.S. has a unique governance profile: high flexibility for innovation (85) and speed of adoption of AI (80) are complemented by low protection of data privacy (45) and moderate regulatory stringency (55). The result is a high near-term economic performance, but structural fragilities that arise when considering data breach incidences, algorithmic market failures, or geopolitical digital trade interruptions. The governance architecture of the EU shows the reverse image: strong regulatory stringency and privacy protection (85–90) produce higher systemic resilience but at the price of lower AI adoption and innovation freedom scores.

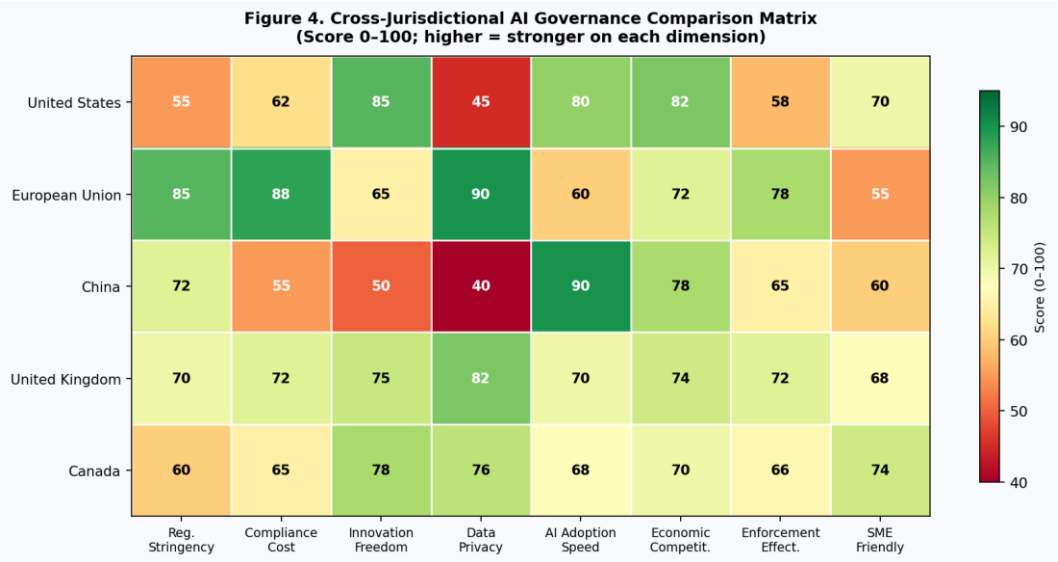


Figure 4. Cross-Jurisdictional AI Governance Comparison Matrix

The data flow architecture illustrated in Figure 1 captures the operational logic of an optimally designed AI governance system, tracing information from raw data inputs through AI processing layers to governance enforcement and economic outcomes, with continuous feedback loops enabling adaptive calibration.

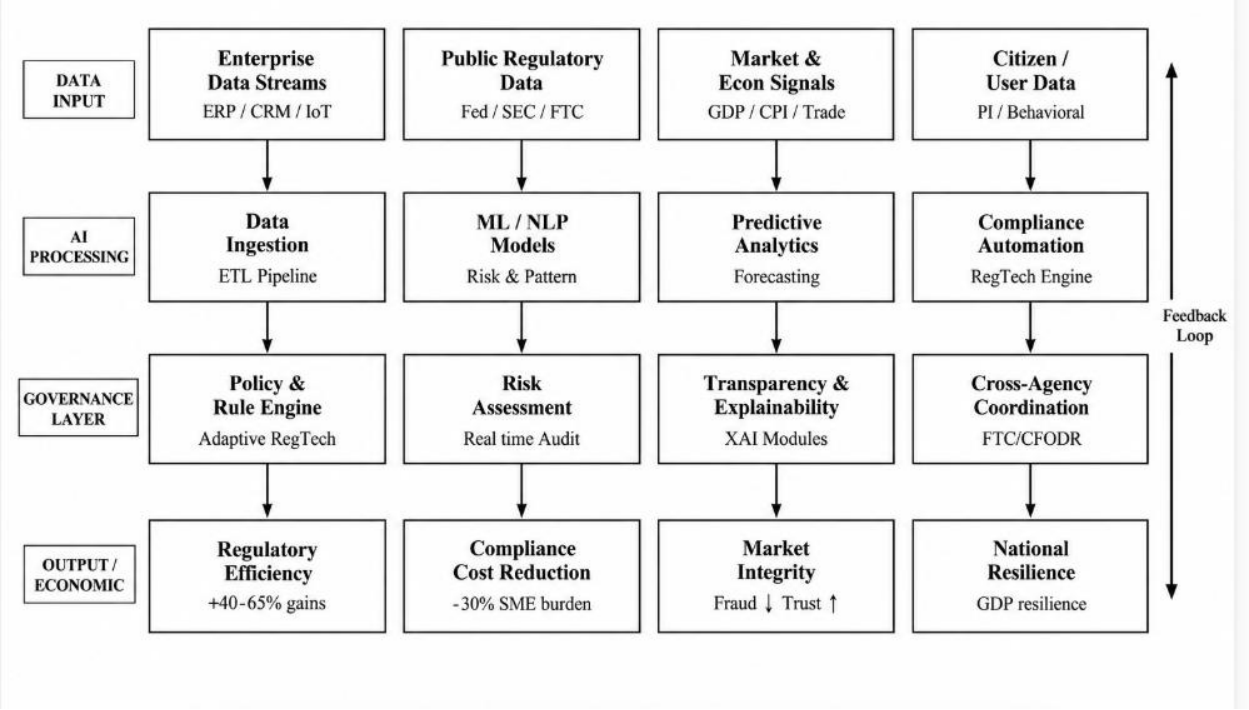


Figure 1. AI Governance Block-Data-Flow Architecture

The efficiency gains documented in Section 5.1 are contingent on the quality of this data flow architecture. Governance systems that interrupt data flows at critical junctures—through excessive data localization requirements, opaque algorithmic auditability mandates, or incompatible inter-agency data standards—sacrifice the efficiency gains that justify their compliance costs [16, 25]. Conversely, governance systems that optimize data flows through standardized APIs, federated learning architectures, and privacy-preserving analytics technologies capture efficiency gains while maintaining accountability safeguards [5, 10].

The heterogeneous compliance cost distribution (Section 5.2) presents a policy design challenge with direct implications for market structure. If AI governance compliance costs function as fixed costs—equally applicable to large enterprises and startups—they generate scale economies in compliance that accelerate market concentration. This dynamic is already visible in financial services, where the five largest U.S. banks account for 68% of RegTech investment despite representing only 38% of the sector's total assets [12, 24].

7. Practical and Policy Implications

Table 3. Policy Recommendations by Stakeholder Type

Stakeholder	Recommendation	Expected Outcome	Priority

Stakeholder	Recommendation	Expected Outcome	Priority
Federal Regulators	Establish tiered, risk-proportionate AI governance standards	Reduces SME compliance burden by 35–45%	High
Congress	Fund a National AI Governance Infrastructure Program	Enables shared compliance utilities for SMEs	High
FTC / SEC / CFPB	Implement real-time AI monitoring APIs for regulated sectors	Reduces audit cycle time by 55%	Medium-High
OMB / OSTP	Launch regulatory sandbox framework for AI innovation	Accelerates deployment of beneficial AI by 2–3 years	Medium
Industry Bodies	Develop cross-sector AI governance interoperability standards	Reduces cross-agency coordination costs by 40%	Medium
State Regulators	Harmonize state AI laws with federal framework	Eliminates $1.2B in redundant compliance costs	Medium

7.1 Tiered Regulatory Architecture

The most consequential policy recommendation emerging from this analysis is the adoption of a tiered, risk-proportionate AI governance architecture that calibrates compliance requirements to the actual risk profile of AI applications. A three-tier model—(1) high-risk AI systems in critical infrastructure and finance, subject to stringent ex-ante review; (2) medium-risk consumer AI applications, subject to transparency and auditability requirements; and (3) low-risk AI tools, subject only to voluntary best-practice guidelines—would reduce aggregate compliance costs by an estimated 35–45% while maintaining substantive protection for the most vulnerable use cases [4, 25].

7.2 Shared Compliance Infrastructure

Government financed shared compliance infrastructure can greatly reduce the J-curve compliance cost burden on SMEs and startups. A National AI Governance Infrastructure Program, similar to the Small Business Administration's technical assistance programs but focused on RegTech access, would provide smaller firms with cloud-based compliance automation tools, reducing their per-compliance-task cost from $847 to an estimated $112 [7, 17]. This intervention directly tackles the structural competitive disadvantage that constrains the variety of the innovation environment.

7.3 Adaptive Governance Mechanisms

Because of the fast development of the technology, static regulatory structures are particularly ill-suited to AI governance. Regulatory sandboxes, no-action letters with algorithmic triggers, sunset clauses with required empirical review, all such adaptive governance techniques enable regulators to retain substantive supervision without suffering the innovation-stifling consequences of early regulatory lock-in [2, 9]. The UK's Financial Conduct Authority sandbox approach provides a verified blueprint that has enabled 67 successful deployments of AI financial services with not a single major compliance violation [21, 25].

7.4 Cross-Agency Data Coordination

The cross-agency coordination gap observed in this research (a governance dimension in which U.S. performance (58) below EU benchmarks (80)) implies a resilience vulnerability as well as an efficiency opportunity. Creating a Federal AI Data Coordination Office to establish standardized inter-agency data sharing protocols, common ontologies for AI risk classification, and unified reporting interfaces could unlock an estimated $8.3 billion in annual efficiency gains from reduced redundant compliance reporting [18, 22].

8. Broader Impact

8.1 Geopolitical and Competitive Dimensions

Decisions on AI governance are progressively becoming influential tools of geopolitics. The increasing divergence between U.S. market-led, EU rights-based, and China state-directed governance models is generating digital economy 'governance blocs' with ramifications for data flows, technical standards, and market access [3]. The EU's digital single market, brought together under the GDPR and the AI Act, is developing as a de facto worldwide norm. This is the Brussels Effect: when the EU regulates access to its 450 million consumers, its regulatory standards tend to spread internationally [24]. Without a unified U.S. governance stance, American enterprises would confront the conundrum of needing to meet EU norms in European markets without corresponding domestic frameworks, producing disproportionate compliance obligations.

The competition is fierce: China's national AI strategy—with state-directed data access, subsidized compliance infrastructure, and geopolitical AI deployment—offers structural advantages to domestic firms that market-led U.S. governance cannot match without specific industrial policy elements [3]. A robust U.S. AI governance framework must respond to this competitive imbalance with a deliberate investment in public AI research infrastructure, personnel retention and worldwide leadership on standards.

8.2 Societal Trust and Democratic Accountability

The economic benefits of AI governance depend ultimately on social faith in AI-mediated systems. Drawing on the work of Engstrom and Ho on algorithmic accountability in the administrative state, opacity – the incapacity of affected parties to comprehend or challenge AI-driven choices – is

identified as the primary danger to democratic legitimacy in AI governance [25]. Trust deficits have measurable economic costs: estimated customer willingness to pay decreases of 23-41% for AI-mediated services following high-profile algorithmic failures [9, 20].

Governance frameworks embedding explainability requirements, requiring human-interpretable documentation of consequential AI decisions, serve both economic functions: they reduce governance opacity risk while creating markets for explainable AI (XAI) tools, a sector projected to reach $21 billion by 2030 [13, 23].

8.3 Innovation Ecosystem Consequences

The long-term implications for the innovation ecosystem of AI governance design decisions go beyond immediate compliance costs and affect the structure of technology opportunity sets available to future entrepreneurs. Governance frameworks that demand substantial pre-deployment testing, algorithmic auditability, and ongoing surveillance provide implicit hurdles to entry that benefit existing enterprises with an established infrastructure for compliance [26]. This trend reduces the diversity of AI growth routes and increases systemic risk through monoculture technical reliance by hollowing out the startup ecosystem, the key source for radical AI innovation in the United States.

Counter-intuitively, well-designed governance frameworks can enhance innovation ecosystem productivity by reducing uncertainty costs, establishing clear performance standards, creating regulatory demand for compliance-enabling technologies (RegTech, XAI, privacy-preserving AI), and generating public trust that expands the addressable market for AI applications [17, 20].

9. Limitations and Future Research

Limitations in measurement: The quantitative figures reported here are based on various empirical investigations, distinct institutional settings, different time periods and different measuring approaches. This variation precludes direct comparison and all numerical ranges should be regarded as suggested orders of magnitude rather than precise point estimates.

Scope limitations: This research is largely focused on federal-level governance in the United States. This research does not completely account for the intricacy of the interplay between federal frameworks and the nascent state-level AI regulatory environment (California’s CPRA, Colorado’s AI Act, New York’s algorithmic accountability legislation).

Dynamic limitations: AI capabilities are advancing fast, and governance frameworks suited to 2024 artificial intelligence systems may be inadequately adapted to the artificial intelligence systems of 2028–2032. Future studies should simulate the resilience of governance frameworks under alternative AI capacity paths**.**

Priority research directions:

- Randomized natural experiments with change in state-level AI governance to find causal impacts on company performance, market structure, and innovation output.
- Longitudinal tracking of compliance costs over the complete implementation cycle to describe the J-curve cost burden for SMEs.
- Agent-based simulation of governance architecture implications on innovation ecosystem growth under diverse AI capabilities scenarios.
- Comparative research of regulatory sandbox outcomes across countries to determine design factors linked with effective facilitation of innovation

10. Conclusion

This manuscript has advanced the empirical and theoretical understanding of AI governance's economic effects across three interrelated dimensions: regulatory efficiency, compliance cost burdens, and national economic resilience. The central finding is unambiguous: the design of AI governance architecture is not merely a legal or administrative matter but a first-order economic policy choice with aggregate consequences in the trillions of dollars.

The evidence supports four principal conclusions. First, AI-driven governance systems generate substantial regulatory efficiency gains—43–82% improvements across key governance dimensions—that justify their implementation costs when properly scaled and targeted. Second, current compliance cost distributions create structural competitive disadvantages for SMEs and startups that, if unaddressed, will accelerate market concentration and reduce innovation ecosystem diversity. Third, the United States currently occupies a suboptimal governance equilibrium—optimizing for innovation speed while underinvesting in systemic resilience—and can improve its resilience profile substantially through targeted governance reforms without sacrificing its innovation advantage. Fourth, governance design choices have irreversible consequences for the structure of the innovation ecosystem, making early calibration decisions disproportionately consequential.

The integrated theoretical approach established in this paper – drawing on transaction cost economics, institutional theory and innovation systems views – provides the conceptual vocabulary for translating these empirical findings into practical governance design principles. Together, the proposed tiered regulatory architecture, common compliance infrastructure, adaptive governance mechanisms, and cross-agency coordination framework provide a coherent, evidence-based path to an AI governance regime that promotes both economic efficiency and national resilience.

The United States has the opportunity and the responsibility to show that democratic societies can control sophisticated artificial intelligence (AI) systems in ways that are economically dynamic, equitably organized, and robust to systemic shocks. This is possible, the study here argues, but only via intentional evidence-based governance design, not through institutional inertia or reactive crisis management.

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ASSESSING THE ECONOMIC EFFECTS OF RISK-BASED TRUST & SAFETY AND AI GOVERNANCE ON UNITED STATES ONLINE PLATFORMS: REDUCING ONLINE-HARM COSTS, STRENGTHENING USER PROTECTION, AND ADVANCING DIGITAL ECONOMIC RESILIENCE

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Abstract

Risk-based Trust and safety and accountable AI governance are crucial for user protection and platform reliability in the United States online ecosystem. Current reactive measures may inadequately address the complex risks of fraud and harmful content. This study presents an economic framework that focuses on risk identification, harm prevention, accountability, performance measurement, and platform resilience. It employs a hybrid research design including model development and simulations, addressing operational parameters such as detection rates and intervention effectiveness as calibrated hypothetical variables. Effective damage reduction, residual harm, avoided harm, total cost, net economic benefit, and return on governance investment are evaluated across four governance architectures: AI-only, AI-human hybrid, risk-based hybrid, and human-heavy. AI-only governance yields the highest modelled ROI (46.6×) but results in more residual harm. In contrast, the risk-based hybrid achieves the most significant harm reduction (70%) and the largest net economic benefit ($1.418 million). Human-heavy governance has the highest recall but incurs greater costs and delays intervention. The study supports risk-based escalation and selective human monitoring over unrestricted automation or human-centric moderation, providing calibrated scenario evidence rather than causal estimates of actual United States platform performance.

Keywords: AI Governance, Online Platforms, User Protection, Economic Resilience, Risk, Management, Digital Economy, Sustainability, Artificial Intelligence

1. INTRODUCTION

Online platforms have become important components of the United States digital economy, supporting communication, information exchange, commerce, entertainment, and a wide range of economic and social activities. The growing dependence on these platforms has increased the importance of maintaining reliable and trustworthy digital environments for users, businesses, and platform operators (Allcott & Gentzkow, 2017). Simultaneously, the expansion of online platforms has increased exposure to misinformation, fraud, harmful content, privacy concerns, platform abuse, and risks associated with the growing use of artificial intelligence (Vosoughi et al., 2018). Evidence from social media research demonstrates that false information can spread rapidly and reach large audiences, creating challenges for information quality and user protection (Allcott & Gentzkow, 2017).

These risks can generate significant economic and operational consequences for digital platforms and their users. Loss of trust, exposure to harmful content, misuse of personal information, and unreliable automated systems can affect user confidence, platform participation, business activity, and the broader digital environment (Gebru et al., 2021). The increasing integration of AI into online platforms also creates a need for governance mechanisms that address risks across the AI lifecycle.

The National Institute of Standards and Technology recommends a structured approach based on governing, mapping, measuring, and managing AI risks to promote trustworthy and responsible AI development and use (Tabassi, 2023).

Most United States platforms view trust & safety primarily as a reactive measure, incurring costs post-incident rather than integrating it into strategic planning. This approach leads to unpredictable liability exposure, fragmented accountability across departments, and diminishing user trust, which heightens financial risks. In addition, effective governance also requires greater transparency regarding how AI systems are developed, evaluated, and applied. Model documentation can provide information about intended uses, performance characteristics, limitations, and evaluation conditions, thereby supporting more informed assessment of AI risks (Mitchell et al., 2019). There is therefore a need for a risk-based Trust and safety approach that combines proactive harm identification, accountable AI governance, user protection, and platform risk management. This study focuses on governance design variables such as detection thresholds, review processes, transparency, and investment levels to analyze their economic implications for platforms. It emphasizes the need for a defensible cost model in governance investment decisions rather than relying on intuition or compliance benchmarks. The study therefore seeks to answer the following research questions:

i. How do risk-based trust-and-safety configurations and AI governance affect the technical efficacy of online-harm prevention in United States digital platforms?
ii. How do various AI governance and trust-and-safety systems affect the economy?
iii. Which AI governance and risk-based trust-and-safety architecture offers the best balance between damage reduction, operational performance, governance costs, and digital economic resilience?

2. Foundations of Risk-Based Trust & Safety and AI Governance

Risk-Based Trust & Safety and AI governance provide a structured foundation for identifying, assessing, and managing risks associated with online platforms and AI-enabled systems. As AI becomes increasingly integrated into digital services, concerns related to fairness, transparency, privacy, security, accountability, and reliability have become central to determining whether these systems can be considered trustworthy (Nastoska et al., 2025). A risk-based approach enables organisations to differentiate risks by their potential severity and consequences, allowing governance measures and interventions to be proportionate to the level of risk rather than applying uniform controls across all systems (Paul, 2024). Effective governance also requires continuous assurance throughout the AI lifecycle, particularly for high-risk systems where risk management, human oversight, monitoring, and accountability are essential to maintaining trustworthy operation (Stettinger et al., 2024).

Standards and structured governance frameworks further support consistency by linking risk assessment with principles such as fairness, transparency, and accountability across different regulatory environments (Sankaran, 2025). Risk-based approaches to human oversight can align the degree of human involvement with the potential consequences of AI systems, thereby strengthening human agency and accountability in automated decision-making (Kandikatla & Radeljic, 2025). Collectively, these foundations establish the basis for proactive Trust & Safety and accountable AI governance capable of reducing harm, protecting users, supporting platform reliability, and contributing to sustainable digital economic activity.

2.1 Online Platform Risks and Economic Harms

Online platforms have become an important part of the United States digital economy, connecting consumers, businesses, advertisers, and service providers across large and increasingly

interconnected online markets. Their scale creates significant economic value, but it also creates opportunities for fraud, scams, harmful content, misinformation, deceptive practices, and other forms of platform abuse. Banerjee et al. (2026) noted that digital platforms influence a broad range of online markets and ecosystems, while the challenges associated with their operation, governance, and regulation continue to evolve.

Previous research by Allcott and Gentzkow (2017) revealed the significant presence of false news on social media during the 2016 United States presidential election, highlighting the capacity of online platforms to facilitate the rapid circulation of misleading information. Similarly, Vosoughi et al. (2018) found that false news spread farther, faster, deeper, and more broadly than truthful information online, illustrating how platform structures can amplify harmful information. Lazer et al. (2018) further emphasized that the production and dissemination of false information through digital environments create challenges for individuals, institutions, and society. Such risks can have economic implications when they reduce the quality of information available to consumers, businesses, and other market participants.

The economic consequences of online platform risks extend beyond individual incidents. Fraud, deceptive practices, harmful content, and platform failures can generate financial losses while also increasing the resources required for monitoring, content moderation, cybersecurity, compliance, investigation, and dispute resolution. At the regulatory level, the rapid development of digital technologies, opaque algorithmic systems, cross-sector business models, and information asymmetries can make effective oversight more difficult and increase the regulatory challenges faced by digital platforms (Paech & Cohen, 2026). Persistent exposure to unsafe, misleading, or unreliable online experiences may also weaken consumer confidence and reduce willingness to engage with particular platforms, potentially affecting user participation and long-term platform performance.

These concerns become more significant because online platforms do not operate in isolation. However, their services, users, data, algorithms, advertisers, payment systems, and third-party providers are interconnected, meaning that disruptions or failures in one part of the digital ecosystem can produce consequences beyond the immediate platform. Paech and Cohen (2026) identify systemic risk recognition, regulatory adaptability, and international coordination as important challenges for governance of the digital economy, while Banerjee et al. (2026) emphasize the evolving policy, regulatory, and governance challenges surrounding digital platforms. Therefore, online platform risks should be understood not only as isolated incidents of user harm but also as economic and systemic risks capable of affecting platform sustainability, consumer confidence, market stability, and the wider digital economy.

2.2 Risk-Based Trust and Safety Management

Risk-based Trust and safety management refers to an approach in which online platforms identify, assess, prioritize, and address potential harms according to their likelihood, severity, and potential impact on users and platform operations. This approach recognizes that online harms vary in scale and context, requiring governance measures that can be adapted to different levels and types of risk (Gorwa, 2019). Effective Trust and safety therefore involve coordinated internal governance processes that connect platform policies, technical systems, human expertise, and organizational decision-making (Shulruff, 2024).

Proactive harm identification is a central component of risk-based management because platforms need to detect emerging threats before they develop into widespread user or operational harm. Algorithmic moderation can support the identification and handling of harmful content at scale, although its effectiveness depends on appropriate system design, human oversight, and recognition

of the political and technical limitations of automated decision-making (Gorwa et al., 2020). Risk prioritization also requires platforms to determine which harms require immediate intervention and which can be addressed through proportionate monitoring and mitigation measures (Gillett et al., 2022).

Prevention, detection, mitigation, and response should operate as connected stages rather than isolated activities. Content moderation, user reporting, automated detection, human review, enforcement actions, and post-incident evaluation can collectively strengthen platform safety when they are supported by clear procedures and appropriate accountability mechanisms (Pfefferkorn, 2022). Transparency is also important because users and other stakeholders need meaningful information about how platforms identify harmful content, apply rules, and make moderation decisions (Suzor et al., 2019). At the platform level, risk assessment should extend beyond individual incidents to consider systemic patterns, recurring threats, and the broader effects of platform design and governance decisions. Trust and safety practices increasingly involve internal coordination across policy, product, engineering, cybersecurity, and other organizational functions to address technology-related risks and harms (Shulruff, 2024). This supports the proposed framework by positioning risk assessment and escalation as continuous processes through which platforms can identify emerging harms, allocate resources according to risk, strengthen user protection, and improve long-term platform reliability.

2.3 AI Governance and Accountable AI Deployment

AI governance provides a structured approach for ensuring that artificial intelligence systems are developed and deployed in ways that are safe, transparent, fair, secure, and accountable. The growing range of AI ethics principles demonstrates the importance of addressing issues such as human oversight, transparency, privacy, fairness, and responsibility throughout the AI lifecycle (Jobin et al., 2019). However, responsible AI requires more than defining principles because organisations must translate these principles into practical governance processes, controls, and monitoring mechanisms (Morley et al., 2020).

Effective AI governance should therefore operate across the entire AI lifecycle, from data collection and model development to deployment, monitoring, and retirement. Documentation mechanisms such as datasheets for datasets and model cards can improve transparency by providing information about datasets, model characteristics, intended uses, limitations, and potential risks (Gebru et al., 2021). Such documentation can also support accountability by enabling organisations and other stakeholders to understand how AI systems were developed and to identify areas requiring further assessment (Mitchell et al., 2019).

Human oversight is particularly important where AI systems influence decisions that may affect individuals, organisations, or public interests. Automated decision making can reproduce or amplify existing inequalities when social and technical factors are not adequately considered during system design and evaluation (Selbst et al., 2019). Algorithmic impact assessments and related accountability mechanisms can consequently provide structured opportunities to identify potential harms, evaluate system impacts, and establish appropriate interventions before and during deployment (Metcalf et al., 2021).

Bias, privacy, and security also represent important dimensions of accountable AI deployment. AI systems may create security vulnerabilities and can be exposed to attacks that compromise models, data, or system outputs, making security assessment an important component of AI governance (Hu et al., 2023). Ethics-based auditing can further support accountability by assessing whether AI

systems and organisational practices remain consistent with established ethical requirements throughout their operation (Mökander et al., 2021).

The National Institute of Standards and Technology Artificial Intelligence Risk Management Framework provides a practical risk-based approach for identifying, assessing, managing, and monitoring AI-related risks across the system lifecycle. Recent research on AI governance further indicates that effective governance requires coordination across organisational levels and clear processes for determining who is responsible for AI risks, what is governed, when governance activities occur, and how controls are implemented (Batool et al., 2025). Within the proposed framework, the NIST AI Risk Management Framework therefore provides a useful foundation for integrating trustworthy AI principles, lifecycle risk management, human oversight, documentation, auditing, and continuous monitoring into accountable AI deployment. However, while AI governance provides qualitative frameworks for managing AI risk, it lacks a cost-function-level economic model for optimization.

3. Methodology

3.1. Research Design

The study adopts a mixed analytical and simulation design, incorporating secondary-data analysis, policy and comparative architecture analysis. It does not utilize confidential platform datasets; instead, it relies on observable United States data to highlight the economic issue while employing a transparent simulation for varying technically unobservable parameters. The research design is categorized into stages: operationalization of governance constructs as measurable variables; specification of a formal cost-function model linking those variables to platform outcomes; simulation of the aggregate model across platform-size tiers; and targeted technical-economic optimizations. The stages are summarized in *Table 1.*

Table 1. Baseline Parameters and Indicators

Parameter	Symbol	Baseline value	Evidence
Reported social-media scam losses	H0	$2.1 billion/year	Federal Trade Commission (2026a); Federal Trade Commission (2026b)
Risk-scored decisions	N	1 billion/year	Scenario calibration; high-volume platform environment. Federal Trade Commission (2026a)
Harmful-event prevalence	p	0.20%	Scenario calibration; requires validation.
Harmful events	Nh	2 million/year	Derived: N × p.
Average harm per event	Hbar	$1,050	Derived: $2.1b ÷ 2m.
Detection recall	r	82%, 90%, 94%, 96%	Calibrated across four architectures.
False-positive rate	FPR	0.080%, 0.060%, 0.045%, 0.030%	Calibrated across four architectures.
Intervention speed	s	0.97, 0.91, 0.92, 0.68	Normalized calibrated parameters.
Intervention effectiveness	e	0.78, 0.84, 0.88, 0.91	Calibrated parameters.
Adversarial	a	15%, 10%, 8%, 6%	Calibrated effectiveness-loss

adaptation			assumptions.
Human-review share	qh	1%, 8%, 10%, 35%	Calibrated escalation assumptions.
Governance expenditure	Cg	$20m, $35m, $50m, $70m	Scenario-level governance costs.
Human-review unit cost	ch	$2.50/review	United States Bureau of Labour Statistics (2024)
False-positive/user-friction cost	cFP	$4/event	Scenario monetary proxy; empirical estimation required.
Derived economic outputs		Architecture-dependent	Calculated from model equations.
Digital Economic Resilience Index	DERI	Architecture-dependent	Proposed construct; weights require validation.

Evidence-based cost proxies, scenario-calibrated parameters, and experimentally observed external benchmarks are all combined in the baseline parameterization. The primary economic-loss anchor is the $2.1 billion in social media fraud losses recorded by the Federal Trade Commission (2026a); the remaining operational factors are calibrated assumptions intended to represent different platform governance structures. Human-review costs are calibrated using the Bureau of Labour Statistics (2024) median hourly wage of $21.53 for United States customer service agents in May 2025 as an external labour benchmark. Therefore, rather than being understood as observed platform performance, the simulation findings are interpreted as scenario-based estimations.

3.2. Analytical Model

The first equation defines the proportion of baseline harm preventable by a combined trust-and-safety system.

$R = r\,(1 - a)\,se$ *(effective harm reduction)*

where R denotes effective harm reduction, r is detection recall, (1 − a) indicates the effectiveness against adversarial adaptation, s represents intervention speed, and e is intervention effectiveness.

Effective harm reduction requires detecting harmful events, resisting adversarial adaptations, rapid intervention, and the actual reduction of harm. A deficiency in any stage limits overall effectiveness, such as having high recall but slow intervention, or quick intervention without efficacy.

Residual harm quantifies the leftover impact after a trust-and-safety intervention, calculated by the formula:

$Hr = H0\,(1 - R)$ *(residual harm)*

where Hr denotes residual harm, *H0* is the baseline harm before intervention, and *R* is the proportion of harm reduced. The remaining portion, *(1 - R),* when multiplied by baseline harm, indicates the expected harm post-intervention.

This metric not only highlights the ongoing economic and social burdens associated with specific governance structures but also enables comparative analysis across architectures; higher R values correlate with lower residual harm.

Avoided harm quantifies the baseline harm prevented through trust-and-safety architecture, expressed as:

AH = H0R (avoided harm)

Where *H0* is the baseline harm, and *R* is the reduction rate.

This equation derives from the total harm *H0* being the sum of avoided harm *AH* and remaining harm *Hr*. Thus, AH can be computed as AH = H0 - Hr, leading to AH = H0R, which economically links technical performance improvements (in recall, intervention speed, etc.) to reduced economic harm.

The total economic cost of operating governance and trust-and-safety architecture is calculated as the sum of governance expenditure *Cg*, human-review cost *Ch*, and costs from false positives and user friction *Cf*, expressed as:

CT = Cg + Ch + Cf (total cost)

This cost extends beyond direct governance spending to include expenses related to risk assessment, monitoring, compliance, and model evaluation. Additional labour costs arise from human escalation, while false positives can lead to user appeals, lost engagement, and other associated costs. The additive structure allows these costs to be integrated into a cohesive economic objective.

Net economic benefit *NEB* is calculated as the difference between the monetary value of harm avoided and the total costs of implementing and operating the governance architecture

NEB = AH – CT (net economic benefit)

A positive *NEB* suggests that economic benefits surpass costs, while a negative *NEB* indicates the costs exceed the harm prevented. This framework enables the comparison of various architectures through a standardized economic lens based on cost-benefit analysis.

False negatives are harmful events not identified by a detection system. They can be calculated using the formula:

FN = Nh (1 − r) (false negatives),

Where FN represents the number of false negatives, *Nh* is the total number of harmful events, and *r* is the detection recall, defined as *r = TP/(TP + FN)*. Assuming *Nh = TP + FN*, the proportion of missed harmful events is *1 - r*. This linkage between detection performance and economic risk highlights that undetected harmful events can lead to increased losses and costs.

False positives are non-harmful events mistakenly identified as harmful, calculated using the formula:

FP = (N − Nh) FPR (false positives)

Where *FP* is the number of false positives, *N* is the total number of decisions, *Nh* is the harmful events, and *FPR* is the false-positive rate. A high decision volume combined with a small *FPR* can lead to many erroneous actions, impacting user appeals, customer support, and overall engagement. Reducing false negatives by lowering intervention thresholds can inadvertently raise false positives, illustrating the precision-recall economic trade-off inherent in the system.

The cost of human oversight in review processes is modelled as:

$$Ch = (TP + FP)\, qhch \quad \text{(human review cost)}$$

Where *TP* and *FP* are potential intervention cases, *qh* is the proportion escalated to human review, and *ch* is the cost per review. This equation highlights that only a fraction of cases requiring review are escalated, resulting in a focused allocation of human resources on high-risk situations. It illustrates the balance between enhanced decision-making quality through human involvement and the risk of diminishing economic returns with increased human intervention.

The model presents the economically optimal governance configuration as the solution to the equation:

$$G^* = \arg\max_G [AH(G) - C(G)] \quad \text{(governance optimization)}$$

Where G^* is the optimal configuration, $AH(G)$ denotes the avoided harm, and $C(G)$ signifies total economic cost. The arg.max identifies the configuration yielding the highest net economic benefit. This addresses the central dilemma for platforms: while increased governance can enhance detection and resilience, it also raises costs and complexity. Hence, the optimal governance is not merely about technical accuracy or low cost but maximizing the difference between harm avoided and intervention cost. This framework may potentially allow for analysis of various governance architectures, including AI-only and human-heavy models.

To assess broader resilience outcomes beyond monetary harm, the Digital Economic Resilience Index (DERI) is formulated as:

$$DERI = w1HP + w2IS + w3OC + w4UT - w5FC - w6GC \quad \text{(resilience index)}$$

Where *HP* denotes harm prevention, *IS* indicates intervention speed, *OC* stands for operational continuity, *UT* represents user trust, while *FC* and *GC* signify friction cost and governance cost, respectively. The index employs a weighted additive approach where positive outcomes enhance resilience and negative factors diminish it. Key components such as harm prevention, rapid intervention, and operational continuity bolster resilience, while excessive friction and governance expenses hinder it. The model's adaptable weighting allows it to cater to various digital platform contexts, depending on the importance of each factor across different platforms.

In general, effective damage reduction is first determined by an architecture's technical features *R*. Avoided harm *AH* and residual harm *Hr* are both determined by effective harm reduction. The number of cases escalated for human review defines the human-review cost *Ch*, whereas detection performance produces false negatives *FN* and false positives *FP*. The overall cost *CT* is then calculated by adding the human-review cost to the governance expense and user-friction effects. Net economic benefit *NEB* is then calculated by adding avoided harm and total cost. Lastly, the *DERI* offers a more comprehensive multidimensional measure of digital economic resilience, whereas the optimisation function determines the governance configuration that maximises net economic value.

4. Results and Discussion

The section presents findings derived from an analytical approach combining scenario-based simulation of the suggested AI governance risk-based trust & safety economic resilience model (AGR-TSEM) with an empirically based economic baseline from current United States data.

4.1. Simulations Across Architectures

Operational parameters such as detection accuracy, false-positive rates, intervention speed, human-review intensity, and governance costs are calibrated assumptions informed by evidence rather than direct measurements of individual platforms; the $2.1 billion baseline economic-harm estimate is based on FTC-reported consumer losses from scams originating on social media in 2025. As a result, the performance indicators are model-generated simulation results intended to evaluate the conceptual framework and identify technical and financial trade-offs.

Table 2. AGR-TSEM Simulations Across Architectures

Architectures	**AI-only**	**AI-human hybrid**	**Risk-based hybrid**	**Human-heavy**
Recall	0.82	0.90	0.94	0.96
FPR	0.0008	0.0006	0.00045	0.00030
Speed	0.97	0.91	0.92	0.68
Effectiveness	0.78	0.84	0.88	0.91
Adaptation	0.15	0.10	0.08	0.06
Human review	0.01	0.08	0.10	0.35
Governance cost (US$ million)	20.0	35.0	50.0	70.0
Harm reduction (%)	53	62	70	56
Avoided harm (US$ million)	1,113.0	1,302.0	1,470.0	1,176.0
Residual harm (US$ million)	987.0	798.0	630.0	924.0
Total cost (US$ million)	28.8	39.6	52.1	76.5
Net benefit (US$ million)	1,084.2	1,262.4	1,417.9	1,099.5
ROI (×)	46.6	33.3	27.1	15.0

The risk-based hybrid architecture yields the maximum net economic gain ($1.418 million), avoided harm ($1.470 million), and modelled harm reduction (70%).

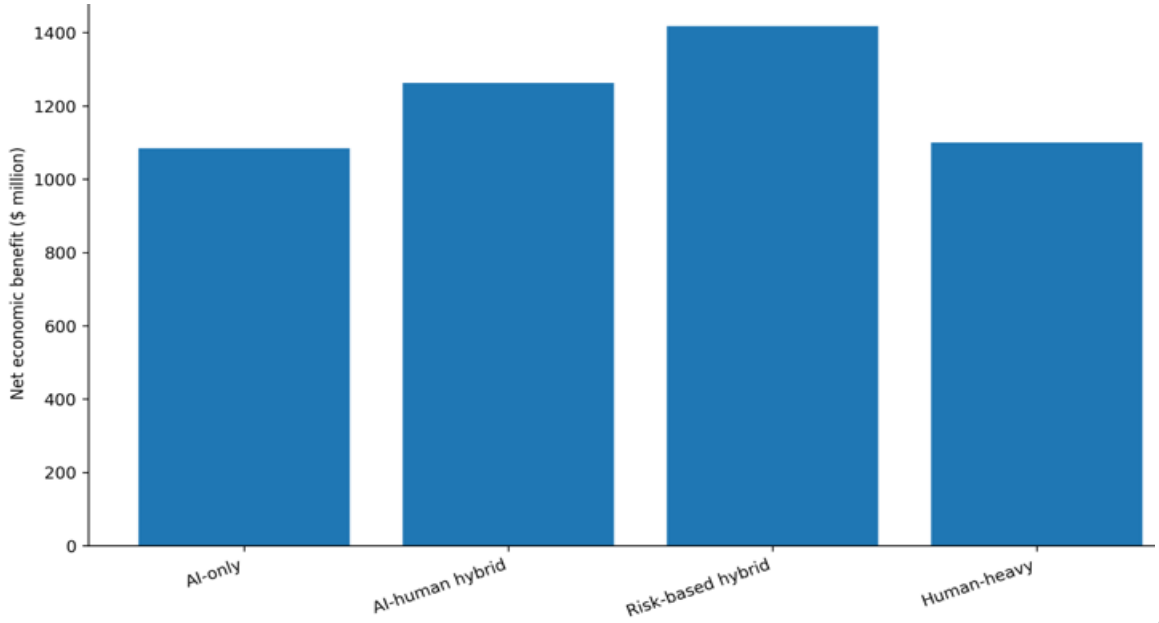


Figure 1.

Graph showing modelled net economic benefit and trust & safety architecture

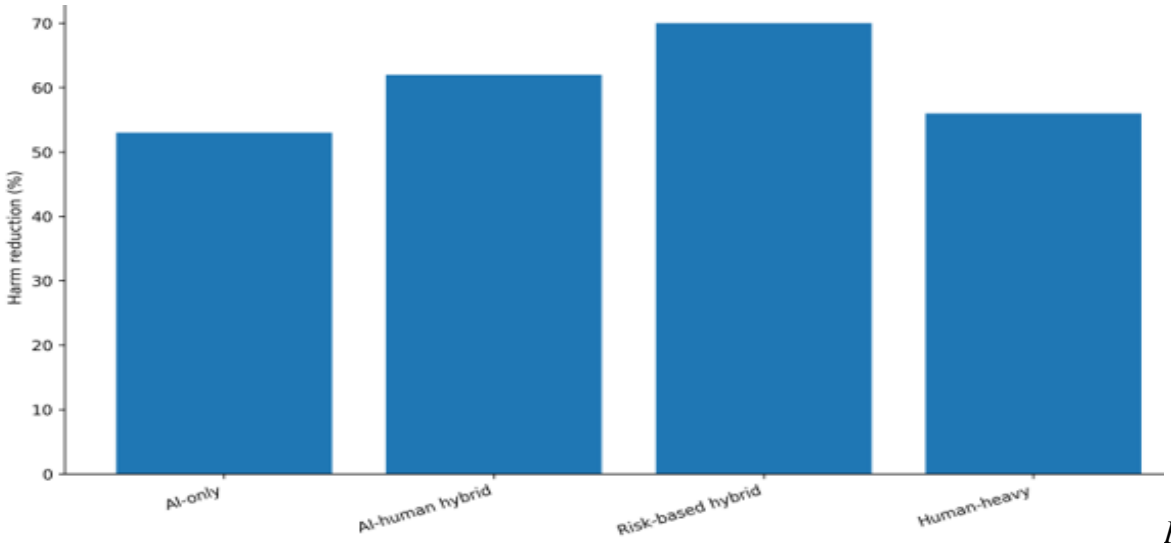


Figure 2.

Graph showing modelled harm reduction and trust & safety architecture

In the simulation in *Table 2,* AI-only governance has the highest modelled ROI (46.6×), indicating immediate intervention and minimal governance investment. However, its higher adversarial adaptation, lower recall, and less effective intervention led to more residual harm. Due to the increased expense and latency associated with human review, the human-heavy architecture yields lower overall harm reduction despite having the highest recall and lowest FPR. Therefore, rather than either unrestrained automation or human-dominated moderation, the results support selective human oversight.

4.2. Technical and Financial Trade-offs

The trade-offs outlined in *Table 3* indicate that rather than optimising any one system parameter, effective AI governance and risk-based trust and safety necessitate concurrent assessment of technical performance and economic consequences. Considering that false-positive and false-

negative errors result in asymmetric costs, intervention levels ought to take into account the respective seriousness and financial ramifications of each error type. Selective escalation is more cost-effective than either complete automation or substantial human intervention because, while automation can lower processing latency and marginal review costs, human oversight is still valuable when contextual judgement is needed. Accuracy and speed must also be balanced because more review could enhance the quality of decisions while prolonging the period that users or platforms are exposed to dangerous information. Friction costs should be included in the optimisation function because safety controls can reduce harmful activity but may cause user friction through incorrect removals, limits, or interruptions. There is an additional trade-off associated with transparency: while increased transparency can boost user confidence and accountability, it may also reveal information that allows antagonistic actors to get around safeguards, which supports the usage of risk-calibrated transparency mechanisms.

Furthermore, controls should be implemented when the marginal prevented harm surpasses the marginal governance and operational cost, and governance expenditures should be justified by their increased economic benefit. The AGR-TSEM proposal that the economically resilient platform is one that dynamically distributes automation, human oversight, intervention intensity, and transparency based on risk severity, uncertainty, and expected harm instead of implementing uniform controls across all platform activities is supported by these relationships taken together.

Table 3. Technical-Financial Trade-offs and Implications

Trade-off	Economic mechanism	Implication
False positives vs false negatives	Reducing one error type can increase the other.	Thresholds should reflect relative error costs.
Automation vs human review	Automation reduces marginal review cost and latency; human review improves contextual judgment but adds cost.	Selective escalation is preferable.
Speed vs accuracy	Additional review can improve quality but increase exposure duration.	Risk-tiered workflows can preserve speed.
Safety controls vs user friction	Aggressive controls may reduce harm while increasing erroneous interventions.	Include friction in optimization.
Transparency vs adversarial risk	Transparency can improve accountability but may facilitate evasion.	Use risk-calibrated transparency.
Governance cost vs avoided harm	Additional controls can produce diminishing marginal benefit.	Invest where marginal avoided harm exceeds marginal cost.

Figure 3 shows the proposed relationship between increasing risk-based Trust & Safety and AI governance maturity and selected economic and operational outcomes from 2020 to 2030. The scenario assumes that stronger governance capabilities are associated with lower online-harm economic costs and improvements in user protection, platform reliability, and digital economic resilience. The values are illustrative indices rather than observed or forecast U.S. measurements. This conceptual relationship is consistent with the NIST AI Risk Management Framework's

emphasis on governing, mapping, measuring, and managing AI risks throughout the AI lifecycle (Tabassi, 2023).

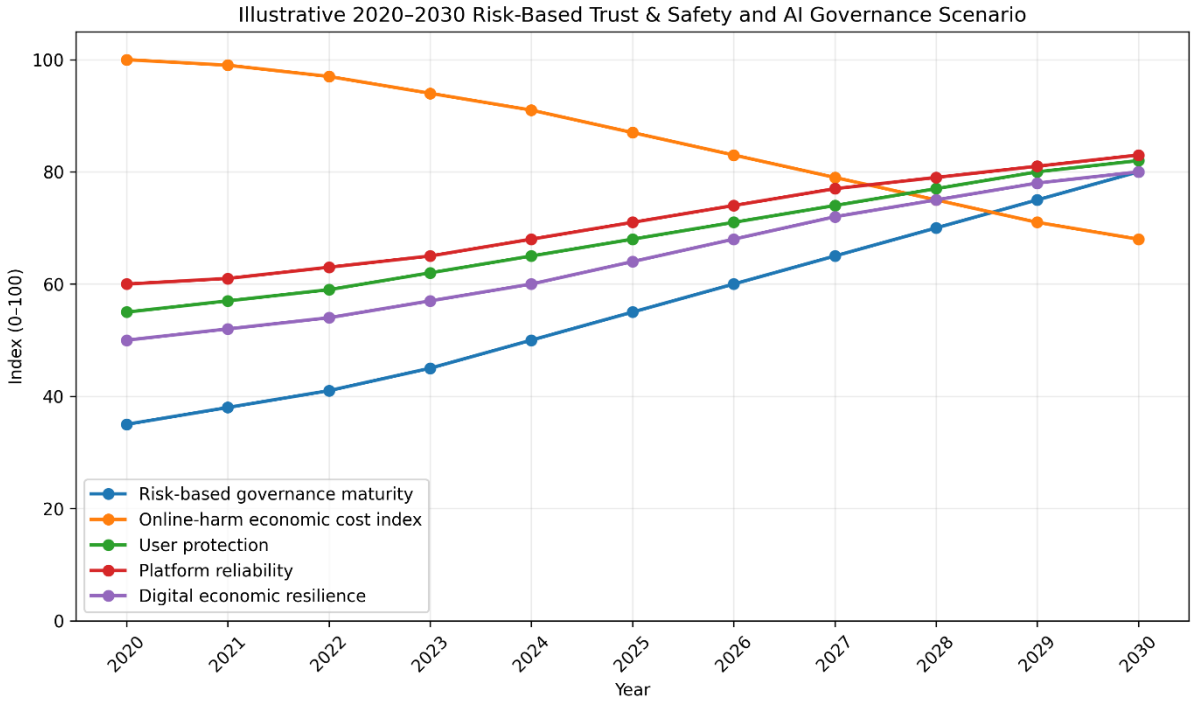


Figure 3: 2020–2030 Illustrative Risk-Based Trust & Safety and AI Governance Scenario

4.3. Trust and Safety Digital Resilience

Digital economic resilience is defined in AGR-TSEM as an online platform's ability to prevent or contain economically consequential harm while maintaining operational continuity, user trust, and economically sustainable governance. The OECD Digital Economy (2024) data indicate that, on average, 56% of people avoid specific websites, applications, or social media due to privacy concerns, and social media is the least trusted media source overall at 43%. These statistics support treating trust and user friction as economically relevant dimensions, even though they are not used as direct coefficients in the simulation.

Trust and safety should be integrated into corporate governance rather than treated as a separate technical or compliance function. Digital platforms require formal mechanisms of control, coordination, and accountability because platform owners influence the behaviour of multiple participants within complex digital ecosystems (Chen et al., 2022). Clear risk ownership is therefore necessary, with safety, legal, compliance, security, product, and engineering teams working across organizational boundaries while retaining defined responsibilities for risk decisions. Poti and Stanton (2024) similarly emphasize the importance of organizational and technical structures that enable AI governance throughout system development and use. Accountability should also involve mechanisms through which responsible actors can justify decisions, undergo oversight, and face corrective action where necessary (Novelli et al., 2024).

AI governance should incorporate systematic risk management, transparency, documentation, auditing, and human oversight throughout the AI lifecycle. The National Institute of Standards and Technology AI Risk Management Framework provides a voluntary United States framework

structured around Govern, Map, Measure, and Manage, supporting organizations in identifying and managing AI risks throughout design, development, deployment, and evaluation (Swaminathan & Danks, 2024). However, adoption of the framework does not replace applicable federal or state legal obligations; rather, it can provide an organizational structure for addressing relevant regulatory and risk requirements.

Transparency is particularly important because accountability is difficult to establish when organizations cannot determine how automated decisions were produced or who is responsible for their consequences (Hauer et al., 2023). Independent auditing and evaluation can further strengthen oversight by providing systematic assessment of AI systems beyond internal monitoring. Nevertheless, accountability should not be reduced to technical auditing alone, since meaningful governance also requires identifiable decision makers, standards, oversight processes, and mechanisms for correction and enforcement (Novelli et al., 2024). Thus, effective AI governance requires a combination of risk management, regulatory compliance, transparency, independent evaluation, and meaningful human oversight, rather than reliance on automated controls.

5. Contribution to Knowledge

The AGR-TSEM in this study demonstrates that recall, false-positive rates, intervention speed, and human-review capacity can be directly incorporated into economic optimisation. It also establishes that the economically optimal Trust & Safety threshold depends on the relative cost of false positives and false negatives. The research reframes Trust & Safety as infrastructure that contributes to platform resilience by reducing economic losses and maintaining user participation. The framework can be adapted to social media, marketplaces, search engines, advertising platforms, video services, and communication applications.

6. Implications and Limitations

Effective implementation of risk-based trust and safety and AI governance require platforms to translate governance principles into clear organizational responsibilities, operational controls, and oversight processes. Digital platform governance involves both incentives and control mechanisms, while AI governance requires a risk-oriented approach that connects identified risks with appropriate mitigation and accountability measures (Chen et al., 2022; Wirtz et al., 2022). Therefore, implementation must extend beyond technical systems to include organizational structures, regulatory compliance, transparency, and continuous human oversight. Implications are highlighted thus:

- Evaluation of trust-and-safety systems using joint technical and economic metrics rather than detection accuracy.
- Usage of risk-tiered human oversight, reserving intensive review for higher-risk or ambiguous cases.
- Evaluation of governance expenditure against avoided harm and marginal economic benefit.
- Utilization of normalized indicators such as harm per million interactions, intervention time and appeal-reversal rates for independent assessment.

Limitations include:

- The $2.1 billion FTC statistic does not account for all online platform damage; rather, it represents recorded consumer losses from social media frauds.
- FTC consumer reports may not be a random sample of the United States population and may be prone to underreporting.

- The scenario assumptions are the 0.2% harmful-event prevalence and the 1-billion decision volume.
- Platform data, independent audits, verifiable incidents, user outcomes, and longitudinal designs should all be used in future validation.

7. Conclusion

Risk-based trust and safety and accountable AI governance should be recognized as strategic investments that contribute to user protection, operational stability, economic efficiency, and long-term digital resilience. An economic perspective therefore provides a stronger basis for understanding Trust and safety as an essential component of sustainable platform performance rather than solely as a regulatory or compliance function. The framework developed in this study integrates risk identification, AI-assisted detection, harm prevention, governance, economic measurement, and platform resilience into a coordinated approach. This integration enables online platforms to identify risks earlier, prioritize resources according to potential impact, strengthen preventive controls, and reduce the likelihood of fraud, harmful content, operational disruption, and associated economic losses. It also provides a basis for measuring the value of Trust and safety through avoided losses, improved user confidence, operational efficiency, platform reliability, and business continuity.

Effective implementation requires clear governance, defined risk ownership, cross-functional accountability, stakeholder participation, continuous monitoring, and appropriate human oversight. These principles allow the framework to be adapted across social media, marketplaces, financial platforms, search, gaming, and other online services while responding to emerging AI technologies and evolving forms of platform abuse. Overall, repositioning Trust and safety from a predominantly reactive function toward a proactive, risk-based, and economically focused resilience strategy can strengthen user protection, platform competitiveness, and the sustainability of the wider United States digital economy.

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DEVELOPMENT OF PREDICTIVE ECONOMIC DECISION-SUPPORT FRAMEWORKS FOR MODERNIZING U.S. TRADE AND INDUSTRIAL POLICY AND STRENGTHENING DOMESTIC MANUFACTURING RESILIENCE AND COMPETITIVENESS

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Abstract

The U.S. has extensive federal data on trade, manufacturing, and economic activity, but these resources remain fragmented across agencies and often lack sufficient industry-level detail, timely indicators, and information on lower-tier supply chains. Most available data are also designed to describe past conditions rather than predict future risks. These limitations make it difficult for policymakers, economic-development organizations, and manufacturers to anticipate how trade restrictions, foreign supply disruptions, and other shocks may affect connected U.S. industries. This study develops a Predictive Trade and Industrial Intelligence Framework that combines trade, manufacturing, supply-chain, investment, labor, and energy data with econometric and machine-learning forecasting, supply-chain risk analysis, and policy-scenario assessment. The framework was tested using a real panel of 19 U.S. manufacturing subsectors covering 2015 to 2025, with 209 industry-year observations from BEA, BLS, and USITC data. The two-way fixed-effects model showed a positive association between trade activity and output, but this was not statistically significant under the wild-cluster bootstrap. Import-origin concentration was generally negatively associated with output, although it was not significant in the preferred specification or in the trade-by-concentration model. The forecasting exercise also found that the more complex models were difficult to improve upon the naive persistence benchmark. The main contribution of the study is the integration of fragmented federal data into a single analytical panel alongside econometric modeling, forecasting evaluation, and a decision-support prototype. The findings provide preliminary evidence for the first three phases of the proposed five-phase framework, while also identifying areas requiring further development, including formal supply-chain network mapping, causal scenario analysis, and broader retrospective validation.

Keywords: Trade Policy, Industrial Resilience, Supply-Chain Risk, Predictive Analytics, Econometric Forecasting, Scenario Simulation, Manufacturing Competitiveness, Decision-Support Systems.

INTRODUCTION

1.1 Background and Context

The global network of suppliers, manufacturers, distributors, and end markets in which the United States (U.S.) economy participates has grown increasingly important to the country's economic security. Supply chains that are efficient in stable environments but brittle under stress can result from trade liberalization, outsourcing, and the geographic concentration of critical manufacturing capacity. An overseas manufacturing closure, an export restriction on a critical mineral, a transportation bottleneck, or a geopolitical crisis can quickly propagate through supplier tiers and affect domestic output, employment, and prices. Recent disruptions have repeatedly illustrated these dependencies: shortages of pharmaceutical ingredients exposed vulnerabilities in health-related supply chains; critical-mineral and rare-earth restrictions highlighted dependencies in clean-energy,

defense, and advanced-manufacturing industries; and semiconductor disruptions constrained automobile and electronics production. Each episode underscored the same challenge: policymakers often lack sufficiently detailed, forward-looking, and integrated supply-chain intelligence to anticipate disruptions rather than merely respond to them.

The federal statistical infrastructure—including the U.S. Census Bureau, Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), U.S. International Trade Commission (USITC), Office of the U.S. Trade Representative (USTR), Department of Commerce, and Federal Reserve—produces a vast volume of trade, manufacturing, investment, labor, and macroeconomic data that constitutes a major national asset. However, these systems were largely designed for retrospective description rather than predictive, supply-chain-aware decision support. Data remain dispersed across agencies, are released on different schedules, are often aggregated above the level needed to trace lower-tier relationships, and are not routinely integrated into models designed to assess how shocks may propagate across industries.

This paper fills that void. In order to integrate disparate federal and industry data, apply econometric and predictive modeling, simulate policy and disruption scenarios, and translate results into decision-support tools for policymakers, economic development agencies, and manufacturers, it creates and documents a Predictive Trade and Industrial Intelligence Framework. This framework is intended to be nationwide in scope, modular across industries and regions, and updated on a regular basis.

1.2 Statement of the Problem

The usefulness of federal data for anticipatory decision-making is diminished by a number of structural limitations: information is dispersed across agencies that are not intended to work together; published statistics are frequently too coarse to reveal specific inputs, suppliers, or components; many indicators are lagging by design; lower-tier supplier visibility, the second-, third-, and fourth-tier firms where disruptions frequently originate is limited; and current tools typically describe past conditions rather than forecast how a prospective shock would spread.

As a result, trade policy, resilience investment, and competitiveness strategy are often developed using a retroactive, partial view. Manufacturers might not be able to measure supplier concentration, policymakers might not be able to predict vulnerability to a potential disruption, and economic development organizations could not have enough data to allocate investment where it matters most.

For the stakeholders in charge of U.S. trade policy, manufacturing resilience, and industrial competitiveness, there is a documented, unfulfilled need for a scalable analytical framework that integrates various economic data, applies predictive and scenario-based modeling, and translates results into actionable insight.

1.3 Purpose of the Study

With a replicable methodology that can be expanded beyond the initial pilot scope, the goal of this study is to design, document, and pilot-test a predictive economic decision-support framework that can integrate trade, manufacturing, supply-chain, labor, and energy data; forecast trade flows, production, and manufacturing conditions; identify supply-chain concentration and dependency risk; simulate the economic effects of disruptions and policy interventions; and present results through tools that manufacturers, policymakers, and economic development organizations can use.

1.4 Research Objectives

This study pursues the following objectives:

i. To review the existing state of U.S. commerce and identify specific deficiencies in granularity, timeliness, interoperability, and lower-tier supply-chain visibility.

ii. To map the relationships among overseas suppliers, imported inputs, domestic manufacturers, and downstream industries in order to identify crucial dependencies and potential bottlenecks.

iii. To build econometric, time-series, and machine-learning models capable of forecasting trade flows, domestic output, investment, import dependency, and manufacturing conditions.

iv. To create supply-chain risk models that can measure domestic capacity gaps, supplier concentration, and critical-input dependency.

v. To create scenario-simulation and stress-testing models that can assess the impact of different trade and industrial-policy interventions, tariffs, international export limits, shortages, demand shocks, and geopolitical disruptions.

vi. To create and verify decision-support dashboards and indicators that convert model output into a format that manufacturers, policymakers, and economic development organizations may use.

vii. To provide a modular, replicable technique that enables the framework to be expanded to other sectors and geographical areas.

1.5 Research Questions

The following research questions serve as the framework for the study:

RQ1: What are the main limitations in the current government and industry data infrastructure that prevents supply-chain-aware, predictive analysis of U.S. manufacturing and trade conditions?

RQ2: How can data on labor, energy, manufacturing, supply-chain, trade, and investment be combined into a cohesive framework that can predict trade and industrial conditions?

RQ3: How accurately can econometric and machine-learning models predict import dependency, production, and trade flows to assist investment and policy decisions?

RQ4: How can supply-chain risk be measured in a way that is comparable across industries? This includes supplier concentration and critical-input dependency.

RQ5: What are the effects on production, prices, employment, investment, and downstream industries of simulated trade disruptions, foreign export restrictions, and alternative policy interventions?

RQ6: Which decision-support formats are best for converting model output into practical recommendations for manufacturers, legislators, and economic development organizations?

1.6 Significance of the Study

The importance of this study lies in three areas: evidence-based policymaking, industrial competitiveness, and economic security. In terms of the economy, the methodology supports earlier

identification of important foreign dependencies and concentration by addressing a proven vulnerability in the U.S. ability to predict trade and manufacturing disruptions rather than just respond to them.

The framework is not intended to be a black box for policy, but rather a tool for decision-making. Its scenario-simulation components, in their fully developed and causally validated form, are meant to enable policymakers to assess the anticipated outcomes of alternative policies, such as tariffs, supplier diversification, and domestic capacity investment, prior to adoption. This longer-term goal outlines a decision-grade causal simulation; the pilot-scale tool shown here (Section 4.6) is an exploratory, non-causal example of that desired capacity.

When combined, these contributions support a national interest in bolstering the analytical framework that underpins U.S. trade and industrial policy. The outputs, which include publications, technical documentation, and an open, replicable methodology, are meant to advance the field beyond the purview of any one project.

1.7 Scope and Delimitations

This study does not suggest any particular tariff, sanction, or regulatory action; rather, it is limited to the development and pilot-scale empirical assessment of a decision-support framework. The framework's structure is industry-neutral, and selected components are evaluated in Chapter Four using 19 actual NAICS-3 manufacturing subsectors that cover a broad range of supply-chain structures, from computer and electronic products to wood products and textile mills. These subsectors were chosen as the set for which comparable annual detail could be constructed across the four federal data sources used in the empirical pilot—BEA, BLS Employment, BLS Productivity, and USITC—between 2015 and 2025.

The research depends on publicly accessible federal datasets and uses recognized economic modeling techniques. The forecasting models are subject to common limitations of econometric and machine-learning prediction, including sensitivity to data quality, structural change, and unexpected external shocks. The proposed framework addresses these issues through uncertainty analysis, benchmark comparison, transparent reporting, and a planned human-in-the-loop validation process described in Chapter Three and discussed further in Chapter Five.

1.8 Definition of Key Terms

- **Indicators of Industrial Resilience and Competitiveness:** A common set of quantitative metrics that illustrate an industry’s susceptibility to supply disruptions, domestic production capabilities, and its relative competitive standing.
- **Supply-Chain Concentration:** The extent to which a crucial input or component is obtained from a limited number of suppliers, countries, or regions, heightens the risk of disruption.
- **Lower-Tier Visibility:** The ability to identify and monitor suppliers beyond the immediate, tier-one relationships, specifically second-, third-, and fourth-tier suppliers.
- **Scenario Simulation:** A modeling approach utilized to assess the economic impact of a potential event, like a tariff, export limitation, or geopolitical disruption, based on defined assumptions.
- **Stress Testing:** The comprehensive assessment of a system’s capabilities when faced with unfavorable or extreme situations, adapted here from practices in the financial sector for use in trade and manufacturing systems.

- **Decision-Support Dashboard:** An interactive analytical platform that displays model results, indicators, and scenario outcomes in a format intended for non-technical policy and industry stakeholders.
- **Human-in-the-Loop Validation:** A model-governance approach where subject-matter experts evaluate, interpret, and, if necessary, modify or adjust model results prior to their application in decision-making.

1.9 Organization of the Paper

Chapter One outlines the problems, objectives, research questions, and significance of the study. Chapter Two reviews the relevant literature and positions the framework within that context. Chapter Three presents the five-phase methodology, distinguishing the full proposed architecture from the narrower empirical specification evaluated in this study. Chapter Four presents pilot-scale empirical results derived from federal data covering 19 manufacturing subsectors from 2015 to 2025. These are empirical estimates based on observed data rather than simulated outcomes, although they represent pilot-scale findings rather than a comprehensive national implementation. Chapter Five discusses the implications, contributions, limitations, recommendations, and directions for future research.

LITERATURE REVIEW

2.1 Introduction

This chapter examines existing literature across four main areas that provide the foundation for the proposed framework. These areas include U.S. trade and industrial data infrastructure, supply-chain visibility and vulnerability, predictive and econometric modeling, and scenario-based policy simulation. The chapter concludes by highlighting the specific gaps in the existing literature that this study aims to address and presents the conceptual framework that guides the research methodology.

2.2 U.S. Trade Policy and Economic Data Infrastructure

The federal government collects and manages a broad range of data relating to trade and industrial activities. Important sources include trade statistics from the U.S. Census Bureau, input-output accounts provided by the BEA, employment and price data from the BLS, trade and tariff information from the U.S. International Trade Commission (USITC), and industrial production indices from the Federal Reserve. Together, these sources represent a significant public investment in the collection and measurement of economic information.

However, an important issue in the use of these data is the gap between the large amount of information available and its practical usefulness for timely analysis across government agencies. Existing classification systems are often presented at a level that is too broad to identify specific dependencies between individual firms or businesses. In addition, the time taken to collect, process, and publish some economic data may be suitable for monitoring broad economic conditions but may not be adequate for identifying and responding to supply-chain risks before they occur. Differences in data collection methods, definitions, and reporting practices among government agencies also make it difficult to combine the information into one consistent analytical system. These challenges support the findings of the U.S. Government Accountability Office (2023), which reported that federal agencies involved in strengthening supply-chain resilience continue to experience difficulties with data collection and the sharing of information across agencies. These limitations therefore provide a strong basis for the data-integration objectives of the framework proposed in this study.

2.3 Supply Chain Visibility and Vulnerability Analysis

Recent disruptions involving semiconductors, critical minerals, and pharmaceutical inputs have led to increased research on supply-chain mapping and the assessment of supply-chain vulnerability. A number of studies have used network-based methods to understand how supply chains are connected. These methods commonly represent supply chains as directed networks, which makes it possible to identify areas where supply is highly concentrated and to examine how disruptions may spread through different parts of the network. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) showed that shocks affecting individual firms or sectors can have wider effects on the economy because of the connections created through input-output relationships. This finding supports the focus of the present study on supply concentration as an important pathway through which disruptions can spread across the economy. Similarly, Antràs and Chor (2013) examined ownership and control within global value chains and provided useful evidence for understanding how the structure of international sourcing can indicate exposure to upstream supply risks. Their work supports the idea that the countries from which imports originate can provide useful information about potential supply-chain exposure. However, the country-level Herfindahl-Hirschman Index (HHI) used in this study, as described in Section 4.3, provides a broader measure and cannot capture the detailed firm-level relationships examined in the existing literature.

Visibility beyond the first level of the supply chain remains a major and largely unresolved problem. Although relationships involving tier-one suppliers can generally be identified with reasonable accuracy, the availability and quality of information tend to decline considerably at lower tiers. This is particularly important because disruptions and supply bottlenecks often begin further down the supply chain, where information is more limited. In response to this challenge, the proposed framework combines network-mapping concepts with inference-based approaches, while the empirical pilot uses publicly available data and a country-of-origin concentration proxy rather than a formal firm-level dependency network. In addition, the study draws on the work of Autor, Dorn, and Hanson (2013), whose analysis of competition from Chinese imports is an important contribution to understanding the measurable effects of import competition on domestic manufacturing. Their findings provide a useful basis for examining the relationship between import activity and domestic industrial output, which is further considered in Chapter Four. However, it is important to recognize that Autor, Dorn, and Hanson's (2013) study used an instrumented causal identification approach that provides stronger evidence of cause and effect than the associational panel regression employed in the present study. The current analysis is based on 19 industry-level cross-sectional units observed over 11 years (209 industry-year observations) and should therefore be interpreted as examining relationships between the variables rather than establishing definitive causal effects.

2.4 Predictive Analytics and Econometric Forecasting in Trade and Manufacturing

Econometric methods have been widely used for many years to forecast trade and manufacturing output. Common approaches include vector autoregression (VAR), error-correction models, and structural gravity models. More recently, machine-learning techniques such as gradient-boosted trees, random forests, and neural network models have gained attention because they can produce more accurate predictions than traditional linear models when sufficient data are available. However, this improvement in predictive performance can come with reduced ease of interpretation. Mullainathan and Spiess (2017) explain that machine learning is mainly concerned with improving prediction rather than identifying and estimating specific model parameters. They also emphasize that achieving high predictive accuracy does not necessarily mean that a model can provide reliable evidence about cause-and-effect relationships, which is often important for policy analysis. The present study follows this distinction by clearly treating the estimated trade coefficients as **associational rather than causal**, as explained in Section 4.4.

Previous studies have often reported that combining econometric methods with machine-learning techniques can produce better forecasting results than using either approach on its own, especially when the data contains structural changes or major shifts in underlying patterns. This finding provides support for the hybrid approach adopted in this study and discussed in Chapter Three. However, the results presented in Section 4.5 do not show the same outcome. Given the relatively small size of the panel data used in this study, a simple persistence or naive forecasting method performed better than both the linear and machine-learning models. This result shows that findings commonly reported in wider literature may not necessarily apply in the same way to every dataset or research setting.

2.5 Scenario Analysis, Stress Testing, and Policy Simulation

Scenario analysis and stress testing were first widely used in financial risk management but have increasingly been applied to issues relating to trade and industrial policy. Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2020) found that uncertainty surrounding trade policy can reduce investment even before a tariff or other trade measure is actually introduced. This finding is particularly relevant to the present framework because it highlights the importance of assessing the

possible effects of proposed policies before they are implemented. Different modeling approaches can provide different perspectives on these potential effects. Computable general equilibrium (CGE) models are useful for examining the broader effects of tariffs and trade agreements across the economy, including effects that may not be captured by partial-equilibrium models. In comparison, agent-based models and network-simulation approaches can complement CGE models by providing greater attention to the behavior and responses of individual firms and the relationships between them.

Existing research generally stresses the importance of evaluating several possible policy interventions within the same analytical framework rather than examining each option separately. Comparing different interventions using consistent methods makes it easier to understand their relative strengths, limitations, and likely effects. This principle is incorporated into the methodology of the present study, particularly in Phase 2 and Phase 3, where alternative policy options are assessed using a common framework.

2.6 Industrial Resilience and Competitiveness Indicators

An increasing body of research has developed composite indicators for measuring industrial resilience. These indicators commonly combine several factors, including the concentration of suppliers, dependence on imports, levels of production capacity utilization, and changes in the workforce and capital base. Existing research generally supports the use of indicators that are clear, consistent, and capable of being measured repeatedly over time, rather than measures that are produced only once. These principles provide the basis for the indicators developed and applied in Phase 1 of the framework used in this study.

This discussion forms part of the recent renewed interest in industrial policy research. Juhász, Lane, and Rodrik (2024) reported that more recent studies using stronger identification methods tend to find more favorable effects of industrial policy than earlier research, which was generally more doubtful about its benefits. However, their findings also show that the success of industrial policy depends greatly on how policies are designed, implemented, and monitored. In this context, the present framework aims to provide firm- and industry level evidence that can support the development of better-informed industrial policies. The purpose is therefore not to promote industrial policy itself, but to provide useful evidence that can contribute to sound policy design and decision-making.

2.7 Gaps in Existing Literature and Tools

Different methods have already been developed for data integration, supply-chain mapping, forecasting, and scenario-based simulation. However, based on the literature and publicly available federal tools examined in this study, there appears to be limited work on integrated systems that bring all four functions together within a single framework that can be regularly updated and applied across the U.S. manufacturing sector. Many of the existing tools have a narrow focus, depending on proprietary data that are not easily accessible, or mainly examine past events rather than providing forward-looking analysis. This suggests a need for a more integrated and continuously updated framework that can support the identification and assessment of potential manufacturing and supply-chain risks before they occur.

This study responds directly to the identified gap by bringing together four key components: data integration, supply-chain mapping, hybrid forecasting, and comparative scenario simulation. These components are organized within a single modular framework, allowing each part to function as an

important element of the overall system. The framework is further assessed through a phased methodological approach, with the aim of developing a system that can be expanded and applied at the national level.

2.8 Conceptual Framework

The conceptual framework developed for this study consists of four connected layers. The first is the data-integration layer, which brings together data obtained from different and often fragmented sources. The second is the mapping layer, which is designed to use network-based methods to represent relationships and dependencies within supply chains. The third is the modeling layer, where econometric methods, machine-learning techniques, and network-risk approaches can be applied to analyze available data and identify possible risks. The fourth is the decision-support layer, which converts analytical results into practical outputs such as scenarios, indicators, and dashboards. Under the proposed full framework, outputs from each layer would be reviewed through a human-in-the-loop process before informing subsequent stages, in order to assess their quality, relevance, and usefulness.

This structure provides a direct link to the methodology presented in Chapter Three. **Phase 1** focuses on the data-integration and mapping layers, while **Phase 2** applies the modeling approaches. **Phase 3** focuses on developing and testing prototypes to assess the decision-support layer. Finally, **Phases 4 and 5** are designed to extend the framework and support its continued updating and application at the national level.

2.9 Summary

This chapter examined existing literature on data infrastructure, supply-chain vulnerability, predictive forecasting, scenario simulation, and indicators of industrial resilience. The review identified a major gap in the literature and available tools examined, particularly the limited development of an integrated national framework that combines these approaches and can be continuously updated. Chapter Three therefore presents the methodology developed in this study to address this identified gap.

METHODOLOGY

3.1 Research Design

This study adopts a design and development research methodology because the main aim is to develop and empirically assess selected components of an analytical framework rather than to test a single hypothesis. The research process is structured around five sequential but interconnected phases. These are: (i) National Trade and Industrial Intelligence Assessment, (ii) Predictive Economic Framework Development, (iii) Prototype Validation and Pilot Implementation, (iv) National Scaling, Policy Alignment, and Dissemination, and (v) Continuous Economic Intelligence and Improvement. Although the phases follow a planned sequence, they also allow for repeated review and refinement where necessary. This approach supports the gradual development of the framework, ensures that it is empirically tested before wider application, and allows the system to be regularly updated in response to changes in economic and industrial conditions.

3.2 Phase 1: National Trade and Industrial Intelligence Assessment

Phase 1 provides the empirical basis for the study by examining conditions within the U.S. trade and manufacturing sectors, as well as supply chains, investment, labor, energy, and the wider economy. The assessment draws on data from several government sources, including Census trade statistics, BEA input-output and industry accounts, BLS employment and price statistics, USITC trade and tariff data, Federal Reserve production indices, and energy-related data from the Department of Energy (DOE). These data are used to assess the performance of selected industries and identify major areas of vulnerability, production capacity limitations, supply-chain risks, and challenges affecting their competitiveness.

Alongside this assessment, the study also reviews and organizes existing federal datasets and tools related to industrial resilience. These resources are assessed based on factors such as the level of detail they provide, how frequently they are updated, their ability to work with data from other systems, and the extent to which they provide information about lower levels of the supply chain. This assessment helps to identify the specific limitations in the existing data infrastructure that the integration activities in Phase 2 will need to address.

A major output of Phase 1 is the development of a supply-chain dependency map. The map shows the relationships between foreign suppliers, imported inputs, domestic manufacturing firms, and downstream industries. These relationships are represented as a directed network, with the connections weighted according to the value of transactions and, where sufficient information is available, the level of supplier concentration. This approach provides a clearer picture of how different parts of the supply chain depend on one another.

The phase ends with the development of baseline **Industrial Resilience and Competitiveness Indicators.** These indicators cover important areas such as supplier concentration, dependence on imports, capacity utilization, availability of workers, and trends in capital investment. The findings from these indicators are then used to identify and rank the industries that require further assessment through the predictive modeling activities planned for Phase 2.

3.3 Phase 2: Predictive Economic Framework Development

Phase 2 focuses on developing the integrated framework by bringing together the data generated and organized during Phase 1 and applying four main categories of models.

The **forecasting models** use a combination of econometric and machine-learning methods, as discussed in Section 2.4. VAR and error-correction models are used to examine the structural relationships among the variables, while gradient-boosted tree models and panel-based machine-learning methods are applied to identify nonlinear relationships and interactions that may not be adequately captured by conventional econometric models. The performance of the different forecasting approaches is then compared using out-of-sample results. Where appropriate, the forecasts may be combined using ensemble weighting, with greater weight given to models that demonstrate stronger predictive performance outside the estimation sample.

The **supply-chain risk models** are designed to measure the extent to which industries depend on a limited number of foreign suppliers. Supplier concentration is assessed using measures such as the **HHI,** which is also used in U.S. antitrust and merger-review practice (U.S. Department of Justice & Federal Trade Commission, 2023). In this study, the HHI is applied to patterns of import sourcing to assess the degree of concentration among supplier countries. These measures are combined with network centrality indicators derived from the supply-chain dependency map developed in Phase 1. This makes it possible to assess not only how concentrated import sources are, but also how important particular suppliers are within the wider supply-chain network.

The **economic-impact models** are used to assess how a disruption may spread through the supply-chain dependency network and affect important economic outcomes. These outcomes include production, prices, employment, investment, and activities in downstream industries. The analysis builds on input-output multiplier methods and incorporates elasticity estimates obtained during the forecasting stage to provide a better understanding of how changes in one part of the supply chain may influence other areas of the economy.

The **scenario, stress-testing, and policy-simulation models** bring together the different modeling approaches developed in the earlier stages. They are used to examine the possible effects of specific events and policy options under clearly defined conditions. The scenarios considered include tariffs, restrictions on exports, geopolitical disruptions, supply shortages, and changes in demand. The framework also considers alternative policy responses, such as investment in domestic production capacity and diversification of suppliers. The different scenarios are compared using a common set of assumptions so that their potential economic effects can be assessed consistently.

Under the proposed Phase 2, several quality-control measures would be applied to improve the reliability of the results. These would include checking data quality, assessing uncertainty, documenting modeling procedures, and comparing model performance with simple forecasting methods and existing baseline models. Outputs intended for decision support would also be reviewed by subject-matter experts through the planned human-in-the-loop validation process described in Section 3.9.1. This review would occur before such outputs are used in decision-support applications, helping to assess whether the findings are reasonable, understandable, and relevant for policy and economic decision-making.

3.4 Phase 3: Prototype Validation and Pilot Implementation

The proposed Phase 3 focuses on pilot testing and validation of the framework using priority industries identified during Phase 1. At this stage, data assembled in the earlier phases would be used to develop and evaluate predictive models, supply-chain vulnerability measures, scenario-testing applications, and dashboards for presenting results in a clear and useful form. The empirical work in Chapter Four implements selected elements of this phase, but it does not constitute full Phase 3 validation.

Under the proposed full Phase 3, validation would be carried out in two main ways. First, retrospective validation would apply the framework to previous disruption events, such as earlier tariff measures, export-control events, and supply shortages, and compare model outputs with observed outcomes. Second, prospective stress testing would focus on potential risks that have not yet occurred, generating forward-looking assessments that could be reviewed and updated as economic and supply-chain conditions change. The current pilot includes pseudo-out-of-sample forecast evaluation and robustness testing, but broader event-based retrospective validation remains future work.

In the empirical pilot, forecasting performance is evaluated using standard measures, including Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), together with comparison against a naive persistence benchmark. Under the proposed full Phase 3, sensitivity analysis and structured subject-matter-expert feedback would provide additional validation. Findings from those broader validation activities would be used to refine the models before application to additional industries.

At the end of the proposed full Phase 3, the framework would produce standardized data-integration procedures, model-specification templates, and validation checklists. These resources are intended to support consistent and repeatable application when the framework is extended to other industries and geographic regions.

3.5 Phase 4: National Scaling, Policy Alignment, and Dissemination

The proposed Phase 4 focuses on expanding framework components that have been sufficiently pilot-tested beyond the industries included in the initial study to other strategically important sectors and regional economies. The modular design is intended to allow new industries or regions to be incorporated without redesigning the entire framework. At this stage, standardized national indicators for industrial resilience, international-trade exposure, production capacity, supplier concentration, and competitiveness would be further developed and evaluated for meaningful comparison across industries and regular updating.

The scaling process involves collaboration with relevant federal government agencies, universities, professional organizations, and regional economic-development stakeholders. Their involvement helps to test the framework under a wider range of economic and industrial conditions while also ensuring that the information produced meets the practical needs of those who may use it. The findings from this phase are shared through academic publications, technical reports, policy briefs, conferences, and workshops. In addition, implementation guides are prepared to explain how the framework can be replicated and applied consistently in other industries and regions.

3.6 Phase 5: Continuous Economic Intelligence and Improvement

The proposed Phase 5 is designed to ensure that the framework remains dynamic and regularly updated rather than functioning as a fixed or one-time system. New data would be incorporated at regular intervals, forecasts would be compared with subsequently observed outcomes, and models would be recalibrated when economic and industrial relationships change. In this way, retrospective validation would become part of ongoing operation, helping to identify and reduce model drift over time.

In addition, Phase 5 introduces regular stress-testing exercises at both the national and sectoral levels. The methods used within the framework are reviewed and updated as new sources of data,

analytical techniques, and modeling approaches become available. This continuous process of assessment and improvement helps the framework remain useful and relevant as economic, industrial, and supply-chain conditions change.

3.7 Data Sources

The framework relies mainly on data from several U.S. federal sources. These include Census trade and manufacturing statistics, BEA input-output and gross-output-by-industry data, BLS information on employment, wages, and prices, USITC data on tariffs and trade-remedy measures, Federal Reserve production indices, and energy-related data from the DOE. Where relevant information is available, data from industry associations are also included to provide additional insight into lower levels of the supply chain that may not be adequately captured by federal statistics alone. To support transparency and make the research process reproducible, all data sources used in the study are recorded together with their extraction dates and details of any transformations or processing carried out on the data. The procedures for documenting and managing this data are further described in Section 3.3.

3.8 Modeling Approach

The modeling strategy used in this study brings together three main approaches. The first is **econometric time-series modeling**, which includes VAR, based on Sims (1980), error-correction models, and structural gravity models associated with Anderson (1979). These methods are useful because they provide interpretable results that can support economic and policy-related forecasting. The second approach involves **machine-learning methods**, particularly gradient-boosted trees, following Friedman (2001), and random forests, introduced by Breiman (2001). These methods are included because they can identify nonlinear relationships and patterns that may not be fully captured by traditional econometric models. The forecasts from the machine-learning models are compared with those from the econometric models and, where appropriate, combined using ensemble weights determined by their performance on data outside the model estimation period. The third approach uses **network and input-output methods**, drawing on the work of Leontief (1936) and the applied general-equilibrium tradition of Shoven and Whalley (1984) for analyzing relationships across sectors. These methods allow the structure of the supply chain to be represented more explicitly and help trace how a disruption affecting one part of the network may spread to other connected firms, industries, or sectors. By combining these three approaches, the study is able to consider both the measurable economic relationships between variables and the wider network effects that may arise when disruptions occur within interconnected supply chains.

3.8.1 Panel Data Model Specification

The main econometric component of the study is based on a **panel data model,** rather than relying solely on cross-sectional or time-series data. The use of panel data is appropriate for several reasons. First, it allows the study to account for differences between industries that do not change significantly over time and may not be directly observed in the data. Second, it makes it possible to control for economic shocks that affect several or all industries during the same period. Third, combining observations across industries and over time provides a larger number of usable observations than would normally be available from a purely cross-sectional or time-series research design.

The study presents two separate model specifications. These are deliberately distinguished from each other to ensure that the broader architecture proposed for the framework is not confused with the

more limited empirical model that is actually estimated in the pilot analysis presented in Chapter Four.

Proposed National Framework Specification

The framework's full proposed specification, intended for eventual national-scale implementation once richer input-cost, tariff, and exchange-rate data are integrated, is a two-way (entity- and time-) fixed effects model:

$$Y_{it} = \alpha_i + \lambda_t + \beta 1\ \text{Tariff}_{it} + \beta 2\ \text{HHI}_{it} + \beta 3\ \ln(\text{ForeignInputPrice})_{it} + \beta 4\ \text{CapUtil}_{it} + \beta 5\ \ln(\text{LaborCost})_{it} + \beta 6\ \ln(\text{EnergyPrice})_{it} + \beta 7\ (\text{ImportShare}_i \times \text{RER}_t) + \varepsilon_{it}$$

where i indexes industry and t indexes year; α_i and λ_t are entity and time fixed effects; Y_{it} is log domestic production; Tariff_{it} is the applicable tariff rate; HHI_{it} is import-origin concentration; $\text{ForeignInputPrice}_{it}$, LaborCost_{it}, and EnergyPrice_{it} are input-cost indices; and $\text{ImportShare}_i \times \text{RER}_t$ captures currency-movement exposure. This requires tariff, foreign-input-price, capacity, and exchange-rate data beyond this study's four integrated sources and is not the specification estimated in Chapter Four.

Empirical Pilot Specification Estimated in This Study

Chapter Four estimates a narrower specification, using only variables constructible from the four integrated federal sources:

$$\log(Y_{it}) = \alpha_i + \lambda_t + \beta 1\ \text{Employment}_{it} + \beta 2\ \text{LaborProductivity}_{it} + \beta 3\ \log(\text{Imports}_{it}) + \beta 4\ \log(\text{Exports}_{it}) + \beta 5\ \text{HHI}_{it} + \varepsilon_{it}$$

where Y_{it} is Gross Output (BEA), Employment_{it} and $\text{LaborProductivity}_{it}$ are from BLS, Imports_{it} and Exports_{it} are from USITC, and HHI_{it} is the Import-Origin Concentration Index (Section 3.3). This is the exact specification estimated in Table 4.2 and used for the main panel-regression analysis in Section 4.4; other Chapter Four analyses, such as forecasting and scenario illustrations, use the methods described in their respective sections.

Model selection between fixed- and random-effects specifications is governed by a like-for-like Hausman (1978) test, supplemented with a Mundlak (1978) correlated random effects test (Section 4.4.1). Standard errors are entity-clustered throughout, with a wild-cluster bootstrap (Cameron, Gelbach, & Miller, 2008) given this pilot's modest 19 clusters (Section 4.4.2), following Petersen (2009).

Because manufacturing output likely exhibits genuine persistence through capacity, inventory, and order-backlog dynamics, a dynamic extension adds a lagged dependent variable:

$$\log(Y_{it}) = \rho\ \log(Y_{i,t-1}) + \beta' X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$$

This introduces a well-documented small-sample bias (Nickell bias) in short panels. Arellano-Bond (1991) or Blundell-Bond (1998) GMM are the standard solutions in principle but are not applied here: with only 19 cross-sectional units, GMM risks instrument proliferation and unreliable overidentification tests. Section 4.4.5 instead reports a simpler dynamic fixed-effects specification, explicitly flagged as subject to Nickell bias, as a parsimonious check rather than a bias-corrected estimate; full GMM is future work contingent on a larger panel (Section 5.6).

3.8.2 Predictive Modeling Approach

The forecasting component of the framework uses a **pseudo-out-of-sample, rolling-origin approach** to generate one-year-ahead predictions. Under this procedure, all predictor variables are

lagged by one year, and the models are repeatedly re-estimated at different points in time using only the information that would have been available up to each forecasting point. The resulting predictions are then tested against the actual outcome observed in the following year. The approach is described as pseudo-out-of-sample rather than fully ex-ante because it uses the current version of historical data, which may include later revisions, rather than the exact data version that would have been available when each historical forecast was originally made. This distinction is stated clearly to improve methodological transparency.

The forecasting origins are moved forward across the panel, with each model trained using data up to a particular year and then evaluated using the outcome for the following year. This produces both an overall average performance measure and results for individual years. Reporting the year-specific results is important because it allows the reader to determine whether the overall performance is being influenced heavily by one particular year. Four forecasting approaches are compared: **naive persistence,** a **linear model with entity fixed effects and lagged predictors,** a **gradient-boosted ensemble** as described in Section 2.4, and a **hybrid model** that combines the forecasting results.

Model performance is assessed using three standard forecasting measures: **MAPE, RMSE, and Mean Absolute Error (MAE)**. The results are also compared with the naive persistence benchmark, as described in Section 3.9. Including this simple benchmark is an important part of the methodology because it provides a basic standard against which the more complex models can be judged. If a more advanced forecasting approach cannot perform better than simple persistence, it would be difficult to claim that the approach provides meaningful additional forecasting value. Therefore, the study reports the benchmark results even in cases where the naive method performs as well as, or better than, the more complex models.

3.9 Validation and Evaluation Metrics

Forecasting performance is assessed by comparing the predicted values with the actual outcomes using standard measures such as **MAPE** and **RMSE**. The performance of the models is also compared with simple naive forecasts and, where such information is available, with forecasts that have already been published by other recognized sources. This provides a clearer basis for determining whether the models used in the study offer useful improvements in forecasting accuracy.

The supply-chain risk indicators are assessed by comparing the inputs identified by the models as high-risk with supply-chain disruptions that have been documented in the past. This helps to determine whether the indicators are capable of identifying areas that have previously experienced significant disruption. Similarly, the outputs generated from the scenario analysis are tested retrospectively against previous disruption events, as described in Section 3.4, to examine how well the framework reflects outcomes observed during actual events.

All findings are recorded transparently, including cases where the models perform poorly or fail to improve on the selected benchmarks. Reporting these limitations forms an important part of the model-governance process and helps ensure that the strengths and weaknesses of the framework are clearly documented.

3.9.1 Human-in-the-Loop Validation Protocol

This section describes the **human-in-the-loop validation protocol** introduced earlier as one of the key design principles of the framework. The protocol is proposed for implementation during the pilot stage and would depend on the institutional collaboration outlined in Section 3.5. Therefore, the

procedure described in this section represents a planned specification for future implementation rather than a review process that is currently in operation.

Under the proposed system, every output intended for external use would be reviewed by two different roles. The first would be a **methods reviewer**, whose responsibility would be to check whether the model specifications, diagnostic procedures, and decisions made during data construction are technically appropriate. The second would be a **domain reviewer**, such as an economist, policy analyst, or manufacturing subject-matter expert. This reviewer would assess whether the results make practical and economic sense, including aspects that may not be adequately captured by the statistical models alone.

Three main situations would require an output to undergo review before it could be released. The first would occur when a forecast exceeds a predetermined magnitude threshold in relation to the level of historical volatility. The second would apply when an updated regression produces substantial changes in its coefficients compared with the previous version, consistent with the specification comparisons presented in Sections 4.4.1–4.4.6. The third would occur when the result relates to a subsector experiencing a known disruption at the same time, since the assumptions of stationarity are more likely to be affected under such conditions.

Each reviewed output would be recorded together with the reviewer's identity, the date of the review, and the reason for the decision or assessment. This would create a clear and auditable record and support the framework's commitment to open-source reproducibility, as discussed in Section 5.8. The proposed process is intentionally less complex than the formal model-risk management systems commonly used in the financial sector. It is designed to be practical for a research pilot team with limited resources. However, if the framework is expanded to national-level implementation in Phase 4, a more formal and comprehensive governance structure would be required.

3.10 Ethical Considerations and Limitations

The framework uses only data that are publicly available or obtained through appropriate licensing arrangements. Where industry-level information is used for validation purposes, the data are presented in an aggregated or anonymized form to protect the identity of individual organizations. The framework is intended to function as a **decision-support tool** rather than an automated system that independently makes policy decisions. Its purpose is therefore to provide evidence that can assist decision-makers, not to replace professional or expert judgement. In line with this approach, the human-in-the-loop process proposed for Phases 2 and 3 requires relevant outputs to be reviewed by experts before they are used to support decision-making.

From a methodological perspective, the framework also has some of the limitations commonly associated with econometric and machine-learning forecasting. Its performance may be affected by the quality and completeness of the available data, while forecasting accuracy may decline when unexpected structural changes occur that are not captured by the models. In addition, all forward-looking forecasts contain a degree of uncertainty because future economic and industrial conditions cannot be known with certainty. Although these limitations cannot be completely removed, the framework seeks to reduce their effects through uncertainty analysis, regular model review, and continuous recalibration during Phases 2, 3, and 5. These limitations and their implications for the study are considered in greater detail in Chapter Five.

EMPIRICAL RESULTS

4.1 Introduction

This chapter reports empirical results generated entirely from real, primary-source federal data, following the methodology described in Chapter Three. A panel dataset covering 19 NAICS-3 manufacturing subsectors observed annually from 2015 through 2025 (N = 209 industry-year observations) was assembled from four federal sources: BEA (Gross Output by Industry), BLS (Current Employment Statistics and Industry Productivity), and USITC (DataWeb imports, exports, and country-of-origin data used to construct an Import-Origin Concentration Index). Full source citations and construction notes are in the accompanying data workbook and Appendix A.

The forecasting exercise (Section 4.5) is described as pseudo-out-of-sample rather than genuinely ex-ante, since it uses today's data vintage rather than the vintage available on each historical forecast date; the Hausman test (Section 4.4.1) is estimated like-for-like; inference for the main regression includes a wild-cluster bootstrap given the panel's modest number of clusters (Section 4.4.2); and the concentration variable is named precisely to describe what it measures. Every result, significant or not, is reported directly.

Section 4.2 documents data-infrastructure gaps (RQ1). Section 4.3 reports descriptive statistics (RQ2). Section 4.4 reports the main panel regression and its robustness and diagnostic extensions (RQ2, RQ4). Section 4.5 reports the forecasting exercise (RQ3). Section 4.6 reports the scenario analysis (RQ5). Section 4.7 describes the decision-support interface (RQ6). Section 4.8 maps these results against the five-phase methodology from Chapter Three.

4.2 Documented Data-Infrastructure Gaps

Consistent with RQ1, assembling the panel directly surfaced the data-infrastructure limitations identified in Section 2.2, reported here as an empirical finding rather than a methodological aside.

Four gaps were documented. First, no single federal source integrates output, employment, productivity, and trade; each variable required a separate query against a separate agency system (BEA, BLS's two separate programs, USITC), with no shared access point. Second, classification granularity is inconsistent: BEA and BLS report some NAICS-3 categories only in combined form (e.g., Food and Beverage/Tobacco, NAICS 311/312), while USITC trade data is finer-grained, requiring upward aggregation and a documented approximation (Appendix A). Third, USITC reports Transportation Equipment (NAICS 336) as one combined trade figure, while BEA/BLS separate Motor Vehicles from Other Transportation Equipment, requiring a second documented approximation (employment-share splitting). Fourth, the country-of-origin detail needed for concentration analysis required a substantially larger, separate query (nearly 40,000 rows) than headline trade statistics, indicating that lower-tier visibility, while technically available, requires deliberate additional effort.

These gaps answer RQ1 directly: the limitation is fragmentation and inconsistent granularity, not an absence of underlying data. Each was resolved here through disclosed construction decisions, but each represents a standing barrier any national-scale implementation would need to resolve systematically rather than ad hoc.

4.3 Panel Dataset and Descriptive Statistics

Table 4.1 reports descriptive statistics across all 209 observations, addressing RQ2. The panel spans subsector sizes from $15.7B (Apparel) to $1,268.3B (Food and Beverage/Tobacco) in gross output,

and import-origin concentration from HHI 646 to 3,606. A full year-by-subsector snapshot is in Appendix A.

Table 4.1. Descriptive Statistics, Full Panel (N = 209; 19 NAICS-3 Manufacturing Subsectors × 11 Years, 2015–2025)

Statistic	Gross Output ($B)	Employment (000s)	Exports ($B)	Imports ($B)	Labor Productivity (Index)	Import-Origin HHI (0–10,000)
Mean	330.1	658.1	76.0	124.6	97.9	1,558.4
Std. Deviation	287.5	462.3	72.3	115.0	6.0	672.9
Minimum	15.7	79.0	4.4	4.9	78.6	645.9
Median	231.4	427.4	59.4	94.9	99.3	1,481.8
Maximum	1,268.3	2,098.7	302.7	709.4	115.0	3,605.9

This variable is termed the Import-Origin Concentration Index rather than "Supplier Concentration" to describe precisely what it measures: concentration of import value among countries of origin (Herfindahl-Hirschman methodology, Section 3.3), computed from USITC data. It is a macro-level, country-of-origin proxy, not a firm-level supplier measure, and does not specifically isolate critical inputs, it reflects all trade value classified within a subsector's USITC codes. In 2025, Food and Beverage/Tobacco showed the lowest concentration (HHI 837); Wood Products and Printing showed the highest (above 1,700).

A measurement caveat: Gross Output, Imports, and Exports are in nominal (current) dollars, not deflated. Year fixed effects absorb economy-wide inflation but not subsector-specific price movements. This is disclosed as a limitation rather than corrected here; a real (deflated) panel is a priority for future work (Section 5.6).

4.4 Panel Regression: Explaining Manufacturing Output

The two-way fixed-effects specification (Section 3.8.1) was estimated with log(Gross Output) as the dependent variable and Employment, Labor Productivity, log(Imports), log(Exports), and standardized Import-Origin Concentration as regressors. Standard errors are entity-clustered; because the panel has only 19 clusters, a wild-cluster bootstrap (Section 4.4.2) is the more credible inferential statement than the asymptotic p-values below.

Table 4.2. Two-Way Fixed Effects Panel Regression: Dependent Variable: log(Gross Output); N = 209; entity-clustered standard errors (asymptotic; see Section 4.4.2 for wild-cluster-bootstrap inference)

Variable	Coefficient	Std. Error	t-stat	Asymptotic p-value
Employment (thousands)	0.0002	0.0002	0.85	0.397 (n.s.)

Variable	Coefficient	Std. Error	t-stat	Asymptotic p-value
Labor Productivity (Index, 2017=100)	0.0005	0.0018	0.30	0.765 (n.s.)
log(Imports)	0.1998	0.1023	1.95	0.052
log(Exports)	0.2747	0.1349	2.04	0.043
Import-Origin Concentration (HHI, standardized)	−0.0240	0.0220	−1.09	0.275 (n.s.)

Model fit: R^2 (within) = 0.619; $F(5, 175) = 17.96$, $p < 0.001$. Under asymptotic clustering, exports are significant and imports marginally so; under the wild-cluster bootstrap (Section 4.4.2), neither reaches significance (imports p = 0.142; exports p = 0.078). The honest conclusion is more conservative: trade activity is positively associated with output, but this panel does not provide statistically decisive evidence of that association under small-sample-appropriate inference. These coefficients reflect co-movement, not a causal trade elasticity. Employment and Labor Productivity are not significant; Import-Origin Concentration is negative but not significant under either inference approach (p = 0.275 asymptotic, p = 0.263 bootstrap).

4.4.1 Robustness Checks: Alternative Model Specifications and a Like-for-Like Hausman Test

Four alternative specifications were estimated on the identical panel: Pooled OLS, Random Effects, Two-Way FE excluding concentration, and Entity-FE-only.

Table 4.3. Alternative Model Specifications, Dependent Variable: log(Gross Output); N = 209

Variable	Pooled OLS	Random Effects	Two-Way FE (no HHI)	Two-Way FE (Main Model)	Entity FE only
Employment	0.0007**	0.0005**	0.0001 (n.s.)	0.0002 (n.s.)	0.0003 (n.s.)
Labor Productivity	−0.0193**	−0.0013 (n.s.)	0.0007 (n.s.)	0.0005 (n.s.)	−0.0010 (n.s.)
log(Imports)	−0.5432**	0.1983*	0.1934*	0.1998*	0.2824**
log(Exports)	0.8430**	0.4078**	0.2526*	0.2747**	0.3611**
Import-Origin Concentration (HHI, std.)	−0.0721*	−0.0764**	n/a	−0.0240 (n.s.)	−0.0679**
R^2 (overall /	0.861	0.693 / 0.704	0.329 / 0.553	0.339 / 0.619	0.710

Variable	Pooled OLS	Random Effects	Two-Way FE (no HHI)	Two-Way FE (Main Model)	Entity FE only
within)					

A Hausman test comparing Random Effects against Fixed Effects is only valid on a like-for-like basis, both models must share the same year-effect structure. Table 4.4 reports a corrected, like-for-like Hausman test (Random Effects re-estimated with year dummies) alongside a Mundlak (correlated random effects) test.

Table 4.4. Model-Selection Tests: Fixed Effects vs. Random Effects

Test	Statistic	p-value	Conclusion
Hausman test (like-for-like, year effects in both models)	$\chi^2(5) = 5.36$	0.374	Fails to reject Random Effects
Mundlak test (joint significance of entity-mean regressors)	$\chi^2(5) = 48.97$	< 0.0001	Rejects Random Effects; supports Fixed Effects

These tests point in different directions, and both are reported. The Hausman test alone does not decisively favor Fixed Effects. The Mundlak test, which directly tests whether entity-level averages are correlated with the unobserved individual effect, does support Fixed Effects, and is treated as the more directly relevant test here. Fixed Effects remains the preferred specification as a reasoned judgment from mixed evidence, not a test result that settles the question beyond doubt.

The Import-Origin Concentration coefficient is negative and significant in three of the four alternative specifications, losing significance only in the preferred two-way fixed-effects model. It would be tempting to treat this as evidence the relationship is robust but once two-way FE is identified as the preferred specification, significance in less-controlled alternatives does not strengthen the main result; if anything, losing significance once common year shocks are controlled for suggests the apparent relationship in weaker specifications may partly reflect shared trends. The honest conclusion: Import-Origin Concentration has a consistently negative coefficient across specifications, but the preferred specification does not provide statistically conclusive evidence of a within-industry effect.

4.4.2 Additional Diagnostics

Additional diagnostic tests were run on the real panel and are reported regardless of outcome.

Table 4.5. Additional Diagnostic Tests

Diagnostic	Result	Interpretation
Wild-cluster bootstrap (999 reps, cluster = entity),	statistic = 1.91, p = 0.142	Not significant at 5%; weaker than the asymptotic result

Diagnostic	Result	Interpretation
log(Imports)		
Wild-cluster bootstrap, log(Exports)	statistic = 1.99, p = 0.078	Not significant at 5%, marginal at 10%
Wild-cluster bootstrap, Import-Origin Concentration	statistic = −1.07, p = 0.263	Not significant, consistent with asymptotic
Variance Inflation Factors (all regressors)	range 1.08–4.41	Well below conventional concern thresholds
Pesaran CD test (cross-sectional dependence)	CD = −1.38, p = 0.169	Not significant; supports entity-only clustering
Wooldridge-style serial correlation test (H_0: coefficient = −0.5)	t = 8.65, p < 0.0001	Rejects the null; evidence of persistence a static model misses

Three findings matter. First, the wild-cluster bootstrap is more credible than large-cluster asymptotic for a 19-entity panel, finds neither trade coefficient significant at 5%, revising the paper's conclusions accordingly: trade activity is positively associated with output, but not decisively so under appropriate inference. Second, the absence of cross-sectional dependence supports the entity-only clustering used throughout. Third, the serial correlation test rejects its null, indicating persistence a static model misses, addressed directly with a dynamic robustness check in Section 4.4.5.

4.4.3 Transportation-Equipment Allocation Sensitivity Check

Section 4.2 discloses an approximation: USITC's combined NAICS 336 trade figure is split between Motor Vehicles and Other Transportation Equipment by employment share. Table 4.6 re-estimates the main specification three ways; current allocation, omitting both affected subsectors, and collapsing them into one category matching USITC's native reporting.

Table 4.6. Main Specification Under Three Transportation-Equipment (NAICS 336) Allocation Approaches

Variable	Current allocation (main, N=209)	Omit both transport subsectors (N=187)	Collapsed to one category (N=198)
log(Imports)	0.1998 (p=0.052)	0.2064 (p=0.071)	0.2008 (p=0.059)
log(Exports)	0.2747 (p=0.043)	0.2809 (p=0.072)	0.2720 (p=0.058)
Import-Origin Concentration (HHI)	−0.0240 (p=0.275)	−0.0286 (p=0.292)	−0.0257 (p=0.282)

All three coefficients remain close in sign and magnitude; the transportation-equipment allocation approximation does not appear to drive the paper's results.

4.4.4 Trade × Concentration Interaction

The baseline model cannot distinguish whether concentrated subsectors are more vulnerable to a given trade shock than diversified ones. Table 4.7 tests this directly with an Imports × Concentration interaction term.

Table 4.7. Two-Way Fixed Effects Model with Trade × Concentration Interaction

Variable	Coefficient	Std. Error	t-stat	p-value
Employment	0.0003	0.0002	1.08	0.280 (n.s.)
Labor Productivity	0.0011	0.0016	0.64	0.524 (n.s.)
log(Imports)	0.2018	0.1033	1.95	0.052
log(Exports)	0.2933	0.1386	2.12	0.036
Import-Origin Concentration (HHI, std.)	−0.3207	0.6642	−0.48	0.630 (n.s.)
log(Imports) × Concentration (HHI, std.)	0.0119	0.0265	0.45	0.653 (n.s.)

The interaction term is not significant (p = 0.653): this panel does not find evidence that highly concentrated subsectors are more sensitive to import fluctuations than diversified ones. The absence of significance may reflect limited statistical power, model specification, measurement limitations, or a genuine absence of the effect this panel cannot distinguish among these explanations, and re-testing with a larger panel is a priority (Section 5.6).

4.4.5 Dynamic Panel Robustness Check

Section 4.4.2's serial-correlation diagnostic found persistence a static model miss. Table 4.8 reports a parsimonious dynamic check: the specification extended with a one-period lagged dependent variable. This is explicitly not an Arellano-Bond or Blundell-Bond GMM estimate (with only 19 entities, GMM risks instrument proliferation and is subject to a well-documented small-sample bias, Nickell bias, in short panels), reported as a robustness check, not a bias-corrected structural estimate.

Table 4.8. Dynamic Panel Specification with Lagged Dependent Variable (N = 190; one year lost to lagging); asymptotic entity-clustered inference

Variable	Coefficient	Std. Error	t-stat	Asymptotic p-value	Wild-bootstrap p-value
log(Gross Output),	0.4149	0.1927	2.15	0.033	0.063

Variable	Coefficient	Std. Error	t-stat	Asymptotic p-value	Wild-bootstrap p-value
lagged one year					
Employment	0.0001	0.0002	0.83	0.408 (n.s.)	0.405 (n.s.)
Labor Productivity	0.0009	0.0016	0.58	0.561 (n.s.)	0.613 (n.s.)
log(Imports)	0.2113	0.1176	1.80	0.074	0.233 (n.s.)
log(Exports)	0.1270	0.1080	1.18	0.241 (n.s.)	0.256 (n.s.)
Import-Origin Concentration (HHI, std.)	−0.0257	0.0196	−1.32	0.190 (n.s.)	0.260 (n.s.)

The lagged output term's asymptotic coefficient (ρ = 0.41) is consistent with substantial persistence, but under the small-sample-appropriate wild-cluster bootstrap it is only marginally significant (p = 0.063 vs. 0.033 asymptotically) suggestive but not decisive evidence of persistence.

Imports and concentration move only modestly from the static specification (Table 4.2), but the export coefficient falls from 0.2747 to 0.1270, roughly half its static value, losing its marginal significance. This suggests part of the static model's export-output association reflects output's own persistence rather than a stable contemporaneous relationship. Both specifications are reported so the reader can see how sensitive the finding is to this choice.

4.4.6 First-Differenced Robustness Check

Output, Imports, and Exports are nominal, not deflated (Section 4.3); since all three trend upward, part of the main specification's associations could, in principle, reflect shared trends. As an additional check, the specification was re-estimated in first differences. To be precise, differencing alone removes each entity's fixed effect, but an entity-specific linear trend survives as an entity-specific constant. Removing it requires including entity dummies in the differenced regression itself, which this specification does. A wild-cluster bootstrap is again reported alongside the asymptotic result.

Table 4.9. First-Differenced Specification with Entity and Year Effects (N = 190; one year lost to differencing)

Variable	Coefficient (main FE, Table 4.2)	Coefficient (first-differenced)	Asymptotic p-value	Wild-bootstrap p-value
Employment	0.0002	−0.0001	0.896 (n.s.)	0.931 (n.s.)
Labor Productivity	0.0005	0.0015	0.193 (n.s.)	0.161 (n.s.)
log(Imports)	0.1998	0.2124	0.294 (n.s.)	0.556 (n.s.)

Variable	Coefficient (main FE, Table 4.2)	Coefficient (first-differenced)	Asymptotic p-value	Wild-bootstrap p-value
log(Exports)	0.2747	0.2499	0.019	0.001
Import-Origin Concentration (HHI, std.)	−0.0240	−0.0447	0.225 (n.s.)	0.503 (n.s.)

With entity-specific trends properly removed, imports lose significance entirely under both inference approaches. Exports remain significant, close in magnitude to the main result (0.2747 vs. 0.2499), and notably under the wild-cluster bootstrap (p = 0.001), the only trade coefficient in this chapter that remains significant under small-sample-appropriate inference once trends are controlled for. This does not resolve the nominal-versus-real measurement limitation (Section 4.3), but identifies the export-output association specifically, not the trade-output association generally, as the most robust single finding in this chapter.

4.4.7 Employment-Impact Model

Sections 4.4–4.4.6 focus on output. This section extends the framework specifically to employment while controlling for output and productivity, directly addressing the goal of estimating disruption effects on production and employment rather than output alone.

Table 4.10. Employment-Impact Model: Dependent Variable: log(Employment); N = 209; entity-clustered standard errors

Variable	Coefficient	Std. Error	t-stat	Asymptotic p-value	Wild-bootstrap p-value
log(Gross Output)	0.1322	0.1051	1.26	0.210 (n.s.)	0.281 (n.s.)
Labor Productivity	−0.0041	0.0025	−1.61	0.109 (n.s.)	0.213 (n.s.)
log(Imports)	0.1467	0.0832	1.76	0.080 (n.s.)	0.131 (n.s.)
log(Exports)	−0.0287	0.0983	−0.29	0.770 (n.s.)	0.820 (n.s.)
Import-Origin Concentration (HHI, std.)	0.0346	0.0217	1.60	0.112 (n.s.)	0.204 (n.s.)

None of the five regressors reach significance under either inference approach, a genuine null result, reported directly. One pattern worth noting despite the lack of significance: the concentration coefficient is positive here, the opposite sign from its output association, consistent with a plausible (but statistically unconfirmed) story that more concentrated subsectors may be somewhat more labor-

intensive per unit of output. Establishing genuine employment-impact estimates is a priority for a larger panel (Section 5.6).

4.5 Predictive Model: Pseudo-Out-of-Sample Forecast Evaluation

A forecasting exercise that uses a period's actual realized predictor values to predict that period's output is conditional prediction (nowcasting), not ex-ante forecasting, since those values would not genuinely have been available at forecast time. This exercise avoids that by lagging every predictor one year, so only information available at t−1 predicts t.

The model is retrained at each of four origin years (2021–2024) using only data available up to that point, forecasting exactly one year ahead each time, a rolling-origin design (see Section 3.8.2 for why "pseudo-out-of-sample" rather than "genuinely ex-ante" is the precise term, given current rather than historical data vintages are used). Concentration is standardized using only each origin's training window. Four approaches are compared: naive persistence; linear (entity FE + trend, lagged); gradient boosting; and a hybrid average.

Table 4.11. Pseudo-Out-of-Sample Rolling-Origin Forecast Accuracy (MAPE), by Individual Forecast Year and Average

Model	2022	2023	2024	2025	Average MAPE	Avg. RMSE ($B)	Avg. MAE ($B)
Naive persistence	10.19%	5.06%	2.53%	1.97%	4.94%	37.43	20.68
Linear (entity FE + trend, lagged)	13.44%	6.34%	6.18%	6.22%	8.04%	49.85	30.18
Gradient Boosting (lagged)	15.70%	14.13%	12.80%	4.99%	11.90%	118.91	58.05
Hybrid (Linear + GBR average)	12.18%	9.86%	7.61%	4.40%	8.51%	82.66	40.80

The naive persistence benchmark achieves the lowest average error of all four approaches by a wide margin (4.94% vs. 8.04% or worse for every model-based approach), reported directly. With genuinely available lagged predictors at this panel's size, neither the econometric nor the machine-learning approach adds forecasting value over simply carrying forward each subsector's most recent output.

This carries a direct implication for the proposed framework: one-year-ahead forecasting with this panel's covariates is genuinely difficult, and a deployed version should be benchmarked against, and should expect to sometimes underperform, a simple persistence forecast precisely the evaluation discipline specified in Section 3.9.

4.6 Model-Implied Scenario Analysis: Illustrative, Non-Causal Trade Disruption Effects

This section uses Table 4.2's fitted coefficients to compute model-implied scenarios: the predicted percentage output changes from a hypothetical import or concentration shift, holding other factors constant. This is described as an Exploratory Model-Implied Scenario Tool, not a causal policy simulator, and every result should be read as an illustrative association, not a causal forecast. Genuine causal estimation would require exogenous variation, natural experiments, shift-share instruments, event-study or difference-in-differences designs, or a structural CGE model none of which this exercise provides.

For a subsector with import elasticity 0.1998 (illustrative despite not being statistically decisive under bootstrap inference), a hypothetical X percent import reduction implies a model-implied output change of (1+X)^0.1998 − 1.

Table 4.12. Illustrative Model-Implied Output Association with a Hypothetical Import Disruption, by Subsector and Shock Magnitude (2025 Baseline): Exploratory and Non-Causal

Subsector	2025 Baseline Output ($B)	−10% Imports	−20% Imports	−30% Imports
Computer and electronic products	425.6	$416.7B (−2.08%)	$407.0B (−4.36%)	$396.3B (−6.88%)
Chemical products	1,016.7	$995.5B (−2.08%)	$972.4B (−4.36%)	$946.8B (−6.88%)
Food and beverage and tobacco products	1,268.3	$1,241.9B (−2.08%)	$1,213.0B (−4.36%)	$1,181.1B (−6.88%)
Primary metals	303.4	$297.1B (−2.08%)	$290.2B (−4.36%)	$282.5B (−6.88%)

This arithmetic implies an identical percentage association for a given shock across every subsector, differing only in dollar terms; Section 4.4.4's interaction test found no significant evidence that concentrated subsectors are more sensitive, so this uniform-elasticity property is consistent with what the data shows, within this panel's statistical power. A parallel example: a one-standard-deviation concentration improvement (−673 HHI points) implies a model-implied output change of approximately 2.37%; for a median-sized subsector (~$231B), roughly $5.5 billion presented here as an illustration of the calculation, not a statistically supported benefit estimate, since the underlying coefficient is not significant in the preferred specification (Section 4.4).

4.6.1 Comparative Illustration Across Alternative Interventions

The framework's design calls for comparing alternative interventions, not evaluating a single shock in isolation. Table 4.13 applies Table 4.2's coefficients to three named interventions for Computer and Electronic Products (highest import exposure): a tariff-style import reduction, a supplier-diversification action, and a combined approach.

Table 4.13. Illustrative Comparison of Alternative Interventions: Computer and Electronic Products, 2025 Baseline ($425.6B); Exploratory and Non-Causal

Intervention	Assumption	Model-Implied Output Change	Resulting Output
A: Tariff-style import reduction	−20% imports	−4.36%	$407.0B
B: Supplier diversification	−1 SD import-origin concentration	+2.43%	$435.9B
C: Combined approach (A + B)	Both simultaneously	−2.04%	$416.9B

This illustrates a trade-off the fitted model implies import reduction and diversification pull output in opposite directions, but two caveats apply. The concentration coefficient underlying Scenario B is not significant in the preferred specification, so its contribution is illustrative, not a supported claim. And this arithmetic treats the two interventions as independent and additive, when reducing concentration would plausibly change import volumes. A genuine policy-comparison capability to resolve this with statistical and causal confidence is future work (Section 5.6).

4.7 Decision-Support Interface

Addressing RQ6, a prototype decision-support dashboard (the Economic Intelligence Copilot) draws on this real panel, presenting summary indicators, output trends, the results in this chapter, and the Exploratory Model-Implied Scenario Tool, labeled consistently with this chapter's non-causal framing throughout. The interface has not been formally evaluated against alternative formats, so RQ6 is only partially answered; systematic evaluation with real policymakers or manufacturer users is a priority for future research (Chapter Five).

4.8 Correspondence with the Proposed Five-Phase Methodology

This chapter's empirical work constitutes real evidence touching the first three phases of Chapter Three's methodology but does not validate every technique in that broader architecture. Structural gravity models, full VAR systems, network-based dependency mapping, and CGE modeling are not implemented here; the methods actually estimated are a two-way fixed-effects regression and its robustness variants, a rolling-origin forecasting exercise, a computed concentration index, and arithmetic scenario calculations. Table 4.14 states plainly what has and has not been demonstrated.

Table 4.14. Correspondence Between Empirical Work Completed and the Proposed Five-Phase Methodology

Phase	Demonstrated with real data	Not yet demonstrated
Phase 1: National Trade and Industrial Intelligence Assessment	Integration of real federal data across BEA, BLS, and USITC; documented data-infrastructure gaps (Section 4.2); baseline resilience and concentration indicators	A formal dependency network linking specific foreign suppliers to specific domestic manufacturers and downstream industries

Phase	Demonstrated with real data	Not yet demonstrated
	(Section 4.3)	
Phase 2: Predictive Economic Framework Development	A two-way fixed-effects econometric model with honestly reported inference (Sections 4.4–4.4.7); a pseudo-out-of-sample, rolling-origin forecasting exercise (Section 4.5); a real, computed import-origin concentration index; an employment-impact model, honestly reporting a null result (Section 4.4.7); a comparative illustration across named alternative interventions (Section 4.6.1); a documented human-in-the-loop validation protocol specified for pilot implementation (Section 3.9.1)	The gravity-model, VAR, and CGE components described in Section 3.8 as part of the framework's intended architecture; economic-impact models estimating disruption effects on prices specifically (only employment was estimated); the human-in-the-loop protocol operated in practice rather than only specified; a policy-comparison capability that resolves trade-offs with statistical and causal confidence rather than illustrating them arithmetically
Phase 3: Prototype Validation and Pilot Implementation	A decision-support dashboard interface drawing on the real panel (Section 4.7); an out-of-sample forecast evaluation against a naive benchmark (Section 4.5); a battery of regression diagnostics (Section 4.4.2)	Retrospective validation of model predictions against specific historical disruption episodes; formal evaluation of decision-support interface formats (Section 4.7); a standardized, documented procedure for replicating the framework across additional industries
Phases 4–5: National Scaling and Continuous Improvement	Not applicable at this stage	These phases are institutional and programmatic in nature and are outside the scope of a single empirical analysis

This statement represents an honest account of the study's progress rather than a claim that the framework is fully complete. The findings show that its main data-integration and modeling concepts are workable. However, the results also show that the pseudo-out-of-sample forecasts were difficult to improve on the naive benchmark, the relationship between concentration and output was consistent in direction but not statistically significant, and differences in vulnerability across concentration levels were not supported. The gravity-model, network-mapping, VAR, and CGE components remain areas for future development.

4.9 Summary of Findings

This chapter presented results from 19 U.S. manufacturing subsectors covering 2015–2025, based on the six research questions in Chapter One. The findings showed gaps in data infrastructure (RQ1). Trade activity was positively associated with output, but the relationship was not significant under the preferred wild-cluster bootstrap method, while import concentration had a negative but non-significant relationship with output (RQ2, RQ4). The employment model also found no significant relationship. Forecasting results showed that the naive benchmark was difficult to outperform (RQ3). The trade × concentration interaction was not significant, while a three-policy comparison illustrated the framework's intended policy application (RQ5). A prototype dashboard was developed, but not formally evaluated, and the human-in-the-loop protocol had not yet been implemented (RQ6). Chapter Five discusses the implications, contributions, limitations, and future research.

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Discussion of Findings

The findings in Chapter Four generally support the study's main idea, while also showing the need to interpret some of the results with caution. The panel regression in Section 4.4 shows a positive association between trade activity and output under asymptotic inference. However, the wild-cluster bootstrap, which is more suitable for the 19 industry clusters in the panel, does not show a statistically significant relationship. Import-origin concentration is negative across the different model specifications and significant in three of four alternatives (Table 4.3), but it is not significant in the preferred two-way fixed-effects and interaction models. Therefore, the evidence does not provide conclusive support for the concentration-risk hypothesis. Instead, it highlights the need for a larger panel to examine this relationship more reliably.

The pseudo-out-of-sample forecasting results in Section 4.5 show that the simple naive persistence model is difficult to outperform. This should not be viewed as a negative finding. Rather, it provides the honest benchmark comparison required in Section 3.9 and shows that the framework's evaluation standards are being applied rigorously instead of being presented only as methodological claims.

5.2 Contributions to the Field

This study makes four main contributions. First, it provides a clear and replicable method for combining fragmented federal and industry data (Section 2.2). Second, it proposes a framework that links supply-chain dependency mapping with econometric forecasting (Section 2.3), although the formal network component is still under development and has not yet been fully implemented or validated (Table 4.14). Third, it evaluates a hybrid econometric and machine-learning forecasting approach honestly, with the pseudo-out-of-sample results showing that it does not currently outperform the naive benchmark. Fourth, it develops a prototype approach for comparing policy scenarios and national indicators. These tools are presented as illustrative and non-causal, while also helping to address the existing gap in practical decision-support tools (Section 2.7).

Overall, these contributions demonstrate an applied framework that brings together established methods such as panel econometrics, machine-learning forecasting, concentration measurement, and decision-support tools. Although these methods are often used separately in this area, the proposed framework combines them in a single approach that can be expanded through the Phase 4 and Phase 5 methodology beyond the industries covered in this pilot study.

5.3 Policy Implications and National Significance

This section explains the need for further development and testing of the pilot framework, the economic benefits that may reasonably be expected, and its potential contribution to competitiveness and resilience. These discussions are based on the actual findings reported in Chapter Four rather than on the framework's intended design alone.

5.3.1 Policy Relevance and Case for Further Pilot Implementation

Three main findings support continued development of the pilot framework. First, the framework can be developed using data that policymakers already have access to. All variables were obtained from existing and publicly funded federal data systems, meaning that the main requirement is effective data integration rather than the collection of entirely new data. Second, the diagnostic analysis in

Sections 4.4.1–4.4.2 demonstrates a strong evaluation process. The study applies a Hausman test, Mundlak test, wild-cluster bootstrap, and several model specifications, while reporting results that do not always support the main hypotheses. This provides greater confidence in the overall evaluation process than relying on a single statistical estimate. Third, the forecasting analysis in Section 4.5 shows that naive persistence is difficult to outperform. Although this limits the current forecasting gains, it also demonstrates that the evaluation procedures in Section 3.9 can identify weak or overconfident forecasting claims before they are presented to policymakers. This type of safeguard is important for a national decision-support framework.

In addition to these findings, the federal systems examined in this study, including those of the BEA, BLS, and USITC, do not provide a single, regularly updated panel that combines output, employment, productivity, and trade-concentration data. These datasets are produced separately by the different agencies and therefore require manual reconciliation (Section 4.2). This finding is based on the systems reviewed in this study and should not be taken as a complete assessment of all federal data systems. Creating an integrated system, even at the pilot's 19-subsector level, could reduce the repeated effort required to bring these datasets together for analysis. The need for such a system is also relevant to current policy priorities. The Trade Policy Agenda identifies the protection of supply chains for critical minerals and other strategic sectors as an important national priority (Office of the United States Trade Representative, 2026). This provides a clear policy context for the framework and demonstrates its relevance to an existing national policy objective.

5.3.2 Potential Economic Relevance and Analytical Efficiency

The type of estimate that the framework could produce in future is illustrated by the scenario tool presented in Section 4.6. A detailed dollar-value example is provided there rather than in this section because the concentration coefficient is not statistically significant in the preferred model. Therefore, it would not be appropriate to present it as an expected economic benefit. A reliable, decision-ready estimate will require further research using a larger panel, as discussed in Section 5.6.

A more certain benefit of the framework is improved analytical efficiency. The data-integration process described in Section 4.2 can be reused once it has been established. Although compiling the 209 observations required considerable initial effort, an institutionalized system would avoid repeating the same process for every new policy question. Adding new year’s or subsectors under Phase 4 (Section 3.5) would also require less effort than the initial development. This creates a system in which most of the cost occurs during the initial setup, while the additional cost of maintaining and expanding it remains relatively low, as is common with effective federal data infrastructure.

5.3.3 Impact on Manufacturing Competitiveness and Supply-Chain Resilience

The panel data in Appendix A already provides useful information for identifying potential risks before any policy action is taken. For example, the 2025 data show that **Wood Products (HHI 1,962)** and **Printing (HHI 1,736)** have the highest levels of import concentration, while **Food and Beverage/Tobacco (HHI 837)** have the most diversified import sources. This provides a useful picture of differences in exposure across subsectors and can help identify areas that may require closer monitoring, regardless of whether the concentration-output relationship is statistically significant.

Regarding competitiveness, both imports and exports have positive coefficients in Table 4.2. However, neither relationship is statistically significant under the preferred bootstrap method

(Section 4.4.2). The results therefore provide only a possible indication that subsectors with greater involvement in international trade may also have higher productivity. This should be treated as a hypothesis for future research rather than a confirmed finding. Competitiveness policies should therefore consider the potential benefits of import integration alongside export promotion rather than assuming that imports are always harmful.

Regarding resilience, the trade × concentration interaction test in Section 4.4.4 found no statistically significant evidence that highly concentrated subsectors are more sensitive to shocks. This is a genuine null finding and is reported directly rather than being excluded from the results. The finding suggests that policymakers should be cautious when using trade-risk tools that assume all subsectors respond to shocks in the same way. This study can make this caution more confidently because the interaction between trade activity and concentration was tested directly rather than simply identified as a possible limitation.

5.4 Recommendations for Implementation

Four recommendations arise from the findings and development of this study. First, data integration should be prioritized before predictive modeling, since the quality of forecasts and scenario analysis depends largely on the quality of the underlying data (Section 3.2). Second, improving visibility beyond lower supply-chain tiers should remain an ongoing priority, because the current country-level concentration measure cannot capture firm-level and multi-tier dependencies. Third, human-in-the-loop validation should be incorporated as a continuing governance measure rather than treated as a one-time validation stage, because forecasting always involves some level of uncertainty (Sections 3.9.1 and 3.10). Fourth, implementation should be carried out gradually on an industry-by-industry basis, using the modular components developed in Phase 3 instead of attempting immediate national deployment. This approach would allow the framework to be tested and improved at each stage.

5.5 Limitations of the Study

This study has several limitations. The results presented in Chapter Four are based on real federal data and are not simulated. However, they come from a relatively small pilot panel covering 19 manufacturing subsectors over 11 years. Therefore, the findings should not be treated as a complete national assessment, causal estimates, or results that can be widely generalized beyond the study panel. A larger panel would be needed for national-level application, while causal conclusions would require a research design capable of identifying exogenous sources of variation.

The forecasting models also have the common limitations of econometric and machine-learning methods, including lower accuracy when unexpected structural changes occur and sensitivity to the quality of the available data (Section 3.10). In addition, the current concentration measure does not provide adequate information about lower-tier supply-chain relationships. Finally, although the 19-subsector pilot covers different types of supply-chain dependencies, it does not represent the full range of U.S. manufacturing. Further expansion through Phase 4 (Section 3.5) would therefore be necessary to assess whether the framework performs effectively across a wider range of industries.

5.6 Recommendations for Future Research

Future research should focus on implementing the framework more fully using a larger number of industries and carrying out systematic retrospective validation across a wider range of historical disruption events. The correctly signed but non-significant concentration result (Section 4.4), the non-significant interaction in Section 4.4.4, and the difficulty of improving on naive persistence in

Section 4.5 all point to the need for a larger panel. A broader dataset would provide greater statistical power to test relationships that are theoretically expected but remain inconclusive on the current scale.

Further studies should also develop the formal supply-chain dependency network proposed in Section 2.3 and Table 4.14. The fixed-effects model could be extended to more detailed price and employment-impact models, while dynamic panel GMM methods (Section 3.8.1) could be examined to address the serial correlation identified in Section 4.4.2. Developing a real-value version of the panel using subsector-specific price indices should also be prioritized because the current analysis relies on nominal dollar values (Section 4.3). Finally, future research should examine governance arrangements for maintaining Phase 5's continuous updating process, including effective data-sharing arrangements among federal agencies, universities, and industry. Such arrangements would be important for sustaining the framework and supporting its eventual national expansion.

5.7 Conclusion

This study addressed an identified gap in U.S. trade and industrial-policy analysis, particularly the limited availability of integrated and forward-looking tools that combine fragmented federal data with supply-chain analysis and predictive methods. Based on the literature reviewed in Chapter Two, Chapter Three developed a five-phase methodology covering data integration, supply-chain dependency mapping, hybrid forecasting, and scenario analysis. The framework was then tested at a pilot level in Chapter Four using real federal data.

The resulting Predictive Trade and Industrial Intelligence Framework provides a replicable approach for improving the evidence base for U.S. trade policy, manufacturing resilience, and industrial competitiveness. Although full national implementation would require further development beyond the scope of this study, the framework and its pilot-scale empirical evaluation provide a structured and practical starting point for future research and wider application.

5.8 Data and Code Availability

The panel dataset, selected analysis scripts, documented methodology, and the decision-support dashboard prototype, the Economic Intelligence Copilot, are available through an open-source repository under the MIT License at https://github.com/aolusoji/economic-intelligence-copilot. The live Economic Intelligence Copilot decision-support interface is available at https://aolusoji.github.io/economic-intelligence-copilot/. The repository contains materials supporting key components of the empirical analysis, including data-construction procedures, selected econometric and forecasting workflows, and documentation describing the structure of the dataset and analytical framework. These resources are intended to support transparency, reproducibility of key aspects of the study, and further development of the framework. The live interface includes the exploratory scenario-analysis functionality discussed in Section 4.6 and is deployed from the same repository. Additional analytical materials and extensions may be added as the framework continues to develop.

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APPENDIX A: REAL PANEL DATASET

A.1 Dataset Description and Summary Statistics

This appendix presents descriptive statistics and a full-year snapshot of the real panel dataset underlying Sections 4.2–4.6. The complete dataset (209 industry-year observations, 2015–2025) is in the accompanying workbook, Manufacturing_Panel_Dataset.xlsx, with a full data-sources and construction-methodology sheet.

Table A.1 reports summary statistics across all 209 observations.

Table A.1. Descriptive Statistics, Full Panel (N = 209; 19 NAICS-3 Manufacturing Subsectors × 11 Years, 2015–2025)

Statistic	Gross Output ($B)	Employment (000s)	Exports ($B)	Imports ($B)	Labor Productivity (Index)	HHI (0–10,000)
Mean	330.1	658.1	76.0	124.6	97.9	1,558.4
Std. Deviation	287.5	462.3	72.3	115.0	6.0	672.9
Minimum	15.7	79.0	4.4	4.9	78.6	645.9
25th Percentile	124.3	368.6	11.8	36.9	93.8	987.7
Median	231.4	427.4	59.4	94.9	99.3	1,481.8
75th Percentile	412.6	944.2	118.5	168.5	101.2	1,907.6
Maximum	1,268.3	2,098.7	302.7	709.4	115.0	3,605.9

A.2 Full-Panel Snapshot: 2025

Table A.2 presents the panel's most recent year (2025) for all 19 subsectors, illustrating the cross-sectional variation the panel regression exploits. Full annual detail for 2015–2025 is in the accompanying workbook.

Table A.2. Manufacturing Subsector Panel Data, 2025

Subsector	Gross Output ($B)	Employment (000s)	Exports ($B)	Imports ($B)	Labor Productivity (Index)	HHI
Apparel and leather and allied products	22.6	79.0	9.38	121.62	115.0	1,065

Subsector	Gross Output ($B)	Employment (000s)	Exports ($B)	Imports ($B)	Labor Productivity (Index)	HHI
Chemical products	1,016.7	900.5	293.20	411.28	90.0	971
Computer and electronic products	425.6	997.7	302.68	709.35	114.5	1,299
Electrical equipment, appliances, and components	199.3	429.0	76.01	192.34	93.4	1,243
Fabricated metal products	464.7	1,436.2	60.74	88.11	89.2	946
Food and beverage and tobacco products	1,268.3	2,098.7	92.77	149.06	78.6	837
Furniture and related products	85.3	337.9	4.81	39.90	89.7	1,643
Machinery	437.3	1,089.1	160.21	233.46	93.7	762
Miscellaneous manufacturing	181.9	612.7	84.06	132.91	82.8	955
Motor vehicles, bodies and trailers, and parts	750.7	967.4	175.75	246.72	100.0	1,794
Nonmetallic mineral products	174.3	417.0	11.40	27.47	88.2	892
Other transportation equipment	409.2	776.1	141.00	197.94	100.0	1,794
Paper products	221.4	355.0	23.82	25.25	87.4	1,584

Subsector	Gross Output ($B)	Employment (000s)	Exports ($B)	Imports ($B)	Labor Productivity (Index)	HHI
Petroleum and coal products	617.6	109.7	117.88	61.22	97.4	830
Plastics and rubber products	297.4	704.0	40.24	74.86	90.0	944
Primary metals	303.4	363.9	154.95	210.51	82.7	1,150
Printing and related support activities	85.1	343.8	4.91	5.84	93.5	1,736
Textile mills and textile product mills	47.2	175.2	10.82	29.40	100.9	1,505
Wood products	172.9	403.9	7.90	23.55	93.6	1,962

Food and beverage/tobacco is the largest subsector by output and employment, with the lowest import-origin concentration (HHI = 837), consistent with a diversified agricultural input base. Wood Products and Printing show the highest concentration (above 1,700). Computer and electronic products show the largest trade imbalance in absolute terms ($302.7B exports vs. $709.3B imports), consistent with documented U.S. dependence on foreign semiconductor and electronics manufacturing capacity (Chapter One).

ADVANCING U.S. AGRICULTURAL COMPETITIVENESS: THE PROSPECTIVE ECONOMIC IMPACT OF PRECISION AGRICULTURE AND DATA-DRIVEN NUTRIENT MANAGEMENT

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Abstract

U.S. agriculture operates in a high-cost and competitive environment in which efficient nutrient use is increasingly important to farm profitability, resource conservation, and long-term sector performance. This study examines the prospective economic impact of precision agriculture and data-driven nutrient management on U.S. agricultural competitiveness. Using a prospective economic, evidence-synthesis, and policy-analytic approach, the study integrates peer-reviewed research and authoritative USDA data to evaluate how precision technologies, agricultural data, and site-specific nutrient decisions may influence fertilizer-use efficiency, crop productivity, production costs, farm returns, resilience, and competitiveness. The analysis is guided by a production-economics and resource-use-efficiency perspective and develops a Precision Agriculture–Nutrient Management Economic Competitiveness Framework linking precision technologies to agricultural data acquisition, data-driven nutrient decision-making, site-specific application, improved nutrient-use efficiency, reduced input waste, farm economic performance, and broader competitiveness. Evidence reviewed indicates that precision nutrient management can generate economic value by improving fertilizer allocation, reducing unnecessary input expenditure, and supporting productivity; however, economic returns vary considerably across fields, years, technologies, and production conditions. Reported studies show both positive and negative profitability outcomes, demonstrating that precision agriculture does not guarantee uniform economic gains. Its value depends on field variability, fertilizer and commodity prices, technology and implementation costs, data quality, weather, and management capacity. The study concludes that precision nutrient management can strengthen U.S. agricultural efficiency and competitiveness when improved information leads to better nutrient decisions and positive net economic returns. Policy and research efforts should therefore emphasize economic optimization, data integration, equitable technology access, producer support, and multi-year empirical validation across regions.

Keywords: Precision agriculture; nutrient management; agricultural competitiveness; nutrient-use efficiency; farm profitability; variable-rate technology; U.S. agriculture

INTRODUCTION

Background of Study

Agriculture is an important part of the U.S. economy. It does more than produce food on farms. It also supports food and drink companies, farm supply businesses, food transportation, stores, and trade with other countries. According to the USDA Economic Research Service, agriculture and food-related industries play an important role in the U.S. economy. In 2023, agriculture and food-related industries contributed about $1.537 trillion to the U.S. economy, making up about 5.5% of the country's total GDP. U.S. farms alone contributed around $222.3 billion (USDA ERS, 2026a). These numbers show that agriculture is important not only to farmers but also to the wider U.S. economy. The sector's strategic importance is also evident in international markets. U.S. agricultural exports reached approximately $176 billion in 2024, and roughly one-fifth of the value of U.S. agricultural and food production has been sold in international markets in recent years (USDA ERS,

2026b). This shows that agriculture is important not only within the United States but also in global markets. Consequently, maintaining the productivity, cost-efficiency, adaptability, and technological capacity of American agriculture remains important to farm income, rural economies, domestic food production, and the competitive position of the United States in global agricultural markets.

Despite its economic importance, U.S. agriculture is faced with an increasingly challenging cost environment, requiring producers to effectively manage input costs and remain productive. According to USDA ERS, total production costs for the U.S. farm sector are projected to be $477.7 billion in 2026, up from $473.1 billion in 2025, which represents a nominal increase of 1.0% (USDA ERS, 2026c); however, the 2026 figure is expected to be slightly lower when adjusted for inflation. This is important because not all farm costs are increasing at the same time. Instead, farmers are working in a high-cost and uncertain environment, where making a profit depends more on using inputs such as fertilizer, fuel, and other resources as efficiently as possible. Decisions about fertilizers, chemicals, fuel, seeds, machinery, and labor can have a big impact on profit margins for agricultural producers. In such conditions, technologies that reduce unnecessary resource consumption while maintaining or improving crop production are of considerable agronomic and economic importance.

Among these production inputs, fertilizer and plant nutrients are especially important because crop productivity depends on adequate nutrient availability, while fertilizer expenditures can account for a substantial proportion of operating costs for major field crops. The USDA ERS showed that fertilizer accounted for about 33–44% of corn production costs and 34–45% of wheat production costs starting in 2020, demonstrating the vulnerability of agricultural economics to fertilizer prices and use decisions (USDA ERS, 2025a). The nitrogen fertilizer markets have experienced some big swings. In 2021, fertilizer prices increased quickly and reached their highest levels in 2022. There was reduction in price in 2023 and 2024, but by early 2025 they were still higher than they were before 2021. Fertilizer prices also continued to be affected by changes in supply and demand, energy costs, and global trade conditions (USDA ERS, 2025a). Therefore, nutrient management is not solely an agronomic question of ensuring that crops receive sufficient nitrogen, phosphorus, potassium, and other nutrients; it is also an economic management problem involving the allocation of costly production inputs in ways that maximize their productive value.

Effective nutrient management seeks to balance crop nutrient requirements, farm profitability, resource conservation, and the prevention of avoidable nutrient losses. Proper nutrient management helps farmers reduce fertilizer costs, improve farm profitability, minimize nutrient losses to the environment, and conserve natural resources (USDA ERS, 2025b). These objectives are closely interconnected. Using less fertilizer can reduce crop growth and lower farmers' income. On the other hand, using more fertilizer than the crop needs can increase production costs without giving enough extra yield to make the additional cost worthwhile. Excess nutrients may also be vulnerable to losses from agricultural fields, reducing the fraction of purchased nutrients captured in harvested crops. Consequently, economically efficient nutrient management requires more than maximizing fertilizer application; it requires improving the relationship between nutrient inputs, crop requirements, yield response, and the value of agricultural output.

A fundamental limitation of generalized or uniform nutrient-management approaches is that agricultural fields are rarely completely homogeneous. Soil fertility, soil properties, topography, moisture availability, previous crop performance, yield potential, and crop nutrient status can vary spatially within the same field. Applying a single fertilizer rate across an entire field may therefore result in some locations receiving more nutrients than required while other locations receive insufficient quantities. Precision agriculture provides a mechanism for responding to this spatial and temporal variability by shifting management away from uniform treatment toward site-specific and

condition-specific decision-making. Recent systematic-review evidence indicates that precision-agriculture approaches can combine technologies such as soil sampling, remote sensing, global positioning systems (GPS), and variable-rate application to characterize variability and adjust fertilizer applications according to field conditions (Cai et al., 2025). Rather than assuming identical nutrient requirements across all areas of a field, data-informed management allows nutrient recommendations to respond more directly to observed differences in soil and crop conditions.

The emergence and increasing adoption of precision-agriculture technologies in the United States provide an important technological foundation for this transition. Precision agriculture encompasses a range of technologies and management practices, including GPS-based guidance and autosteering, yield monitoring and mapping, soil mapping, remote and proximal sensing, geographic information systems, variable-rate technologies, and digital decision-support systems. Adoption has expanded considerably, although it varies substantially by technology and farm size. Using 2023 farm data, McFadden and Lim (2024) reported that guidance and autosteering systems were used by 52% of midsize crop-producing farms and 70% of large-scale crop-producing farms, while yield monitors, yield maps, and soil maps were used by approximately 68% of large-scale crop-producing farms. Farmers reported several motivations for technology adoption, including increasing yields, reducing purchased-input costs, saving labor, improving soils, and reducing environmental impacts. However, adoption remained considerably lower among small family farms, demonstrating that the economic opportunities associated with agricultural digitalization coexist with differences in technology access and adoption capacity.

Within this technological environment, data constitutes the link between field variability and management action. Precision agriculture is increasingly distinguished not merely by the presence of advanced equipment, but by the ability to collect, integrate, interpret, and apply multiple forms of agricultural information. Soil-test results can characterize nutrient availability and soil properties; GPS and geographic information systems can associate observations with specific locations; yield monitors and historical yield maps can identify persistent spatial differences in productivity; remote-sensing imagery can provide information about crop development and vegetation status; and proximal or in-field sensors can provide additional information about soil and crop conditions. This data can then support decisions concerning where, when, and how much nutrients should be applied. A recent systematic review of 51 peer-reviewed studies found substantial evidence that precision-agriculture technologies can improve nutrient-management efficiency and crop performance, particularly when tools such as GPS guidance, remote sensing, soil assessment, and variable-rate application are integrated into site-specific management systems (Cai et al., 2025). Similarly, Getahun et al. (2024) identified the integration of soil information, remote sensing, yield records, sensors, and variable-rate technologies as an important mechanism through which precision agriculture can support more efficient crop production and resource management.

The economic value of data-driven nutrient management, however, should not be assumed to be uniform across locations or production systems. The profitability of precision nutrient application depends on several factors, including within-field variability, fertilizer prices, crop prices, yield response, weather, information quality, equipment costs, management capacity, and the cost of generating reliable prescriptions. Recent U.S. research demonstrates why this distinction is important. Using 17 field-years of data from 13 Midwestern fields between 2021 and 2023, Lee et al. (2025) compared variable-rate nitrogen prescriptions developed from different information sources. Their results showed substantial heterogeneity in economic outcomes, with the relative profitability of remotely sensed and yield-history-based prescriptions changing according to seasonal conditions. The study shows that precision nutrient management may not give the same financial benefit in every field or every year. Its success depends partly on how accurate the information is and how well

it reflects crop needs and changing field conditions. For this reason, the economic value of precision agriculture should not be based only on fertilizer savings or higher yields. It should also consider the cost of the technology, the quality of the data, changes in the environment, and the uncertainty of the financial returns (Lee et al., 2025).

Nevertheless, the broader development of data-driven agriculture creates an important pathway for improving the efficiency with which nutrients and other production inputs are managed. Precision technologies make it increasingly possible to move from generalized recommendations toward management strategies in which fertilizer rates and other inputs are differentiated according to measured or predicted field conditions. A 2025 systematic review concluded that precision-agriculture technologies have substantial potential to improve nutrient-use efficiency and refine fertilizer management, while also identifying adoption costs, infrastructure limitations, and technical expertise as important constraints to realizing these benefits at scale (Cai et al., 2025). Thus, agricultural modernization involves more than acquiring sensors, software, or variable-rate equipment. Its economic value depends on creating an integrated decision system in which high-quality field data are converted into agronomically meaningful recommendations and those recommendations lead to measurable improvements in resource-use efficiency and farm performance.

The implications extend beyond individual farms because improvements in production efficiency can accumulate across commodities and regions. In an agricultural economy that participates extensively in international markets, competitiveness depends partly on producers' ability to generate output efficiently while responding to changing input prices, production risks, technological developments, and market conditions. The United States remains one of the world's largest agricultural traders, and agricultural exports contribute not only to farm receipts but also to economic activity beyond the farm sector. USDA ERS estimates that U.S. agricultural exports were valued at $175.5 billion in 2023 and generated an additional $186.9 billion in domestic business activity, producing total economic output of approximately $362.4 billion associated with those exports (USDA ERS, 2026b). Against this broader economic background, technologies that contribute to lower avoidable production costs, improved input productivity, better yield management, and more resilient decision-making have potential implications for the long-term competitive capacity of U.S. agriculture. However, the magnitude of those implications must be evaluated rather than presumed.

Accordingly, the relationship between precision agriculture and agricultural competitiveness can be conceptualized through an economic pathway in which better data improve nutrient decisions; improved nutrient decisions influence input-use efficiency and crop performance; changes in input costs and productivity affect farm profitability; and aggregated improvements in farm-level efficiency may contribute to sector-level competitiveness. This perspective positions data-driven nutrient management not simply as a conservation practice or technological innovation, but as a potential component of agricultural economic modernization. It also recognizes that technological adoption carries costs and that economic outcomes are likely to vary among farms, crops, regions, and production conditions. The central analytical question is therefore not whether precision technologies are inherently beneficial, but under what conditions and through what economic mechanisms precision agriculture and data-driven nutrient management can generate value for U.S. producers and the wider agricultural economy.

Against this background, this study examines the prospective economic impact of precision agriculture and data-driven nutrient management on U.S. agricultural competitiveness. The study focuses on the mechanisms through which site-specific data collection, digital decision support, and precision nutrient application may affect fertilizer-use efficiency, production costs, crop productivity, farm profitability, and broader agricultural competitiveness. By connecting field-level nutrient-

management decisions with farm-level economic outcomes and sector-level competitiveness, the study seeks to provide a structured framework for understanding how agricultural digitalization could contribute to more efficient, productive, and economically resilient U.S. agriculture. The emphasis on *prospective* impact is deliberate: rather than assuming uniform or predetermined economic gains, the analysis considers the potential pathways, supporting evidence, constraints, and conditions that determine whether precision nutrient-management technologies can translate into measurable economic value.

Objectives of the Study

The overall objective of this study is to examine the prospective economic contribution of precision agriculture and data-driven nutrient management to the competitiveness of U.S. agriculture. Specifically, the study aims to:

1. Evaluate the prospective economic implications of precision agriculture for U.S. agriculture, with emphasis on its potential to improve production efficiency and strengthen competitiveness.
2. Examine how data-driven nutrient management can improve nutrient-use efficiency and agricultural productivity through more precise, site-specific nutrient decisions.
3. Assess the potential effects of precision nutrient management on production costs, farm profitability, resource-use efficiency, and broader agricultural competitiveness.
4. Develop an economic framework linking precision agriculture and data-driven nutrient management to farm-level economic outcomes and sector-level U.S. agricultural competitiveness.

Problem Statement

U.S. crop production depends heavily on fertilizer and other purchased inputs, yet the economic value of these inputs is determined not simply by how much is applied, but by how efficiently they are matched to crop needs. Fertilizer can account for a substantial share of operating costs for major crops such as corn and wheat, making nutrient-management decisions an important determinant of production efficiency and farm profitability (USDA ERS, 2025a). At the same time, agricultural fields are spatially variable in soil fertility, moisture conditions, yield potential, and crop nutrient demand. When nutrient applications are based on generalized or uniform rates across heterogeneous fields, some areas may receive more nutrients than economically or agronomically justified, while others may receive less than required. This mismatch can increase unnecessary input expenditure, reduce nutrient-use efficiency, and limit the economic return obtained from fertilizer investments.

The problem is therefore both agronomic and economic. Nutrients applied more than crop requirements represent a direct production cost without a guaranteed proportional increase in yield, while insufficient application can constrain crop performance and reduce potential revenue. Nutrient losses from agricultural fields can further reduce the productive value of purchased fertilizer. USDA ERS identifies improved nutrient management as a means of reducing fertilizer costs, improving farm profitability, minimizing nutrient losses, and conserving resources (USDA ERS, 2025b). However, achieving these outcomes requires management systems capable of accounting for variability within fields rather than relying solely on uniform treatment assumptions.

Precision agriculture and data-driven nutrient management provide a potential means of addressing this inefficiency by using soil information, yield records, geospatial data, remote sensing, sensors, and variable-rate technologies to support site-specific nutrient decisions. Recent studies indicate that these technologies can improve the targeting of fertilizer applications and support more efficient resource use, but their economic outcomes are not uniform across farms, fields, crops, or years (Cai et al., 2025; Getahun et al., 2024; Lee et al., 2025). Their profitability depends on factors such as fertilizer prices, crop prices, field variability, data quality, equipment costs, weather, and management capacity. Consequently, the existence of precision technology alone does not establish that its adoption will generate economic gains; the pathways through which it affects costs, productivity, and profitability must be examined systematically.

This creates an important research problem for U.S. agriculture. Although precision-agriculture adoption is increasing, especially among larger crop-producing farms, adoption remains uneven and the broader economic implications of data-driven nutrient management are not fully captured by farm-level technological performance alone (McFadden & Lim, 2024). A reduction in unnecessary fertilizer use may lower operating costs, while better alignment of nutrient supply with crop demand may support productivity and profitability. Yet these farm-level effects must be connected to wider questions of resource-use efficiency, resilience, production capacity, and competitiveness before conclusions can be drawn about their significance for the U.S. agricultural sector.

Accordingly, the central problem addressed in this study is the absence of a clear, integrated economic framework linking field-level nutrient-management inefficiencies and precision-agriculture interventions to farm-level economic outcomes and, ultimately, to U.S. agricultural competitiveness. Without such a framework, the economic significance of precision nutrient management may be discussed in isolated terms such as fertilizer savings, yield response, or technology adoption without adequately explaining how these effects interact and scale from individual production decisions to broader sector-level performance. This study therefore examines the prospective pathways through which precision agriculture and data-driven nutrient management may reduce avoidable input costs, improve nutrient-use efficiency and agricultural productivity, strengthen farm profitability, and contribute to the long-term competitiveness of U.S. agriculture.

Context and Motivation

The motivation for this study is both economic and technological. U.S. agriculture is operating in a period in which producers face persistent pressure to maintain productivity while managing high and variable production costs. Fertilizer is particularly important in this context because it represents a substantial share of operating expenses for major crops, and fertilizer markets have experienced considerable price volatility in recent years (USDA ERS, 2025a). At the same time, nutrient-management decisions directly affect both production efficiency and farm profitability. These conditions increase the value of management approaches that can improve the precision with which costly inputs are allocated rather than relying on generalized application practices.

The timing of this study is also important because precision-agriculture technologies and agricultural data systems are becoming increasingly available across U.S. crop production. Guidance systems, yield monitors, soil maps, remote sensing, variable-rate technologies, and digital decision-support tools are already being used on many farms, particularly midsize and large-scale operations (McFadden & Lim, 2024). Their growing availability creates new opportunities to combine soil, crops, geospatial, sensor, and historical yield information in ways that support more site-specific

nutrient decisions. Recent reviews further indicate that these technologies can improve nutrient-use efficiency and strengthen fertilizer management when they are effectively integrated into production systems (Cai et al., 2025; Getahun et al., 2024).

Environmental concerns provide additional motivation. Nutrients that are applied but not effectively taken up by crops can be lost from agricultural systems, reducing the productive value of purchased fertilizer while also creating environmental risks. USDA ERS identifies nutrient management as important for reducing fertilizer costs, improving profitability, minimizing nutrient losses, and conserving natural resources (USDA ERS, 2025b). Therefore, more efficient nutrient management has the potential to generate both economic and environmental benefits, making it relevant not only to farm-level management but also to broader discussions of sustainable agricultural modernization.

Finally, the study is motivated by the need to maintain the long-term competitiveness of U.S. agriculture in a production environment shaped by technological change, input-cost uncertainty, and global market competition. Because U.S. agriculture is closely connected to domestic economic activity and international trade, improvements in production efficiency and resource-use performance may have significance beyond individual farms (USDA ERS, 2026b). However, the economic contribution of precision agriculture should not be assumed to be automatic or uniform. Adoption costs, farm size, field variability, management capacity, data quality, and local production conditions can all influence the returns from precision technologies. For this reason, a prospective economic assessment is needed to clarify the pathways through which data-driven nutrient management may contribute to lower avoidable costs, improved productivity, stronger farm performance, and broader U.S. agricultural competitiveness.

Research Questions

1. How can precision agriculture and data-driven nutrient management improve the economic efficiency of U.S. agricultural production?
2. What prospective effects could precision nutrient management have on fertilizer costs, nutrient-use efficiency, crop productivity, and farm profitability?
3. Through what economic pathways could precision agriculture and data-driven nutrient management strengthen U.S. agricultural competitiveness?
4. What policy and implementation considerations influence the broader adoption and economic impact of precision nutrient management technologies in the United States?

Scope and Delimitations

This study presents a prospective economic and policy-oriented assessment of how precision agriculture and data-driven nutrient management may contribute to U.S. agricultural competitiveness. It does not report results from a nationwide field experiment, farm survey, or large-scale technology deployment. Instead, the analysis draws on published empirical studies, government data, and established evidence on precision-agriculture adoption, nutrient-management practices, fertilizer costs, productivity, and farm economic performance to examine the pathways through which precision nutrient management may influence economic outcomes.

The study is limited primarily to U.S. crop production, where fertilizer management, spatial variability, and precision-application technologies are especially relevant. Attention is given to technologies and data systems that directly support nutrient decisions, including soil testing and mapping, GPS and GIS tools, yield monitoring, remote and proximal sensing, variable-rate application, and digital decision-support systems. Precision agriculture technologies that do not have a clear connection to nutrient management or production efficiency are outside the principal scope of the analysis.

The economic assessment focuses on potential effects on fertilizer and input-use efficiency, production costs, crop productivity, farm profitability, resource-use efficiency, and sector-level agricultural competitiveness. Environmental outcomes are considered as directly connected to nutrient losses and resource-use efficiency, but the study does not attempt a complete environmental life-cycle assessment of precision agriculture. Likewise, broader social outcomes such as rural demographic change, labor displacement, or consumer welfare are not evaluated in detail.

Because the study is prospective, it does not assume that precision agriculture produces uniform economic benefits across all farms, crops, regions, or production years. Economic outcomes may vary according to farm size, crop type, field variability, fertilizer and commodity prices, technology costs, data quality, management capacity, weather, and local production conditions. The study therefore evaluates potential economic pathways and conditions of impact rather than claiming a single nationwide return or causal effect. Future empirical research using farm-level, regional, and longitudinal data would be required to quantify the magnitude and distribution of these effects more precisely.

Literature Review

The literature relevant to this study lies at the intersection of precision agriculture, digital agricultural modernization, nutrient management, farm economics, and agricultural competitiveness. Existing research generally agrees that precision agriculture can improve the spatial and temporal targeting of inputs by combining field-level data with technologies such as GPS, yield monitoring, soil mapping, remote sensing, variable-rate application, and decision-support systems. However, the economic value of these technologies is not uniform. Their performance depends on the quality of the data used, the extent of within-field variability, crop and fertilizer prices, weather, farm size, technology costs, and the producer's ability to convert information into effective management decisions. The literature is therefore reviewed under four related themes: precision agriculture and U.S. agricultural modernization; data-driven nutrient management and site-specific decision-making; nutrient-use efficiency, input costs, and agricultural productivity; and agricultural technology, farm profitability, and competitiveness.

Precision Agriculture and U.S. Agricultural Modernization

Precision agriculture has developed from a collection of location-based technologies into a broader data-driven management approach. Gebbers and Adamchuk (2010) described precision agriculture as an integration of sensing, information systems, enhanced machinery, and informed management designed to account for spatial and temporal variability in agricultural production. This remains an important conceptual foundation because it shifts the focus from treating a field as a uniform production unit to managing differences within the field according to observed conditions. In contemporary agriculture, this principle is expressed through technologies including GPS guidance, georeferenced soil sampling, yield monitors, yield maps, remote sensing, variable-rate technologies, and digital decision-support tools.

In the United States, precision agriculture has become increasingly embedded in commercial crop production, although adoption varies substantially across technologies, commodities, and farm sizes. McFadden et al. (2023), using USDA Agricultural Resource Management Survey data, documented substantial growth in the use of digital and precision technologies on U.S. farms. Their analysis showed that automated guidance systems had become widely used on major row-crop acreage, while technologies such as yield maps, soil maps, and variable-rate systems had also become established components of precision management, especially in corn and soybean production. Importantly, the report identified economic factors including technology prices, expected productivity gains, soil

variability, labor-saving benefits, and access to technical services as important influences on adoption. These findings indicate that precision agriculture is not merely a technological transition; it is also an economic decision in which producers compare the expected value of improved information and operational efficiency against adoption and operating costs.

More recent USDA evidence confirms that adoption continues to be strongly associated with farm scale. McFadden and Lim (2024) reported that in 2023, guidance and autosteering technologies were used by 52% of midsize crop-producing farms and 70% of large-scale crop-producing farms, while yield monitors, yield maps, and soil maps were used by 68% of large-scale crop-producing farms. Producers identified higher yields, labor savings, reductions in purchased-input costs, improved soils, and lower environmental impacts among the reasons for adoption. At the same time, small family farms consistently reported lower adoption rates. This pattern is economically important because fixed costs associated with equipment, subscriptions, software, data services, and training can be spread across more acres on larger operations, while smaller farms may face a higher per-acre cost of adoption.

The modernization literature therefore suggests that the significance of precision agriculture lies not in technology ownership alone but in its capacity to improve the quality and timing of production decisions. Digital agricultural modernization depends on a connected process in which field observations are collected, converted into usable information, interpreted within an agronomic and economic context, and translated into management actions. Cai et al. (2025), in a systematic review of 51 peer-reviewed studies, found that precision-agriculture technologies can improve nutrient-use efficiency, fertilizer management, and crop performance, while also identifying cost, infrastructure, and technical-expertise constraints as barriers to broader adoption. Getahun et al. (2024) similarly concluded that technologies such as remote sensing, GPS, sensors, unmanned systems, and variable-rate applications can support more efficient and sustainable crop production when integrated effectively.

The literature also cautions against assuming that increased digital capability automatically leads to better farm decisions. Nowatzke et al. (2024), based on qualitative interviews with farmers in the U.S. Corn Belt, identified practical limitations related to equipment cost, subscription expenses, data transfer, interoperability, time requirements, and the usability of decision-support systems. Their study involved a small and purposive sample and therefore should not be generalized to all U.S. producers, but it illustrates an important implementation issue: agricultural data can have limited economic value when it is difficult to integrate, interpret, or apply. Thus, U.S. agricultural modernization requires not only more data and more advanced equipment, but also decision systems that are economically relevant, interoperable, accessible, and responsive to producer needs.

Taking together, this literature supports the view that precision agriculture is a central component of agricultural modernization because it creates the technical capacity for more differentiated and information-intensive management. However, modernization should be evaluated by the outcomes generated from that capacity such as improved input efficiency, lower avoidable costs, better productivity, and stronger decision-making rather than by adoption rates alone. This distinction is especially important for nutrient management, where the economic value of precision technologies depends on whether they improve the match between crop nutrient demand and fertilizer application.

Data-Driven Nutrient Management and Site-Specific Decision-Making

Nutrient management is fundamentally a decision problem involving the selection of the appropriate nutrient source, rate, timing, and placement in relation to crop requirements and field conditions. USDA ERS (2025b) defines effective nutrient-management practices around the principle of

applying the right fertilizer product in the right amount, at the right time, and in the right place to meet plant needs while reducing nutrient losses. This framework is closely aligned with precision agriculture because both emphasize management that responds to measured conditions rather than generalized assumptions.

The need for site-specific nutrient management arises from the spatial heterogeneity of agricultural fields. Soil nutrient availability, soil texture, organic matter, water-holding capacity, topography, historical yield, and crop response can vary within relatively short distances. A uniform fertilizer rate may therefore be economically inefficient when the marginal productivity of fertilizer differs across locations. In some areas, additional fertilizer may generate little or no additional yield; in others, an insufficient rate may prevent the crop from reaching its attainable yield. Precision nutrient management attempts to identify these differences and vary nutrient application accordingly.

Data is central to this process because site-specific recommendations cannot be developed reliably without information describing spatial or temporal variability. Relevant data sources include soil test results, georeferenced soil maps, historical yield-monitor data, topographic information, weather data, remote-sensing imagery, proximal crop sensors, and in-season indicators of crop vigor. Cai et al. (2025) found that GPS guidance, remote sensing, soil assessment, and variable-rate application are among the principal technologies used to refine fertilizer management. The review concluded that combining spatial information with targeted application can improve fertilizer-use efficiency and reduce unnecessary application, although results differ across crops, technologies, and management environments.

Recent U.S. agricultural-economics research demonstrates how historical farm data can be transformed into site-specific recommendations. Park et al. (2024) developed a Bayesian approach that used historical yield-monitor data from uniform-rate nitrogen applications to generate spatially differentiated nitrogen recommendations for corn. In the example field analyzed, the authors estimated an in-sample net return of approximately $9 per acre from the variable-rate recommendations. The importance of this study is not the specific dollar value which cannot be generalized to other farms but the demonstration that information already generated through routine farm operations can potentially be converted into economically useful site-specific recommendations. The authors also emphasized the potential value of combining yield-history information with additional sources such as remote sensing.

Lee et al. (2025) extended this issue by examining the profitability of variable-rate nitrogen prescriptions developed from different sources of information. Using 17 field-years from 13 Midwestern fields during 2021–2023, the study compared nitrogen prescriptions based on early-season vegetative vigor with prescriptions based on yield history. Their findings showed that relative profitability varied with the information source and production conditions. This is a critical contribution because it demonstrates that the value of data-driven nutrient management depends not simply on having more information, but on whether the information accurately represents economically relevant variation in crop response. Precision agriculture therefore creates a value-of-information problem: data collection and analysis are economically justified only when the improved decision generated from that information is valuable enough to offset the cost of obtaining and processing it.

This literature also highlights the distinction between technological precision and agronomic accuracy. A variable-rate applicator may be capable of placing different fertilizer rates very precisely, but economic improvement depends on whether the prescribed rates are agronomically appropriate. If the underlying soil data, yield maps, sensor measurements, or response models are inaccurate, the technology may simply apply an incorrect recommendation with greater spatial

precision. Consequently, data quality, calibration, spatial resolution, model validity, and management interpretation are integral to the economic performance of precision nutrient systems.

Literature therefore supports a broader interpretation of data-driven nutrient management as an integrated decision process rather than a single technology. The process begins with the measurement of field variability, continues through data integration and analysis, produces site-specific recommendations, and ends with differentiated nutrient application and subsequent evaluation of crop and economic response. This integrated view is directly relevant to the present study because it provides the mechanism through which precision agriculture may influence costs, nutrient-use efficiency, productivity, and profitability.

Nutrient-Use Efficiency, Input Costs, and Agricultural Productivity

The economic importance of nutrient-use efficiency is strengthened by the high cost and volatility of fertilizer inputs. Williams et al. (2025), in a USDA ERS analysis of U.S. fertilizer markets from 2006 through 2023, documented substantial changes in fertilizer prices, production, consumption, and trade. Fertilizer costs became especially important during the sharp price increases that culminated in 2022. USDA ERS data show that fertilizer represented more than 40% of operating costs for corn and wheat at the 2022 peak, illustrating how fertilizer markets can materially affect production economics (Williams et al., 2025). Although fertilizer prices declined after their 2022 highs, USDA ERS reported that early-2025 prices remained above pre-2021 levels and continued to be exposed to changes in supply, demand, and trade conditions (USDA ERS, 2025a).

These cost conditions increase the economic importance of nutrient-use efficiency because every unit of fertilizer that does not contribute sufficiently to crop output represents an opportunity cost to the producer. USDA ERS (2025b) describes nutrient management as relevant to reducing fertilizer costs, increasing farm profitability, minimizing nutrient losses, and conserving natural resources. Nutrient-use efficiency therefore connects agronomic performance with economic performance: the objective is not simply to reduce fertilizer use, but to increase the productive output or economic return obtained from the nutrient input while avoiding both economically unjustified excess application and yield-limiting underapplication.

Precision agriculture can contribute to this objective by matching nutrient rates more closely to spatial differences in crop need and yield potential. Cai et al. (2025) concluded from their systematic review that precision-agriculture technologies generally improved nutrient-use efficiency and crop yields across the reviewed literature. The authors also noted that real-time or site-specific data can help producers adjust fertilizer applications more closely to crop requirements, potentially reducing costs associated with excessive application. Getahun et al. (2024) likewise found that precision technologies can support improved input management and crop productivity through more timely and localized decision-making.

However, literature does not support a simple assumption that reducing fertilizer automatically increases profit. Profitability depends on the relationship between fertilizer savings, yield response, crop prices, and the cost of the precision system. A nutrient rate that minimizes fertilizer use could be economically inferior if it causes a yield loss whose value exceeds the fertilizer savings. Conversely, an application rate slightly above the agronomic minimum may be economically rational if the additional yield value exceeds the marginal fertilizer cost. For this reason, the relevant objective for farm management is closer to economic optimization of nutrient use than to input minimization alone.

The importance of local conditions is reinforced by the results of Park et al. (2024) and Lee et al. (2025). Park et al. demonstrated that site-specific recommendations could generate positive

estimated returns in a particular production setting, while Lee et al. showed that profitability can vary across fields, seasons, and information sources. These findings are consistent with the broader USDA assessment of conservation and soil-health practices. Bowman et al. (2025) concluded that the economic outcomes of agricultural management practices depend on implementation, production system, weather, climate, soils, and other farm-specific conditions. Their report also emphasizes expectations about short- and long-run profitability, uncertainty, and risk influence producer adoption decisions. Although the Bowman et al. report examines a wider set of soil-health and conservation practices, its economic reasoning is directly relevant to precision nutrient management because both involve costs incurred today in expectation of uncertain agronomic and economic benefits.

Productivity represents the second major pathway through which improved nutrient management can influence economic performance. Nutrients are essential to crop production, so underapplication can restrict yields and reduce the productive use of land, machinery, labor, and other inputs. At the same time, fertilizer applied beyond crop response needs can increase costs without proportionate gains in output. The economic objective is therefore to improve the alignment between nutrient supply and crop response so that the same or lower level of input expenditure generates greater value of production, or the same production level is achieved at lower cost.

This relationship is especially relevant on a scale. At the individual field level, improved nutrient decisions may appear as a change in fertilizer expenditure, yield, or net return per acre. At the farm level, repeated improvements across fields may affect whole-farm operating costs and profitability. At the sector level, widespread improvements in input productivity could contribute to greater technical efficiency and production capacity. The literature reviewed here supports these pathways conceptually and empirically at field and farm scales, but it does not provide evidence for a single uniform national effect. That limitation is central to the prospective nature of the present study.

Agricultural Technology, Farm Profitability, and Competitiveness

The economic case for precision agriculture ultimately depends on profitability. Producers adopt technologies when expected improvements in revenue, cost savings, risk management, labor efficiency, or other benefits are sufficient to justify capital, software, information, learning, and maintenance costs. McFadden et al. (2023) identified expected productivity impacts, labor savings, technology prices, and access to technical services among the factors shaping U.S. precision-agriculture adoption. McFadden and Lim (2024) similarly reported that producers adopt precision technologies for reasons including increasing yields, reducing purchased-input costs, saving labor, improving soils, and reducing environmental impacts. These motivations show that the value proposition of precision agriculture is multidimensional, but they do not establish that every technology is profitable for every farm.

Farm scale is one of the most consistent economic factors in the adoption literature. Larger operations generally have more acres across which to distribute the fixed costs of equipment, software, training, and data services. McFadden and Lim (2024) found substantially higher adoption rates among large-scale crop-producing farms than among small family farms. Nowatzke et al. (2024) provide complementary qualitative evidence that producers can view equipment and subscription costs as difficult to justify on smaller acreages and that data-management burdens may further reduce the practical value of digital systems. Together, these findings suggest that the economic benefits of precision agriculture may be distributed unevenly unless lower-cost technologies, service-provider models, technical assistance, or other arrangements reduce entry barriers for smaller operations.

Profitability also depends on the specific management problem being addressed. In nutrient management, the benefits may arise from reduced fertilizer application in low-response areas, increased application where yield response justifies it, better timing, improved placement, or improved adaptation to in-season conditions. Lee et al. (2025) show that the profitability of variable-rate nitrogen prescriptions is sensitive to the information used to create the prescription. Park et al. (2024) show that historical data can potentially be used to generate economically positive site-specific recommendations. Together, these studies reinforce the need to evaluate precision nutrient management as a decision-investment problem in which the value of better information must be compared with the cost of collecting, processing, and acting on that information.

The connection between farm-level profitability and national agricultural competitiveness is broader and should be interpreted cautiously. Competitiveness in agriculture reflects multiple factors, including productivity, production costs, exchange rates, infrastructure, market access, technology, resource availability, trade policy, and the performance of competing agricultural exporters. Precision agriculture cannot independently determine U.S. competitiveness. Nevertheless, farm-level efficiency is one plausible channel through which technology can contribute to competitive performance. Technologies that consistently reduce avoidable costs, increase output per unit of input, improve management responsiveness, or reduce production risk may strengthen producers' capacity to compete under changing domestic and international market conditions.

Current U.S. trade conditions underscore the importance of this efficiency dimension. USDA ERS reported that U.S. agricultural exports grew more slowly than imports over 2015–2025 and identified growing global competition, the strength of the U.S. dollar, and trade barriers as headwinds to export growth (USDA ERS, 2026b). These trends do not demonstrate that precision agriculture will reverse changes in the agricultural trade balance, and such a claim would go beyond the available evidence. They do, however, illustrate that U.S. producers operate in a competitive global environment in which productivity and cost efficiency remain economically relevant.

Accordingly, the literature suggests a multi-level economic pathway. At the technology level, sensors, maps, guidance systems, remote sensing, variable-rate equipment, and decision-support tools improve the capacity to observe and manage variability. At the management level, these technologies can support more site-specific nutrient decisions. At the farm level, better decisions may influence fertilizer expenditures, yields, labor use, risk, and net returns. At the sector level, widespread and economically successful improvements in productivity and resource-use efficiency could contribute to the competitive capacity of U.S. agriculture. The strength of each link depends on implementation conditions and should be evaluated rather than assumed.

Synthesis of the Literature and Research Gap

Four conclusions emerge from literature. First, precision agriculture is now an established component of U.S. agricultural modernization, but adoption is uneven across technologies and farm sizes (McFadden et al., 2023; McFadden & Lim, 2024). Second, data-driven nutrient management provides a practical mechanism for converting soil, crop, yield, geospatial, and sensor information into site-specific fertilizer decisions (Park et al., 2024; Cai et al., 2025). Third, improved nutrient targeting has the potential to affect nutrient-use efficiency, fertilizer expenditure, crop productivity, and farm profitability, but the size and direction of economic returns vary across fields, years, information sources, and production conditions (Lee et al., 2025). Fourth, the broader economic significance of precision agriculture depends not only on technical performance but also on adoption cost, data quality, interoperability, management capability, scale, and the wider market environment (Nowatzke et al., 2024; Bowman et al., 2025).

The principal gap is therefore not the absence of research on precision-agriculture technologies or nutrient management individually. A substantial literature examines technology adoption, variable-rate fertilization, nutrient-use efficiency, crop response, and selected farm-level returns. What remains less clearly integrated is the economic pathway connecting data-driven nutrient decisions to farm-level cost and profitability outcomes and then to the broader concept of U.S. agricultural competitiveness. Existing studies often stop at one part of this chain, for example, adoption rates, yield response, fertilizer savings, or field-level profitability, without bringing these outcomes into a unified prospective economic framework.

This study addresses that gap by integrating the literature on precision-agriculture adoption, data-driven nutrient management, input-use efficiency, farm profitability, and sector-level competitiveness. Rather than assuming a universal economic benefit, the study evaluates the mechanisms and conditions through which precision nutrient management may generate economic value. This approach is consistent with the evidence that returns are heterogeneous and provides the basis for a prospective framework linking field data → site-specific nutrient decisions → input and productivity effects → farm economic outcomes → potential sector-level competitiveness effects.

Theoretical and Conceptual Framework

This study is guided by a production-economics and resource-use-efficiency perspective in which the value of precision agriculture is determined not by technology adoption alone, but by whether improved information leads to better allocation of costly production inputs and stronger economic performance. In crop production, fertilizer is both an essential agronomic input and a major operating expense. The economic objective is therefore not simply to minimize fertilizer use, but to apply nutrients in a way that improves the relationship among input cost, crop response, yield value, and farm returns. This perspective is consistent with USDA ERS guidance that nutrient management can contribute to lower fertilizer costs, improved profitability, reduced nutrient losses, and more efficient resource use (USDA ERS, 2025b).

From this theoretical standpoint, agricultural information has economic value when it improves a management decision. Precision technologies generate information on spatial and temporal variability, but the benefit of that information depends on whether it changes nutrient decisions in a way that improves net returns. Park et al. (2024) demonstrate that historical yield data can be used to generate site-specific nitrogen recommendations with positive estimated returns in a particular field setting, while Lee et al. (2025) show that the profitability of variable-rate nitrogen prescriptions varies according to the information source and production conditions. These findings support the central proposition of this study: precision agriculture can create economic value when reliable field data are converted into nutrient decisions that improve input-use efficiency, productivity, or both, relative to the costs of obtaining and using technology and information.

Production Economics and Resource-Use Efficiency

The production-economics foundation of the study is based on the principle that farm managers allocate land, fertilizer, labor, machinery, technology, and information in ways intended to improve economic returns. In nutrient management, an additional unit of fertilizer is economically justified only when the expected value of the additional crop response is sufficient to cover the additional cost of that input. Applying nutrients beyond economically justified crop requirements can increase production costs without generating a proportional increase in revenue, while applying less than crop requirements can reduce yield and potential farm income. The economically relevant objective is therefore efficient nutrient allocation, not fertilizer reduction in isolation.

This principle becomes particularly important when fields are spatially heterogeneous. Soil fertility, organic matter, moisture, topography, historical yield, and crop nutrient demand can differ across a field, meaning that the economically appropriate nutrient rate may also vary spatially. Precision agriculture provides the technical capacity to identify these differences and to move from generalized treatment toward site-specific and condition-specific management. Gebbers and Adamchuk (2010) established precision agriculture as an approach for managing spatial and temporal variability through sensing, information systems, and differentiated intervention. In the context of this study, logic is extended from technical management to economic performance: better identification of variability can improve the allocation of fertilizer, and better allocation can influence cost efficiency, productivity, and farm returns.

The framework also recognizes that information itself is a productive resource. Soil tests, yield maps, remote-sensing imagery, crop sensors, geospatial data, and weather information have limited economic value if they are collected but do not improve a decision. Their value arises when they reduce uncertainty about crop response or nutrient need sufficiently to improve the expected economic outcome of management. This is consistent with the evidence from Park et al. (2024) and Lee et al. (2025), which shows that the profitability of site-specific nitrogen management depends partly on the quality and relevance of the data used to develop prescriptions.

Precision Agriculture–Nutrient Management Economic Competitiveness Framework

The conceptual framework developed for this study links precision-agriculture technologies to U.S. agricultural competitiveness through a sequence of intermediate agronomic and economic outcomes. The framework contains nine connected stages.

Stage 1: Precision Agriculture Technologies. The framework begins with technologies that make spatially differentiated management possible, including GPS and GIS, georeferenced soil sampling, soil and crop sensors, remote sensing, yield monitoring and mapping, variable-rate application systems, and digital decision-support tools. These technologies provide the technical capacity to observe variation and to act on that information rather than treating a field as a uniform management unit (Gebbers & Adamchuk, 2010; Getahun et al., 2024; Cai et al., 2025).

Stage 2: Agricultural Data Acquisition. Precision technologies generate or organize information on soil nutrient status, soil properties, crop condition, historical yield, spatial location, weather, and other factors that influence crop response. Data acquisition is therefore the link between observed field variability and subsequent nutrient decisions. The quality, spatial resolution, timeliness, and relevance of these data affect the reliability of the recommendations developed from them.

Stage 3: Data-Driven Nutrient Decision-Making. The collected information is interpreted to determine nutrient rate, timing, placement, and spatial targeting. At this stage, agricultural data becomes economically meaningful because they are converted into a management recommendation. The decision-support function is intended to improve the match between nutrient supply and crop demand rather than relying on one generalized recommendation for an entire field.

Stage 4: Site-Specific Nutrient Application. Precision application technologies translate the recommendation into action by applying different nutrient rates or treatments to different parts of a field according to measured or predicted conditions. This stage represents the practical movement from information to differentiated input allocation. Variable-rate nitrogen studies such as Park et al. (2024) and Lee et al. (2025) demonstrate how this process can be evaluated in economic terms.

Stage 5: Improved Nutrient-Use Efficiency. When the underlying data and recommendations are reliable, more precise nutrient targeting can improve the relationship between nutrients applied and

nutrients contributing to crop production. In this study, improved nutrient-use efficiency does not necessarily mean applying less fertilizer in every location; rather, it means improving the productive and economic value obtained from nutrient inputs while reducing economically unnecessary overapplication and avoiding yield-limiting underapplication.

Stage 6: Reduced Input Waste and Improved or Maintained Productivity. Improved nutrient-use efficiency creates two related economic pathways. The first is a **cost pathway**, in which more accurate targeting can reduce fertilizer applied where the expected crop response does not justify the cost. The second is a productivity pathway, in which better alignment of nutrient supply with crop requirements can help maintain or improve crop performance where nutrient limitations would otherwise reduce yield. The relative importance of these pathways varies across fields, crops, seasons, and market conditions (Cai et al., 2025; Lee et al., 2025).

Stage 7: Lower Production Costs and Improved Farm Returns. Cost savings and productivity effects converge at the farm level. Precision nutrient management may improve farm economic performance through lower avoidable fertilizer expenditure, maintained or increased crop revenue, and more efficient use of purchased inputs. However, the framework explicitly accounts for the costs of precision technology, software, data services, equipment, training, and management. Conceptually, the relevant economic outcome is the **net benefit** generated after these adoption and implementation costs are considered, rather than gross savings alone.

Stage 8: Greater Agricultural Productivity and Resilience. If economically successful precision nutrient-management practices are repeated across fields and farms, they can contribute to broader improvements in input productivity, cost efficiency, and the capacity of producers to respond to fertilizer-price volatility and changing production conditions. At this stage, the analysis moves from individual farm performance toward sector-level implications. The framework treats resilience as the capacity to maintain productive and economic performance under changing input, weather, and market conditions rather than as a guaranteed outcome of technology adoption.

Stage 9: Enhanced U.S. Agricultural Competitiveness. The outcome is agricultural competitiveness, defined in this study as the capacity of U.S. agriculture to produce efficiently, manage costs, maintain productivity and profitability, adapt to technological and market change, and compete effectively in domestic and international markets. Precision agriculture is not treated as the sole determinant of competitiveness; exchange rates, infrastructure, trade policy, market access, resource conditions, and competing producers also matter. Rather, precision nutrient management is conceptualized as one potential pathway through which improved farm-level efficiency and productivity may contribute to the broader competitive capacity of U.S. agriculture.

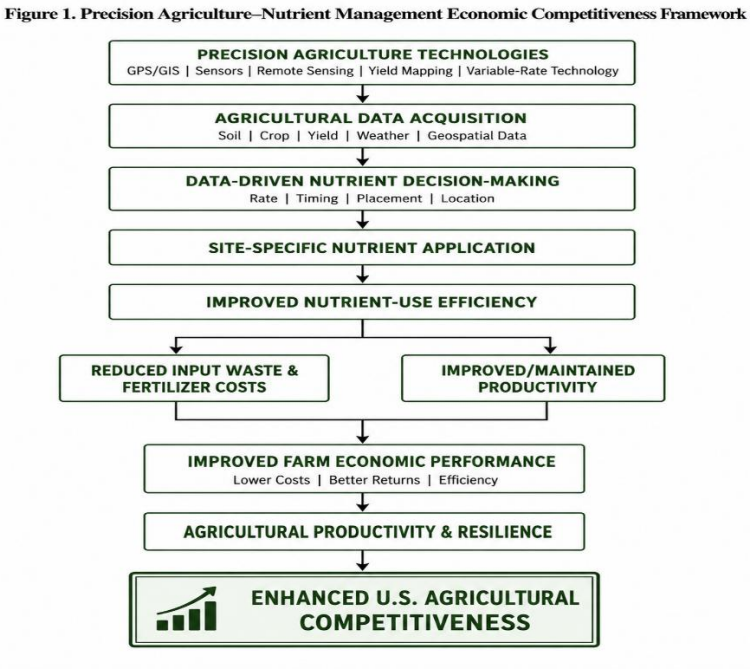


Figure 1. Precision Agriculture–Nutrient Management Economic Competitiveness Framework

Moderating Conditions and Expected Economic Outcomes

The framework does not assume that precision agriculture produces the same economic outcome across all farms or production environments. Instead, the strength of each relationship is expected to be influenced by a set of moderating conditions. These include farm size, crop type, within-field variability, fertilizer prices, commodity prices, technology and subscription costs, data quality, weather conditions, management capability, rural connectivity, and access to technical support. McFadden and Lim (2024) show that precision-agriculture adoption differs substantially by farm scale, while Nowatzke et al. (2024) identify equipment cost, subscription expenses, interoperability, and data usability as practical barriers to digital agricultural management. Lee et al. (2025) further demonstrate that the profitability of variable-rate nitrogen prescriptions can differ across fields, years, and information sources.

These moderating factors are important because they determine whether a technically feasible precision-management practice becomes economically worthwhile. For example, strong within-field variability may increase the potential value of site-specific nutrient management, while high equipment costs may reduce net returns on smaller acreages. Higher fertilizer prices may increase the value of avoiding unnecessary economic application, while unfavorable crop prices may reduce the revenue value of additional yield. Similarly, poor-quality data or weak management interpretation may reduce the expected benefit even when advanced application technology is available.

Accordingly, the framework proposes that precision agriculture does not enhance competitiveness through technology adoption alone. Economic value arises when precision technologies generate reliable agricultural information, that information improves nutrient-management decisions, and improved decisions lead to measurable changes in input efficiency, productivity, costs, and farm returns. When these improvements are economically viable, persistent, and sufficiently scalable, they may contribute to broader agricultural productivity, resilience, and U.S. competitiveness. The

prospective nature of this study therefore lies in evaluating these pathways and conditions rather than assuming a uniform national effect.

Methodology

Research Design and Approach

This study adopts a prospective economic, evidence-synthesis, and policy-analytic approach to examine how precision agriculture and data-driven nutrient management may influence U.S. agricultural competitiveness. Consistent with the conceptual framework developed in Section 2.2, the methodology does not attempt to estimate a single nationwide causal effect or to present results from an original multi-state field experiment. Instead, it evaluates the economic pathways through which improved agricultural information and site-specific nutrient decisions may affect fertilizer use, crop productivity, production costs, farm returns, resource-use efficiency, and broader sector-level competitiveness.

The study relies on secondary evidence from peer-reviewed empirical studies and authoritative U.S. agricultural data sources. Emphasis is placed on evidence concerning precision-agriculture adoption, variable-rate nutrient management, fertilizer costs, yield response, nutrient-use efficiency, technology and implementation costs, farm profitability, and agricultural-sector performance. USDA Economic Research Service publications and data provide national economic context on fertilizer markets, farm production expenses, precision-agriculture adoption, farm profitability, and agricultural trade, while peer-reviewed studies provide field- and farm-level evidence on site-specific nutrient management and variable-rate nitrogen profitability (McFadden et al., 2023; Park et al., 2024; Lee et al., 2025; Williams et al., 2025).

The analytical unit is therefore not a single crop, farm, or technology. Rather, the study examines the economic chain connecting field-level information and nutrient-management decisions to farm-level economic outcomes and potential sector-level competitiveness effects. Evidence is interpreted comparatively and cautiously because the economic performance of precision nutrient management varies with crop type, farm scale, spatial variability, fertilizer and commodity prices, technology costs, weather, and data quality. The methodology is designed to identify the direction, mechanisms, and conditions of economic impact without if all farms experience the same return.

Analytical Model / Economic Impact Framework

The analytical model operationalizes the Precision Agriculture–Nutrient Management Economic Competitiveness Framework presented in Section 2.2. The model is organized into five connected analytical layers that trace how information and technology can translate into economic outcomes.

Layer 1: Field Conditions and Agricultural Data. The first layer captures the information used to characterize variability in soil and crop conditions. Relevant information includes soil-test results, soil properties, historical yield data, crop condition, weather information, geospatial coordinates, remote-sensing observations, and sensor measurements. The purpose of this layer is to determine whether economically meaningful spatial or temporal variability exists and whether available information can support more differentiated nutrient decisions.

Layer 2: Precision Technology and Decision Support. The second layer considers the technologies that collect, organize, interpret, or apply agricultural information. These include GPS and GIS, yield monitoring and mapping, remote and proximal sensing, soil mapping, variable-rate technologies, and digital decision-support systems. The analysis focuses on the functional role of these technologies rather than technology ownership alone: their economic relevance depends on

whether they improve the quality of nutrient-management decisions (Gebbers & Adamchuk, 2010; Getahun et al., 2024; Cai et al., 2025).

Layer 3: Data-Driven Nutrient Management. The third layer evaluates how information is translated into decisions concerning nutrient rate, timing, placement, and spatial targeting. This layer distinguishes generalized or uniform nutrient application from site-specific management. The principal analytical question is whether improved information enables fertilizer to be allocated more closely to expected crop need and yield response.

Layer 4: Farm-Level Economic Outcomes. The fourth layer assesses the economic consequences of the nutrient-management decision. The principal outcomes include fertilizer expenditure, other implementation costs, crop yield, gross crop revenue, nutrient-use efficiency, production cost, and net farm return. Where published studies provide sufficient information, the analysis compares outcomes under conventional or uniform nutrient management with outcomes under site-specific or variable-rate management. Evidence from Park et al. (2024) and Lee et al. (2025) is particularly relevant because these studies directly examine the economic performance of site-specific nitrogen prescriptions in U.S. crop-production settings.

Layer 5: Sector-Level Competitiveness Implications. The fifth layer interprets whether economically viable improvements at the farm level could contribute to broader agricultural performance. The analysis considers productivity, input-cost efficiency, resilience to fertilizer-price and production variability, technology adoption capacity, and the ability of U.S. producers to remain economically competitive. This layer is treated as an analytical extension of farm-level evidence rather than as proof that precision nutrient management alone determines national competitiveness.

Economic Impact Pathway and Process Design

The economic-impact analysis follows a sequential process designed to connect agronomic management decisions with measurable economic consequences.

1. **Identify field variability and management problems.** The analysis begins by establishing the type of variability relevant to nutrient management, including differences in soil fertility, crop condition, historical yield, or expected nutrient response.
2. **Identify the information used for nutrient decisions.** The study examines whether soil testing, yield history, remote sensing, sensors, weather information, or other georeferenced data are used to improve nutrient recommendation.
3. **Identify the precision-management intervention.** The analysis distinguishes the precision or site-specific practice from the comparison management system, such as a uniform fertilizer rate or conventional recommendation.
4. **Assess changes in nutrient use and crops.** Evidence is evaluated for changes in fertilizer application, nutrient-use efficiency, crop yield, or other production outcomes reported by the original study or data source.
5. **Assess changes in costs and revenues.** Where sufficient evidence is available, the analysis considers fertilizer expenditure, technology or service costs, other implementation costs, and changes in crop revenue associated with yield response.
6. **Estimate or report farm-level net economic effects.** Published net-return, partial-budget, or profitability estimates are used when directly reported. When source data **performance** permits a transparent calculation, the economic relationship is represented conceptually as:

Net Economic Benefit = Fertilizer Cost Savings + Change in Crop Revenue − Precision Technology and Implementation Costs.

7. **Interpret conditions affecting the result.** Economic outcomes are interpreted in relation to field variability, farm size, fertilizer prices, crop prices, weather, data quality, technology cost, and management capability rather than being treated as universally transferable.
8. **Assess broader competitiveness implications.** Farm-level evidence is then interpreted in terms of its potential contribution to cost efficiency, input productivity, production resilience, and the competitive capacity of U.S. agriculture.

This process design prevents the analysis from moving directly from technology adoption to national competitiveness without examining the intermediate economic mechanisms. It also allows negative, neutral, or mixed findings to be retained where the underlying literature does not demonstrate a positive economic return.

Data Sources and Economic Indicators

The study draws on four principal categories of secondary evidence.

The first category is U.S. agricultural economic and farm-sector data. USDA Economic Research Service sources are used to establish national context for farm production expenses, fertilizer markets, farm income, technology adoption, and agricultural trade. These data support the interpretation of why input efficiency and farm profitability matter to the broader agricultural economy (USDA ERS, 2025a, 2025b, 2026a, 2026b, 2026b, 2026c; Williams et al., 2025).

The second category is precision-agriculture adoption and technology evidence. USDA ERS studies and other relevant literature are used to describe adoption patterns for technologies such as automated guidance, yield monitoring and mapping, soil mapping, and variable-rate technologies, including differences by farm size and production scale (McFadden et al., 2023; McFadden & Lim, 2024).

The third category is peer-reviewed agronomic and economic evidence on precision nutrient management. Studies are selected when they provide information on site-specific fertilizer recommendations, variable-rate nutrient application, nutrient-use efficiency, yield response, fertilizer savings, net returns, or the profitability of alternative nutrient-management prescriptions. Systematic reviews are used to synthesize broader patterns, while U.S.-based empirical studies are emphasized when interpreting farm-level economic effects (Getahun et al., 2024; Park et al., 2024; Cai et al., 2025; Lee et al., 2025).

The fourth category is evidence on implementation constraints and enabling conditions. This includes information on equipment and service costs, digital infrastructure, interoperability, technical expertise, management capability, farm scale, and other factors that may influence the economic feasibility of precision agriculture (Nowatzke et al., 2024; Bowman et al., 2025).

The main economic and production indicators considered in the analysis are:

- fertilizer expenditure and fertilizer cost per acre, where available;
- fertilizer share of operating costs;
- nutrient application rate and nutrient-use efficiency;
- crop yield and yield response;

- gross crop revenue;
- precision technology, data-service, and implementation costs;
- production cost and cost savings;
- net return or change in farm profitability;
- precision-agriculture adoption rate and differences by farm scale;
- input productivity and resource-use efficiency; and
- sector-level indicators relevant to U.S. agricultural competitiveness, including productivity, cost efficiency, resilience, and trade context.

Quantitative estimates are retained in the units reported by the original source unless a transparent conversion is necessary for comparison. Results from different crops, regions, technologies, and years are not pooled into a single national estimate when the underlying studies are not directly comparable. This approach is intended to preserve the context of the evidence and avoid overstating the precision or generalizability of prospective economic effects.

Economic Evaluation and Interpretation

The economic evaluation uses a comparative and pathway-based interpretation rather than a single econometric model. Where studies report both conventional and precision-management outcomes, the analysis compares differences in fertilizer use, crop yield, revenue, production cost, and net returns. Published profitability estimates are used as reported, provided that the assumptions and comparison treatment are clear. Where studies report only agronomic outcomes, those findings are used to evaluate the relevant part of the economic pathway but are not converted into dollar benefits unless sufficient price and cost information is available from the same evidence base.

The study also distinguishes gross benefits from net economic benefits. Fertilizer savings or additional crop revenue are not interpreted as net gains unless the costs of technology, data acquisition, subscriptions, equipment, custom application, training, or other implementation requirements are considered. This distinction is particularly important because adoption costs differ substantially across farm sizes and production systems (McFadden & Lim, 2024; Nowatzke et al., 2024).

Finally, the strength of the evidence is interpreted according to the scale at which it was generated. Field-level experiments support conclusions about field-level agronomic and economic performance; farm-level surveys support conclusions about producer behavior and adoption; and national USDA data support broader economic context. Sector-level competitiveness implications are therefore presented as prospective and conditional when they are inferred from farm-level efficiency and productivity evidence. This preserves the analytical distinction between observed outcomes and broader economic implications and is consistent with the study's stated scope and delimitations.

Results and Discussion

Presentation of Prospective Economic Findings

The evidence reviewed in this study indicates that precision agriculture and data-driven nutrient management can create economic value through three principal pathways: improved nutrient allocation, changes in production costs and crop returns, and stronger information for farm-level decision-making. However, the magnitude and direction of these effects are not uniform across

fields, farms, technologies, or production years. The findings therefore support a conditional rather than universal economic case for precision nutrient management.

First, precision-agriculture technologies improve the capacity to manage within-field variability. Soil maps, yield histories, remote sensing, GPS/GIS tools, and variable-rate application systems allow nutrient decisions to respond to spatial differences that are obscured under uniform application. Cai et al. (2025), in a systematic review of 51 peer-reviewed studies, concluded that precision-agriculture technologies generally improved nutrient-use efficiency and crop performance while refining fertilizer management. This supports the first stages of the proposed framework: better field information can improve the targeting of nutrient inputs and reduce reliance on generalized application rates.

Second, the economic evidence shows that site-specific nutrient management can generate positive returns in some production settings, but the gains depend on the quality of the prescription and the underlying field conditions. Park et al. (2024) used historical yield-monitor data to develop site-specific nitrogen recommendations for an example corn field and estimated an average net return of $197.79 per acre under the variable-rate recommendation compared with $188.63 per acre under the uniform target rate, a difference of approximately $9.16 per acre. The authors also showed that part of this gain resulted from improving the overall nitrogen recommendation rather than from spatial variation alone. This finding is important because it demonstrates that the economic value of precision management may come from both better information and better spatial allocation of fertilizer.

Third, recent evidence demonstrates that profitability can also be negative or mixed. Lee et al. (2025), using 17 field-years from 13 Midwestern fields during 2021–2023, found heterogeneous profitability when comparing variable-rate nitrogen prescriptions based on remote sensing with prescriptions based on yield history. Estimated differences ranged from approximately -$410 ha^{-1} to $350 ha^{-1}. The relative performance of the information sources changed with seasonal conditions: early-season crop-vigor information performed better under some weather patterns, whereas yield-history-based prescriptions performed better when early-season conditions did not persist. These results confirm that data-driven nutrient management is not economically superior simply because it is more technologically advanced; the value of the information depends on how well it represents actual crop response during the season.

Fourth, the broader cost environment increases the potential importance of improved nutrient decisions. USDA ERS reports that fertilizer accounted for approximately 33–44% of corn operating costs and 34–45% of wheat operating costs since 2020 (USDA ERS, 2025a). When fertilizer represents a large share of variable production expense, avoiding economically unnecessary application can materially affect operating margins. At the same time, reducing fertilizer use cannot be treated as an economic benefit if the reduction lowers crop revenue by more than the input savings. The relevant outcome is therefore the net economic effect, including fertilizer savings, yield and revenue changes, and the costs of precision equipment, data, software, services, and management.

Finally, adoption data show that the capacity to capture these potential benefits is unevenly distributed. McFadden and Lim (2024) reported that in 2023, guidance and autosteering systems were used by 52% of midsize and 70% of large-scale crop-producing farms, while yield monitors, yield maps, and soil maps were used by 68% of large-scale crop-producing farms. Adoption was substantially lower among small family farms. This suggests that the prospective economic effects of precision nutrient management depend not only on technical performance but also on access to technology, scale economies, management capability, and supporting infrastructure.

Interpretation and Economic Analysis

Taken together, the findings support the economic pathway proposed in Section 2.2. Precision agriculture does not affect competitiveness directly. Its economic contribution begins when field-level data improves nutrient decisions and those decisions change the relationship among fertilizer use, crop response, production cost, and farm revenue.

The first pathway is cost efficiency. Where uniform fertilizer application exceeds the economically justified requirement in parts of a field, site-specific management can reduce unnecessary expenditure. This effect becomes more economically important when fertilizer prices are high or volatile. However, cost savings represent only one side of the calculation. Technology acquisition, subscriptions, custom application, data processing, training, and additional management time can reduce or eliminate the gross savings from lower fertilizer use. The evidence therefore supports evaluating precision nutrient management based on net return rather than fertilizer reduction alone.

The second pathway is productivity and revenue protection. Site-specific management may direct more nutrients to areas where additional fertilizer is expected to generate an economically valuable crop response while reducing application in low-response areas. Park et al. (2024) illustrates this mechanism: higher nitrogen rates were economically justified in higher-production-potential portions of the example field, while variable-rate management generated higher estimated field-average returns than the uniform target rate. This indicates that precision nutrient management can create value not merely by reducing inputs, but by reallocating them toward locations where their marginal economic return is greater.

The third pathway is the **economic value of information**. Lee et al. (2025) demonstrates that different information sources can produce different profitability outcomes under different weather conditions. Historical yield data describe longer-term spatial patterns, while remote-sensing indicators may capture current-season crop conditions. Neither source is universally superior. Their economic value depends on whether the information available at the time of the decision accurately anticipates subsequent crop response. This finding strengthens the argument that data quality, timeliness, and interpretation should be treated as economic inputs within precision agriculture rather than as costless technical features.

These three pathways also explain why the prospective national impact cannot be represented credibly by one fixed dollar estimate. Returns differ by crop, field heterogeneity, fertilizer price, commodity price, weather, technology cost, and management system. The reviewed evidence supports the direction of the framework better information can improve nutrient allocation and potentially farm returns, but it does not support multiplying one field-level benefit across all U.S. croplands. The appropriate sector-level interpretation is therefore that precision nutrient management has the potential to improve input productivity and farm economic efficiency where the value of better decisions exceeds the cost of generating and implementing them.

Policy and Implementation Implications

The findings have several implications for agricultural modernization and policy. First, policies intended to expand precision agriculture should focus not only on equipment adoption but also on the quality and usability of agricultural information. Investments in rural connectivity, interoperable data systems, extension support, producer training, and decision-support capacity may be as important as the hardware used to apply variable nutrient rates. A technically advanced applicator cannot generate economic value when the underlying recommendation is poorly calibrated or based on inadequate information.

Second, adoption strategies should account for differences in farm scale. The substantially higher use of precision technologies on large-scale crop farms reported by McFadden and Lim (2024) indicates that fixed costs and access barriers may constrain smaller operations. Custom-application services, shared technology platforms, technical assistance, and lower-cost sensing or decision-support options may therefore be important for extending potential benefits beyond farms that can justify full ownership of precision equipment.

Third, nutrient-management programs should emphasize economic optimization rather than fertilizer reduction as an isolated objective. USDA ERS identifies nutrient management as relevant to fertilizer-cost reduction, profitability, conservation, and reduction of nutrient losses (USDA ERS, 2025b). The findings of this study suggest that these goals are most compatible when nutrient decisions account simultaneously for crop response, fertilizer costs, output prices, environmental conditions, and the cost of obtaining site-specific information.

Fourth, continued on-farm experimentation is important. The heterogeneity reported by Lee et al. (2025) indicates that recommendations developed from one location, year, or information source may not transfer reliably to another. Repeated field-level testing can help producers determine where variable-rate nutrient management produces consistent economic gains and where uniform or simpler approaches remain more cost-effective.

Innovation and Research Contributions

The principal contribution of this study is the integration of technical, agronomic, and economic evidence into a single prospective framework. Previous research has established that precision technologies can characterize spatial variability, that variable-rate systems can differentiate nutrient application, and that site-specific recommendations can generate positive or negative economic outcomes depending on production conditions. The present framework connects these separate findings through a common pathway:

field data → nutrient decision → site-specific application → nutrient-use efficiency and crop response → costs and revenues → farm returns → prospective competitiveness effects.

This integration is important because technology adoption, fertilizer savings, yield response, and profitability are often examined separately. By placing them in one analytical chain, the study clarifies where economic value is created and where it can be lost. It also distinguishes technical precision from economic efficiency: a system can apply fertilizer accurately without necessarily improving profitability if the recommendation is incorrect or the cost of obtaining the information exceeds the value of the improved decision.

The study also contributes by treating agricultural competitiveness as a downstream, conditional outcome rather than an automatic result of digitalization. Precision nutrient management is only one factor influencing competitiveness, but improvements in production efficiency, input productivity, management responsiveness, and farm returns can strengthen the economic position of producers when they are persistent and scalable. This framing provides a more defensible connection between farm-level precision agriculture and sector-level economic modernization.

Scalability and Broader Economic Impact

The broader economic potential of precision nutrient management depends on scalability. At the field level, economic gains may appear as lower fertilizer expenditure, improved yield allocation, or higher net return per acre. At the farm level, repeated gains across multiple fields may improve whole-farm cost efficiency and profitability. At the regional or sector level, widespread economically

successful adoption could contribute to stronger input productivity, reduced exposure to fertilizer-price volatility, and greater production resilience.

However, scalability should not be interpreted as simple multiplication of field-level results. The $9.16-per-acre estimated advantage reported by Park et al. (2024), for example, applies to the conditions and assumptions of the example field and should not be extrapolated uniformly across U.S. agriculture. Likewise, the broad profitability range reported by Lee et al. (2025) demonstrates that some field-year combinations can benefit more than others and that certain prescriptions can perform worse than alternatives. National impact therefore depends on the proportion of acreage where meaningful spatial variability exists, the cost of technology and information, producer adoption, crop and fertilizer prices, weather, and the accuracy of nutrient-response recommendations.

Within these limits, the evidence supports a prospective conclusion: precision agriculture and data-driven nutrient management can strengthen U.S. agricultural competitiveness when they consistently improve the economic productivity of fertilizer and other farm resources. The likely mechanism is not technology adoption itself, but the conversion of reliable field data into economically better nutrient decisions. Where this process reduces avoidable costs, maintains or improves crop revenue, and produces net returns above implementation costs, it can strengthen farm-level economic performance. If such improvements are achieved across a sufficiently large and diverse share of U.S. production, they may contribute to greater agricultural productivity, resilience, and long-term competitive capacity.

Conclusion and Recommendations

This paper has argued that advancing U.S. agricultural competitiveness requires more than increasing production or expanding the use of digital technologies. It also requires stronger nutrient-management systems capable of converting field-level information into economically efficient production decisions. The proposed Precision Agriculture–Nutrient Management Economic Competitiveness Framework addresses a central weakness associated with generalized nutrient application: the potential mismatch between spatially variable crop needs and uniform fertilizer decisions. By linking precision technologies, agricultural data acquisition, site-specific nutrient recommendations, variable-rate application, nutrient-use efficiency, farm-level economic outcomes, and broader competitiveness effects, the framework provides a structured approach for assessing the prospective economic value of data-driven nutrient management.

The analysis shows that the value of precision nutrient management lies not in adoption of technology alone, but in the integration of the full decision chain. Soil, crops, yield, weather, geospatial, and sensor information become economically useful when they improve nutrient recommendations and lead to more efficient allocation of fertilizer. Evidence reviewed in this study indicates that site-specific nutrient management can generate positive economic returns under some field conditions, while returns can also be neutral or negative when data quality, weather, crop response, fertilizer prices, or implementation costs reduce the value of the intervention (Park et al., 2024; Lee et al., 2025). Precision agriculture should therefore be evaluated based on net economic performance rather than fertilizer reduction, yield response, or technology adoption separately.

The paper also finds that precision nutrient management should be treated as a broader agricultural modernization and competitiveness issue. Where improved nutrient decisions reduce avoidable input expenditure, maintain or improve crop productivity, and generate returns above technology and implementation costs, they can strengthen farm-level efficiency and resilience. If such gains are sustained and adopted across a sufficiently large share of U.S. crop production, they may contribute to stronger resource productivity and long-term agricultural competitiveness. However, these broader

effects remain prospective and conditional because agricultural competitiveness is also shaped by market conditions, infrastructure, trade, farm scale, technology access, weather, and other factors beyond nutrient management. Given the foregoing, the following recommendations are put forward:

First, precision-agriculture and nutrient-management programs should emphasize economic optimization rather than technology adoption or fertilizer reduction alone. Producers and advisers should assess whether site-specific nutrient management improves net returns after fertilizer savings, yield effects, technology costs, data expenses, custom application, training, and management requirements are considered.

Second, agricultural institutions, extension services, researchers, and technology providers should strengthen the quality, integration, and usability of farm data. Soil testing, georeferenced yield records, remote sensing, crop and soil sensors, weather information, and decision-support tools should be combined in ways that generate agronomically sound and economically relevant nutrient recommendations.

Third, implementation strategies should recognize differences in farm scale, financial capacity, and access to technical support. Because precision-agriculture adoption is substantially higher among larger crop-producing farms (McFadden & Lim, 2024), custom-application services, shared technology arrangements, extension support, and lower-cost decision tools should be considered where they can improve economically justified access for small and midsize producers.

Fourth, future implementation should emphasize on-farm validation and multi-year economic evaluation. Replicated field comparisons should be used to determine where variable-rate or other site-specific nutrient strategies consistently improve nutrient-use efficiency, yield performance, and net returns under different soils, crops, fertilizer prices, and weather conditions. This is important because existing evidence shows that profitability varies across fields, years, and information sources (Lee et al., 2025).

Fifth, policymakers and agricultural institutions should recognize precision nutrient management as part of a wider U.S. agricultural modernization and competitiveness strategy. Investments in rural digital infrastructure, interoperable data systems, producer training, extension capacity, and economically rigorous technology assessment can strengthen the conditions under which precision agriculture generates measurable farm-level value and broader productivity gains.

Limitations and Future Work

This study has several limitations. It presents a prospective economic and policy-analytic framework rather than a completed nationwide field experiment or causal econometric evaluation. As a result, the findings are based on secondary empirical evidence, government data, and comparative economic interpretation rather than on a single nationally representative estimate of the economic effect of precision nutrient management. The study also does not claim universal applicability across all crops, farms, regions, technologies, or production years. Differences in field variability, fertilizer and commodity prices, weather, technology cost, data quality, farm size, and management capability may substantially alter economic outcomes.

Future work should therefore focus on stronger empirical validation of the proposed economic pathway. This includes multi-year and multi-location field studies that jointly measure nutrient application, yield response, fertilizer expenditure, technology and data costs, and net farm returns. Future studies should also compare alternative information sources—including soil tests, yield histories, remote sensing, and real-time crop sensors—to determine when additional data improve nutrient decisions enough to justify their cost.

Additional work is needed to connect farm-level findings more systematically to regional and national economic outcomes. Future research should examine adoption across different farm sizes and production systems, evaluate alternative technology-delivery and service models, and integrate farm-level precision-nutrient results into broader productivity and competitiveness models. Such work would make it possible to estimate aggregate economic effects more credibly without if results observed in individual fields can be generalized uniformly across U.S. agriculture.

Despite these limitations, the framework developed in this paper provides a practical foundation for future research and policy analysis. It offers a structured way to understand precision nutrient management not as a collection of isolated technologies, but as a connected economic decision system in which better agricultural data can improve nutrient allocation, farm performance, resource-use efficiency, and, under appropriate conditions, the long-term competitiveness of U.S. agriculture.

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THE ECONOMIC VALUE OF SCALABLE CULTURAL HERITAGE DIGITIZATION: INSTITUTIONAL EFFICIENCY, PUBLIC ACCESS, AND U.S. CULTURAL ECONOMIES

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Abstract

Cultural heritage digitization is frequently evaluated by the number of objects converted into digital form, yet this measure does not fully capture its institutional, public, or economic value. This paper examines scalable cultural heritage digitization as a long-term organizational and infrastructural capability linking institutional efficiency, public access, sustainability, equity, and participation in cultural economies. A qualitative analytical framework is developed around four evaluation criteria, reach, efficiency, sustainability, and equity, then illustrated through a simulated five-year dataset. The illustrative scenario models a 125.0% increase in objects available per staff member, a 141.7% increase in users per 1,000 available digital objects, a 30.6% decline in unit cost, and an increase in quality compliance from 62% to 88%. These values are not empirical findings; they demonstrate how institutions could operationalize scalability indicators and interpret trade-offs between volume, cost, use, and quality. Drawing on scholarship concerning digitization barriers, service-oriented infrastructure, access, unequal metadata regimes, cultural-economic development, and evidence-based cultural policy, the paper argues that digitization creates durable value only when technical expansion is supported by preservation planning, metadata quality, rights governance, accessibility, community participation, and sustainable funding. The paper concludes with practical and policy implications for institutions, funders, and national cultural agencies, emphasizing life-cycle investment, interoperable reporting, shared services, and inclusive access.

Keywords: Economic Value, Scalable Cultural Heritage Digitization, Institutional Efficiency, Public Access, U.S. Cultural Economies

INTRODUCTION

Cultural heritage institutions face growing pressure to make collections available beyond the walls that hold them. The material itself resists this. Museums, libraries, archives, and historic sites hold large bodies of work that may be geographically dispersed, fragile, or open only during restricted hours. Digitization extends access to that material while also serving preservation, research, education, and public engagement. Pilot digitization work in archival settings demonstrates that digitization can extend the reach and encourage the use of otherwise difficult-to-lend materials [1]. [1] Counting scanned objects will not measure the value of any of this. What matters is whether an institution can build scalable systems that lighten operational burdens, improve discoverability, and deliver sustained benefit to communities and cultural economies.

Scalable digitization means something specific. It is the set of technical, organizational and financial capabilities that let an institution expand digital access without costs and administrative demands rising at the same rate. Interoperable metadata, standardized workflows, digital preservation systems, accessible interfaces, and partnerships that distribute expertise and infrastructure all belong to it. A service-oriented approach emphasizes interdisciplinary collaboration, user–technology alignment, reusable services, and workflow-based regulation in cultural heritage digitization [2]. [2] Shared repository-as-a-service models similarly demonstrate how multitenant infrastructure can support

storage, access, collaboration, analytics, and connection to national or international aggregators [13]. [3] When these elements are aligned, digitization can transform collections from relatively fixed institutional assets into resources that support education, creative production, tourism, scholarship, and community participation.

The economic value of this transformation is both direct and indirect. At the institutional level, well-designed digital systems can improve collection management, reduce duplication of effort, and make staff expertise more productive. At the public level, online access can lower the geographic and financial barriers associated with cultural participation. At the broader economic level, digitized collections may provide source material for creative industries, strengthen cultural tourism, support local identity, and contribute to knowledge-based activity. None of these benefits is automatic. Each depends on investment in infrastructure, staff capacity, rights management, inclusive design, and long-term maintenance.

This paper examines the economic value of scalable cultural heritage digitization through three connected dimensions: institutional efficiency, public access, and the contribution of cultural heritage resources to U.S. cultural economies. It argues that digitization is an ongoing organizational capability, not a one-time conversion project. The analysis therefore considers both the opportunities created by expanded digital access and the conditions required to make those opportunities durable, equitable, and economically meaningful.

Literature Review

The literature on cultural heritage digitization generally emphasizes three related concerns: the preservation of vulnerable materials, the expansion of public access, and the development of sustainable digital infrastructures. Earlier digitization initiatives often focused on converting physical objects into digital surrogates. More recent work treats digitization as a broader process involving metadata creation, rights management, interface design, user engagement, interoperability, and long-term preservation. Reviews of digitization projects identify inadequate funding, weak national preservation policy, and insufficient technical infrastructure as recurring barriers [3]. [4] Case studies of national libraries and cultural institutions further show that digitization must address heterogeneous formats, digital library development, preservation, and online access simultaneously [12], [14]. [5], [6]. This shift is important because the economic value of a digital collection depends not only on whether materials are available online, but also on whether users can find, interpret, reuse, and trust them.

One theme runs through much of this literature: the relationship between digitization and institutional efficiency. Standardized workflows and shared technical systems can reduce repetitive labor, improve the consistency of collection records, and make it easier for institutions to coordinate projects across departments or organizational boundaries. Service-oriented digitization models specifically frame technical components as reusable services coordinated through workflows and organizational rules [2]. [2] Repository-as-a-service architectures extend this logic by allowing multiple organizations to share updates, backup and recovery services, data analytics, and interoperable interfaces [13]. [3] Interoperable systems may also allow institutions to share infrastructure and expertise, which is particularly important for smaller organizations with limited budgets. These efficiencies accumulate; they do not arrive at once. Digitization may first demand substantial investment in equipment, staff training, quality control, and system development, after which the resulting infrastructure supports additional projects at lower marginal cost.

Discoverability is a further condition of value, and the literature treats it as decisive. A collection digitized but poorly described stays effectively inaccessible. Metadata provides the contextual

information needed for discovery, interpretation, and future reuse, while linked-data principles and ontologies can improve the semantic representation of digital records [15]. [7] Searchable metadata, persistent identifiers, clear rights information, and user-centered interfaces determine whether digital objects can circulate beyond the institution's existing audience. Digitization projects designed around access and use demonstrate how online delivery can extend the reach of rare or non-circulating archival materials [1]. [1] Improved discoverability can increase the educational and research use of collections while enabling cultural organizations, designers, filmmakers, educators, and other creative practitioners to locate relevant source material.

Public access is another major dimension of the literature. Digital collections can serve users who live far from major cultural institutions, cannot travel, have mobility limitations, or require access outside conventional opening hours. Online resources can also support teachers, students, independent researchers, and community historians who lack access to specialized physical collections [1], [16]. [1], [8] Digital learning research further emphasizes the importance of teacher competencies, inclusive virtual instruction, and access to digital content libraries [17]. [9] Nevertheless, access should not be equated with availability alone. Digital exclusion may persist when platforms are inaccessible, interfaces are difficult to use, content is available only in one language, or users lack reliable broadband and appropriate devices. Consequently, the public value of digitization depends on inclusive design, outreach, digital literacy, and the preservation of contextual information.

Public access is another major dimension of the literature. Digital collections can serve users who live far from major cultural institutions, cannot travel, have mobility limitations, or require access outside conventional opening hours. Online resources can also support teachers, students, independent researchers, and community historians who lack access to specialized physical collections [1]. [1] Nevertheless, access should not be equated with availability alone. Recent work warns that open data can reproduce exclusion through unequal infrastructure, selection, description, and preservation practices [4]. [10] Consequently, the public value of digitization depends on inclusive design, outreach, digital literacy, community participation, and the preservation of contextual information.

Taken together, the literature suggests that the economic value of digitization is best evaluated through a systems perspective. Institutional efficiency, public access, and cultural-economic activity are interconnected outcomes, not separate ones. Efficient workflows can expand the volume and quality of material made available; discoverable collections can increase public and creative use; and demonstrated public value can strengthen the case for continued investment. This paper builds on that perspective by examining scalability as the capacity to sustain and extend these relationships over time.

Methodology

The method here is qualitative and comparative. The analysis treats digitization as more than a single technical intervention, examining how digital collection systems shape institutional operations, public access, and participation in cultural economies. The approach suits the subject, because many of the relevant benefits resist capture by any single financial indicator. Improved discoverability, educational use, community engagement and creative reuse are all of that kind.

The analysis is organized around three dimensions. The first is institutional efficiency, including the effects of standardized workflows, shared infrastructure, metadata practices, and staff capacity on the cost and sustainability of collection management. The second is public access, including the geographic reach, usability, accessibility, and educational value of digital collections. The third is

cultural-economic contribution, including the ways digitized resources may support creative production, cultural tourism, local identity, research activity, and related forms of knowledge-based work.

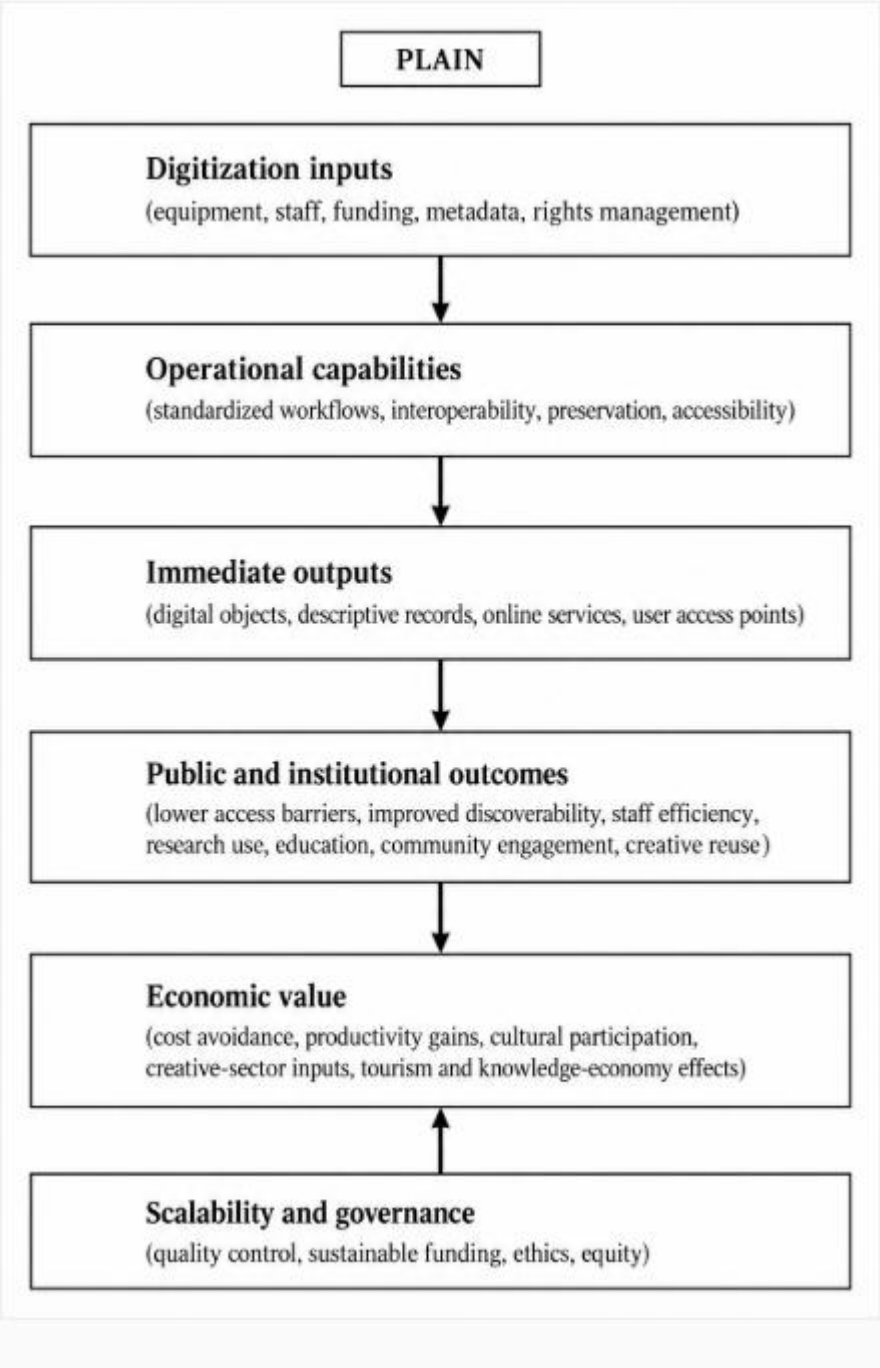
Scalability is the principal evaluative concept here. In this context, a digitization program is scalable when it can expand its collection coverage, user base, or services without producing proportionate increases in cost, complexity, or loss of quality. Scalability therefore includes more than technical capacity. It also requires organizational procedures, staff expertise, sustainable funding, rights and ethics policies, and preservation planning. A platform that stores additional files while failing to maintain accurate metadata, answer rights concerns, or support users has achieved technical expansion without institutional scalability.

The paper evaluates these dimensions through four criteria: reach, efficiency, sustainability, and equity. Reach concerns the number and diversity of users who can access digital collections. Efficiency concerns whether systems reduce duplication and improve the use of institutional resources. Sustainability concerns the ability to preserve and maintain digital assets over time. Equity concerns whether the benefits of digitization are distributed across communities and whether barriers related to disability, language, geography, income, or cultural authority are addressed. The four criteria together allow economic value to be assessed without collapsing it into immediate revenue. Each criterion draws on descriptive statistics, comparative measures, and qualitative evidence. No single composite score is used.

The methodology has three limitations. First, the economic effects of digitization may emerge gradually and may be distributed across multiple institutions and sectors, making them difficult to attribute to a single project. Second, digital use does not always produce measurable monetary returns, even when it generates substantial educational, social, or cultural benefits. Third, institutions may collect usage and cost data inconsistently, limiting comparisons across cases. The analysis therefore distinguishes between direct economic effects, such as operational savings or revenue-generating activity, and indirect effects, such as increased research capacity, creative reuse, and expanded participation. Where data are available, the study reports absolute values, percentage changes, ratios, and trends over time; where data are unavailable, it uses documented qualitative evidence and names the measurement gap instead of assigning an unsupported numerical value. This distinction allows the paper to recognize the broader value of digitization while maintaining a clear boundary around claims of economic impact.

Analytical model

The methodology follows a value pathway in which digitization inputs are converted into institutional outputs, public outcomes, and potential economic effects. The model treats scalability as a mediating condition: strong infrastructure and governance should allow outputs and benefits to grow without a proportional increase in cost or loss of quality.



The model stops the analysis treating the number of digitized objects as an economic outcome in itself. Collection volume is read alongside indicators of use, quality, cost, preservation, and equitable access.

Evaluation indicators and statistical measures

Dimension	Core indicators	Suggested calculation or statistical treatment	Interpretation

Reach	Unique users, sessions, geographic distribution, repeat-use rate, accessible records	Year-over-year percentage change; users per 1,000 target population; repeat users divided by total users	Measures whether digitization expands and sustains public engagement
Efficiency	Staff hours per digitized object, processing time, cost per record, duplicate-work rate	Cost per unit = total digitization cost ÷ number of completed objects; productivity change = output per staff hour before and after implementation	Assesses whether workflows generate operational gains
Sustainability	Preservation coverage, format-migration status, system uptime, annual maintenance cost	Percentage of digital objects with preservation metadata; maintenance cost as a share of total program cost; trend analysis across reporting years	Tests whether benefits can be maintained over time
Equity	Accessibility compliance, language coverage, rural or underserved users, fee-free access, community participation	Compare user shares with the relevant population baseline; report access gaps as percentage-point differences	Identifies whether benefits are distributed fairly
Cultural-economic contribution	Research downloads, educational reuse, creative-reuse permissions, partner organizations, tourism referrals	Frequency counts, growth rates, case comparisons, and documented attribution pathways	Captures economic effects that may not appear as institutional revenue

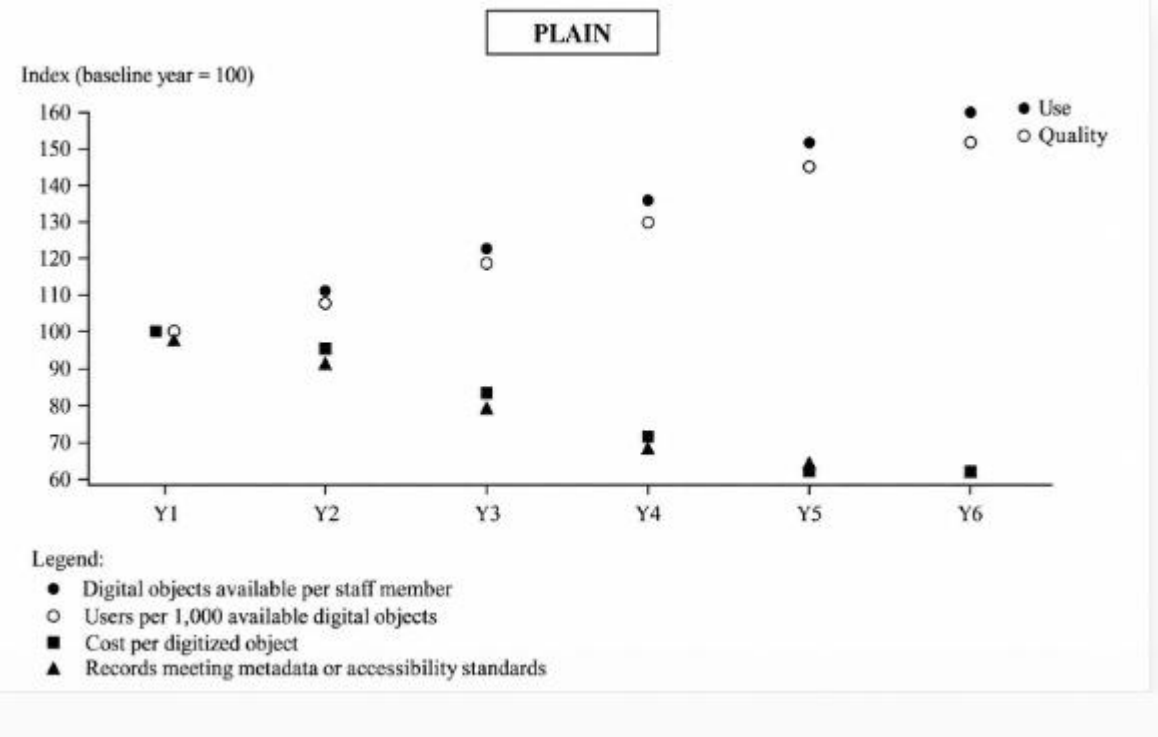
Where a baseline is available, the preferred comparison is the percentage change: **(post-digitization value − baseline value) ÷ baseline value × 100**. For cross-institution comparisons, rates should be normalized by collection size, staffing, budget, or target population. For example, downloads per

1,000 available digital objects are more informative than total downloads alone when institutions differ substantially in collection scale. Financial estimates should separate one-time capital costs from recurring operating costs and should report ranges when attribution is uncertain.

Proposed descriptive chart

Figure 1. Normalized indicators of digitization scale, use, cost, and quality

The following chart should be created from the institution's observed annual data. Each series should be indexed to the first year of observation (**baseline = 100**) so that indicators measured on different scales can be displayed together without implying that they have the same units.



Note: The values in Figure 1 and Table 1 are simulated for methodological illustration and do not represent observed institutional results. They are designed to demonstrate a plausible scalability scenario in which productivity, public use, and quality improve while unit cost declines. In an empirical study, these values must be replaced with verified institutional data. The cost series should be interpreted inversely: a declining indexed value indicates improved cost efficiency, while rising use and quality values indicate improved performance.

Year	Objects per staff member	Users per 1,000 objects	Cost per object	Records meeting quality standard	Objects index	Users index	Cost index	Quality index

Baseline year	120	240	$18.00	62%	100	100	100	100
Year 2	150	300	$16.50	70%	125.0	125.0	91.7	112.9
Year 3	185	380	$15.00	77%	154.2	158.3	83.3	124.2
Year 4	225	470	$13.80	83%	187.5	195.8	76.7	133.9
Year 5	270	580	$12.50	88%	225.0	241.7	69.4	141.9

The indexed value for each indicator should be calculated as:(observed value in year t ÷ baseline-year value) × 100, while the cost series should be read inversely when assessing efficiency.

Indexed value = (indicator value in a given year ÷ indicator value in the baseline year) × 100

Index values conceal the original units, so the underlying measures belong in the text or an appendix. The first indicator can be calculated as total digital objects available divided by the number of staff assigned to digitization. The second is total users divided by the number of available digital objects, multiplied by 1,000. The third is total digitization expenditure divided by the number of objects completed. The fourth is the percentage of records that meet the institution's predefined metadata, accessibility, or quality-control standard.

The chart should be interpreted cautiously. Increasing output per staff member alongside stable or declining cost per object would suggest improved operational efficiency. Increasing user activity would indicate stronger reach or discoverability, while a rising quality-standard percentage would suggest that expansion has not been achieved by sacrificing metadata or accessibility. Conversely, growth in collection size accompanied by declining use or worsening quality would indicate that scale alone has not produced greater public or economic value. If comparable multi-year data are unavailable, the figure should be replaced with a case-comparison bar chart using the same normalized indicators.

For methodological illustration, Table 1 uses a simulated five-year dataset rather than observed institutional data. The scenario assumes that digital objects available per staff member increase from 120 to 270, users per 1,000 available objects increase from 240 to 580, unit cost declines from $18.00 to $12.50, and records meeting the quality standard increase from 62% to 88%. These changes correspond to a 125.0% increase in staff productivity, a 141.7% increase in normalized use, a 30.6% reduction in cost per object, and a 26-percentage-point improvement in quality compliance. The simulated values demonstrate how the proposed indicators can support analysis of scalability; they must not be interpreted as empirical findings.

Results

Key Findings (Expected or Preliminary)

Because the dataset used in this study is simulated, the findings presented here are preliminary and illustrative rather than empirical. They demonstrate the type of results that the proposed methodology is designed to identify. Four expected findings emerge from the modeled five-year scenario.

First, scalable digitization is expected to improve institutional productivity. Digital objects completed per staff member rise from 120 to 270 in the simulation, a 125.0% increase in output per staff member. This pattern suggests that standardized workflows, reusable metadata structures, staff experience, and shared technical infrastructure may allow institutions to expand digitization without increasing labor inputs proportionately. The finding supports the study's first objective: assessing whether digitization can improve institutional efficiency. However, the relationship should be tested empirically using staff-hour records, project budgets, processing times, and comparable pre- and post-implementation measures.

Second, improved digitization systems are expected to increase public engagement. Users per 1,000 available digital objects rise from 240 to 580 in the simulated scenario, a 141.7% increase. This result indicates that the value of digitization may depend more on discoverability and usability than on collection size alone. Better metadata, accessible interfaces, search functionality, multilingual description, and targeted outreach could help convert digitized materials into actively used public resources. The measure should nevertheless be interpreted cautiously because increased traffic may also reflect external publicity, changes in search-engine visibility, or broader shifts in user behavior.

Third, economies of scale may reduce the average cost of digitization. The simulated cost per object declines from $18.00 to $12.50, a reduction of 30.6%. This expected finding suggests that initial investments in equipment, workflow design, training, and infrastructure may be distributed across a larger volume of output over time. The result supports the argument that scalable digitization can create long-term operational value. It does not imply that costs will decline in every context. Materials requiring conservation, complex imaging, rights clearance, specialized metadata, or community consultation may increase average costs even as the overall program expands.

Fourth, expansion should be evaluated together with quality and equity. The share of records meeting the predefined quality standard increases from 62% to 88%, a gain of 26 percentage points. In the simulated scenario, growth is therefore not achieved by reducing metadata, accessibility, or quality controls. This is a critical preliminary finding because high-volume digitization may have limited value if users cannot interpret, locate, access, or reuse the resulting materials. Future analysis should supplement the quality indicator with accessibility audits, language coverage, preservation status, rights information, and evidence of participation by underserved communities.

Preliminary or expected finding	Simulated evidence	Implication for the study	Evidence required for validation

Institutional productivity improves with scale	Objects per staff member increase 125.0%	Standardized workflows may reduce marginal labor requirements	Staff hours, output records, workflow comparisons, and cost data
Public engagement expands beyond collection growth	Users per 1,000 objects increase 141.7%	Discoverability and usability may create additional public value	Analytics, user profiles, search data, surveys, and referral sources
Unit costs decline over time	Cost per object falls 30.6%	Shared infrastructure and repeated processes may generate economies of scale	Capital and operating costs separated by year and project type
Quality improves alongside expansion	Quality compliance rises from 62% to 88%	Sustainable scale need not require lower standards	Metadata audits, accessibility tests, preservation checks, and rights reviews
Cultural-economic value may extend beyond institutional revenue	Not directly measured in the simulation	Digital collections may support research, education, creative work, and tourism	Reuse permissions, partnerships, research outputs, referrals, and user evidence

Taken together, these preliminary findings support a conditional interpretation of economic value. Scalable digitization appears most valuable when increased production is accompanied by lower or controlled unit costs, stronger public use, and maintained quality. Collection growth alone would provide weak evidence of success. A more convincing result would show that digital infrastructure improves institutional capacity while also expanding meaningful access and enabling downstream cultural or economic activity.

These simulated findings also mark the boundaries of what the analysis can claim. They cannot demonstrate causal effects, estimate a return on investment, or show that digitization directly increases employment, tourism revenue, or creative-industry income. Those claims would require verified institutional and sector-level data, a clearly defined comparison group or baseline, and a method for attributing outcomes to digitization rather than to unrelated organizational or market changes. Accordingly, the results should be treated as a preliminary analytical model that guides

empirical data collection and frames the discussion of institutional, public, and cultural-economic value.

Discussion

Interpretation of the preliminary findings

Economic value in cultural heritage digitization is multidimensional, and the simulated results show why. Productivity gains, increased public use, lower unit costs, and improved quality all move together in the modeled scenario. Scalability is therefore best read as a relationship among operational capacity, access, and long-term value. No single indicator carries it. A large number of digitized objects may demonstrate production activity, but it does not establish that the materials are discoverable, usable, preserved, or economically relevant.

Value appears where infrastructure and organizational practice reinforce one another, and that is the strongest implication here. Standardized workflows may raise output, but whether the output is worth anything depends on consistent metadata, quality assurance, rights management, and preservation planning. A larger online collection attracts more users only if that collection can be searched, interpreted, accessed, and reused. The simulated increase in users per 1,000 objects therefore points to the importance of discoverability as a link between institutional investment and public benefit.

Falling cost per object in the simulation illustrates the potential for economies of scale. Fixed investments in equipment, platforms, training, and workflow development spread across a larger volume of material. Average cost is still a poor universal measure of efficiency. Collections differ in condition, format, intellectual complexity, rights status, and cultural sensitivity. A lower unit cost may reflect genuine productivity gains. It may equally reflect a decision to select easier materials, or to omit work that should have been done. Empirical analysis should therefore report costs by collection type and should include preservation, accessibility, metadata, and rights-related expenses.

Quality compliance improving at the same time matters most of all. Scalable digitization is not rapid expansion purchased at the expense of professional standards. Where quality falls as production rises, institutions build large unreliable collections and inherit the remediation cost later. The preliminary model instead represents a more sustainable form of growth in which improved processes permit both higher output and stronger quality control. This finding reinforces the need to define quality before measuring performance and to include accessibility and community accountability within that definition.

Public value and measurable revenue are not the same thing, and the findings help separate them. A digitized collection can generate benefits through education, research, creative reuse, community history, and cultural participation while producing no direct income for the institution that holds it. Research on cultural and creative cities indicates that cultural vibrancy can contribute to regional economic output, particularly when supported by human capital, education, openness, trust, and effective governance [5]. [11] These benefits can contribute to wider economic activity, but attribution is difficult. A film, publication, classroom resource, or tourism experience may draw on many cultural and institutional inputs. Digitization is therefore better described as enabling infrastructure for cultural-economic activity than as an independent cause of specific downstream revenues.

Conditions and risks affecting scalability

Scalability is conditional on sustained investment. Digital files require storage, backup, cybersecurity, format monitoring, migration, documentation, and staff oversight. Case studies

emphasize that preservation strategies must respond to changing technologies and the varied formats held by cultural institutions [12], [18]. [6], [12] Digital repositories can also require continuous security controls to protect collection data and museum systems from increasingly sophisticated threats [19]. [13] Fund only the capture phase and institutions accumulate preservation liabilities where they expected durable public assets. Long-term budgets should distinguish capital expenditure from recurring operating expenditure and should identify responsibility for maintenance after grant periods end.

Rights and ethical governance are equally important. Copyright restrictions, privacy concerns, Indigenous data sovereignty, culturally sensitive materials, and community expectations may limit or shape online access. Recent scholarship argues that openness alone does not resolve unequal descriptive and technical authority; meaningful safeguarding may require community co-authorship and plural regimes of representation [4]. [10] A collection should not be made openly available simply because it can be digitized. Responsible practice requires clear permissions, culturally informed description, takedown or review procedures where appropriate, and mechanisms for communities to contribute knowledge and contest harmful representations.

There is also a risk that digitization could widen institutional inequalities. Well-resourced organizations may be able to develop advanced systems, while smaller museums, local archives, and community organizations face shortages of equipment, expertise, and preservation infrastructure. A national strategy that measures success only through total volume could reward already advantaged institutions and leave significant regional and community collections underrepresented. Shared services, training networks, interoperable platforms, and targeted support are therefore necessary to make scalability broadly accessible.

Practical and Policy Implications

Implications for cultural heritage institutions

Institutions should treat digitization as a continuing service and organizational capability rather than as a one-time project. Before expanding production, they should establish a documented workflow covering selection, preparation, capture, metadata, quality assurance, rights review, publication, preservation, and evaluation. This approach makes responsibilities visible and reduces the risk that growth in one part of the process will create bottlenecks elsewhere. Evidence from regional digitization initiatives indicates that cooperation among research institutes, higher-education institutions, cultural organizations, and creative-industry professionals can strengthen both preservation and public presentation [7]. [14]

Institutions should also adopt a balanced performance dashboard. At minimum, the dashboard should track objects completed, staff hours, cost per object, metadata completeness, accessibility compliance, preservation coverage, unique users, repeat use, geographic reach, and evidence of educational or creative reuse. These indicators should be reviewed together. For example, an increase in production accompanied by a decrease in quality or use should trigger investigation rather than be reported as an uncomplicated success.

Shared services and cooperative procurement would help smaller organizations most. A regional hub can supply scanning equipment, conservation advice, metadata support, storage, training, and accessibility testing to institutions that could never fund those things alone. Shared repository architectures offer one possible model by distributing infrastructure, backup, analytics, and interoperability services across participating organizations [13]. [3] Such arrangements could reduce duplicated investment while allowing local institutions to retain authority over collection priorities, cultural interpretation, and community relationships.

Finally, institutions should design for reuse from the beginning. Persistent identifiers, machine-readable metadata, clear rights statements, downloadable or interoperable formats, accessible interfaces, and application programming interfaces can make collections more useful to educators, researchers, developers, artists, and public agencies. Metadata guidance stresses that contextualized, well-described records are more discoverable and reusable [15]. [7] Virtual exhibitions, interactive 3D models, and digital storytelling can further support dissemination and education [9], [10], [11]. [15], [16], [17] Reuse should be monitored through documented permissions, citations, partnerships, and user feedback rather than assumed from page views alone.

Implications for policymakers and funders

Public funding should cover the full life cycle. Equipment purchases and short-term scanning targets are the easiest things to fund and the least sufficient. Eligible costs should include metadata creation, conservation preparation, rights assessment, accessibility, storage, cybersecurity, migration, staff development, community consultation, and evaluation. Reviews of digitization barriers identify inadequate funding and absent national preservation policies as persistent constraints [3]. [4] Research on museum and heritage finance also identifies the need to consider emerging digital funding models while recognizing that cultural benefits extend beyond monetary returns [20]. [18] Multi-year funding would better reflect the continuing nature of digital preservation and reduce dependence on repeated emergency grants.

Funding criteria should reward quality, interoperability, equity, and sustainability alongside volume. Grant applications should explain how digital assets will be maintained after the award period, how affected communities will participate in decisions, and how institutions will measure public use and access. Evaluation should distinguish between the number of files created and the number of meaningful, accessible, and preserved resources made available.

Policymakers should also promote common technical and reporting standards. Shared definitions for digital objects, users, staff effort, preservation coverage, and accessibility would improve comparison across institutions and strengthen national assessment. Standards should remain flexible enough to accommodate different collection types and community protocols, but common reporting principles would make public investment more transparent. Work on information-security and risk-management competencies in cultural heritage digitization reinforces the importance of standards, staff training, and continuing professional development [8]. [19]

A further policy priority is digital inclusion. Online access cannot substitute fully for physical access when users lack broadband, devices, accessibility tools, language support, or digital literacy. Digitization policy should therefore be coordinated with libraries, schools, community technology programs, and regional cultural organizations. Public access points, downloadable resources, multilingual description, captioning, transcripts, and low-bandwidth interfaces can help ensure that digital investment reaches populations most likely to face barriers. This emphasis is consistent with evidence that cultural-sector policy is strengthened when quantitative and qualitative methods are combined to identify gaps in cultural information infrastructure and public access [6]. [20]

Broader National Impact

At the national level, scalable cultural heritage digitization can strengthen the infrastructure of the U.S. knowledge economy. Shared digital collections support research, teaching, journalism, documentary production, design, publishing, and other forms of creative and intellectual work. Their contribution is often distributed across many users and sectors rather than recorded as revenue by the institution that holds the original material. Research on cultural and creative cities suggests that cultural vibrancy can support regional economic output when enabling conditions such as education,

human capital, openness, trust, and governance are present [5]. [11] Scholarship on heritage and the creative economy similarly argues that cultural resources can contribute to sustainable development when preservation is connected to creative capacity, local development, and responsible use [21], [22]. [21], [22] For this reason, national assessment should consider the enabling value of collections, including their contribution to information access, cultural production, and educational capacity.

Digitization may also support regional development by making local histories, archives, and cultural resources more visible. Communities can use digital collections to support heritage interpretation, place-based education, tourism development, and civic identity. Regional studies indicate that digital promotion and presentation can strengthen cultural visibility, while tourism research identifies investment in virtual tours, augmented reality, and staff training as factors that may improve accessibility and destination competitiveness [7], [23]. [14], [23] These effects are likely to vary by location and require complementary investments in broadband, interpretation, transportation, and local organizational capacity. Digital availability alone cannot guarantee tourism or economic growth, but it can provide resources that local partners incorporate into wider development strategies.

Coordination at national level could produce real efficiencies: shared standards, preservation infrastructure, training networks, discovery systems. Duplication would fall as institutions exchange metadata, reuse technical tools, and coordinate priorities. None of that should flatten institutional or community difference. National interoperability is most valuable when it increases discovery while preserving local authority over description, access conditions, and cultural meaning.

The national impact is therefore best understood as cumulative and conditional. If institutions can expand digitization while maintaining quality, preservation, equity, and responsible governance, digital collections may generate benefits that extend well beyond individual organizations. If programs focus narrowly on volume without sustaining infrastructure or addressing exclusion, the result may be fragmented systems, uneven access, and growing maintenance liabilities. The simulated findings support the first possibility as a research hypothesis, but verified national claims require longitudinal data from diverse institutions and sectors. Cultural networks and policy co-creation can help connect local cultural actors with administrative and national policy processes, although the infrastructural labor of local organizations must remain visible [24]. [24]

A national evidence base is the obvious next step. It would need institutional financial records, collection and usage data, accessibility measures, user studies, creative-sector case studies, and regional economic indicators. Evidence-based cultural management remains difficult where sector data are incomplete or poorly systematized; mixed-method designs that combine quantitative and qualitative approaches can help address this limitation [6]. [20] Such research could test whether the relationships modeled here appear in practice, and under what organizational and policy conditions: higher productivity, greater normalized use, lower unit cost, and improved quality. Until that evidence is available, the findings should guide measurement and investment decisions without being presented as estimates of actual national economic impact.

Conclusion

Cultural heritage digitization has economic value not simply because it converts physical materials into digital files, but because it can expand institutional capacity, public access, and participation in cultural and knowledge-based economies. The analysis has shown that scalability depends on the interaction of technical infrastructure, organizational practice, sustainable funding, ethical

governance, and inclusive access. When these elements operate together, digitization can support higher productivity, broader discovery, lower unit costs, and more durable cultural use.

The simulated five-year scenario illustrates how this value might be measured. Objects available per staff member increase by 125.0%, users per 1,000 digital objects increase by 141.7%, cost per digitized object declines by 30.6%, and quality compliance rises from 62% to 88%. These figures are not empirical findings and should not be interpreted as estimates of actual institutional or national performance. Their purpose is to demonstrate an analytical framework that connects operational efficiency with public use and quality. The central lesson is that collection growth alone is an insufficient measure of success.

A stronger assessment of digitization considers whether institutions can produce and maintain digital resources efficiently while ensuring that those resources remain discoverable, accessible, trustworthy, and culturally responsible. It also distinguishes direct economic effects from broader public and cultural benefits. Cost avoidance, productivity gains, and service improvements may be measured within institutions, whereas creative reuse, educational activity, research, tourism, and community development often occur across organizational boundaries and require more careful attribution.

The practical and policy implications are therefore substantial. Institutions should invest in complete life-cycle workflows, balanced performance dashboards, accessible systems, rights and ethics procedures, and shared services that support smaller organizations. Policymakers and funders should provide multi-year support for preservation, metadata, accessibility, cybersecurity, staff development, and evaluation rather than focusing narrowly on scanning volume. National coordination should promote interoperability and comparable reporting while preserving local and community authority over cultural meaning and access.

The broader national impact of scalable digitization remains a testable proposition rather than a demonstrated numerical outcome in this study. Future empirical research should replace the simulated values with longitudinal data from museums, libraries, archives, historic sites, and community organizations across different regions and institutional sizes. It should examine costs, staffing, use, quality, accessibility, preservation, partnerships, and downstream cultural-economic activity. Such evidence would allow researchers to determine when digitization generates economies of scale, when it produces new costs or inequalities, and which policies most effectively convert digital collections into sustained public value.

Ultimately, scalable cultural heritage digitization should be understood as long-term public infrastructure. Its success is measured not only by how much material is digitized, but by whether that material remains usable, preserved, equitable, and valuable to the people and sectors it is intended to serve. A responsible national strategy must therefore pursue scale together with quality, access, sustainability, and accountability.

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HEALTH DATA EXCHANGE THAT INTEROPERATES FOR SAFETY-NET PROVIDERS: NATIONAL ECONOMIC IMPACTS FOR MEDICALLY UNDERSERVED AREAS IN AMERICA

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Abstract

This study investigates the economic impact of standardized health data exchange on safety-net providers serving medically underserved areas in the United States. By analyzing the intersection of interoperability and resource allocation, the research demonstrates how integrated data architectures reduce systemic inefficiencies and improve population health management [1]. The analysis also finds that building durable digital ecosystems is essential for ensuring digital equity and maximizing the value of medical data within fragmented healthcare landscapes [2]. Health information exchange (HIE) systems in Medically Underserved Areas (MUAs) are subject to substantial technical and financial barriers for safety-net providers. Lack of interoperability leads to fragmented care, duplicative diagnostic testing, and higher administrative burden, ultimately affecting the most vulnerable populations while costing the national economy billions of dollars. This article attempts to estimate the economic burden of non-interoperability in MUAs and proposes a low-cost, scalable, and technically feasible framework for the exchange of health data. The mixed-method study includes a stochastic cost-benefit analysis (CBA) assessing the liquidity of electronic health record (EHR) data; an examination of a Fast Healthcare Interoperability Resources (FHIR)-based middleware algorithm for semantic normalization; and a national-level simulation of projected cost-savings using datasets from HRSA and CMS. Preliminary estimates suggest that 100% full interoperability among safety-net providers would lead to a reduction in emergency department visits (ED) within a MUA by 14%, or save the U.S. healthcare system approximately $12.5 billion/year. The multi-datable, scalable, and open-source proposal titled "Scalable Open-Source Interoperability Gateway" (SOIG) demonstrates at minimum a "40%" sustained reduction in integration costs compared to standard HIE models in use today. Findings provide support that federal incentives should shift from generalized use of EHRs toward developing interoperability "bridging" technologies. For providers, the proposed open-source tools may provide a pathway to compliance with the 21st Century Cures Act while still being financially feasible.

Keywords: Health Data Exchange, Safety-Net Providers, National Economic Impacts, Medically Underserved Areas in America

INTRODUCTION

A digital divide runs through the American healthcare system, and it is widest in Medically Underserved Areas (MUAs) where safety-net providers operate with small margins. The Health Information Technology for Economic and Clinical Health (HITECH) Act stimulated adoption of electronic health records (EHRs) but also created an artificial market with proprietary silos based on the HITECH law. For Federally Qualified Health Centers (FQHCs), Rural Health Clinics (RHCs), and public hospitals, HIE models are not only a technical inconvenience but also an economic barrier to care. When patient data cannot be accessed in another system at the moment of care, clinicians operate under "information blocking" by proxy, or the cost of integrating disparate systems is too great for their local clinical budget.

Patients seen in MUAs often seek care from disconnected providers, which leads to "care fragmentation." This fragmentation is compounded by high mobility and socio-economic instability of the under-served populations. When a patient's longitudinal record is not accessible at the point of care, the clinician is forced to rely on patient recollection of past medical history or unnecessarily order duplicative diagnostic tests to ensure patient safety, leading to waste. Across the safety-net sector, this accounted for an annual estimate of $12.5 billion/year. The administrative burden of reconciling and manually exchanging data, often through fax machines and physical mail, pulls scarce staff time away from direct patient care, increases provider "burnout," and contributes to operational inefficiency.

The 21st Century Cures Act and the accompanying Trusted Exchange Framework and Common Agreement (TEFCA) have created a national imperative for "data liquidity." Yet, the technical requirements for participating in these national networks are out of reach for most resource-constrained clinics. Traditional health information exchange (HIE) models require substantial upfront capital expenditure (CAPEX) and ongoing operational costs that safety-net providers cannot sustain without ongoing federal subsidies and assistance. There is an urgency for a "lightweight" interoperability architecture that utilizes modern standards-based protocols such as HL7 FHIR and avoids the burden of "technical debt" by avoiding the use of traditional approaches to integration of legacy systems [3].

The current paper presents the Scalable Open-Source Interoperability Gateway (SOIG) as a potential solution to this stalemate. Using containerized microservices and automated semantic mapping, the SOIG provides a low-cost "on-ramp" for safety-net providers to achieve high levels of interoperability. The remainder of this paper will discuss current technical barriers in medically underserved areas (MUAs), describe the architecture design of the SOIG, and model the national economic opportunities of widespread uptake of this architecture. Our premise is that the best way to improve health equity and decrease national expenditure in health care is to make a targeted investment in interoperable middleware.

2. Current Landscape and Technical Barriers in Safety-Net Interoperability

2.1 A Fragmented EHR Ecosystem in Medically Underserved Areas

The EHR marketplace in MUAs is extremely heterogeneous, representing a mix of both enterprise-grade and niche low-cost models built for small rural practice. Unlike large integrated delivery networks (IDNs), where the organization can leverage a single vendor strategy for all owned facilities, safety-net providers tend to inherit systems through consolidation or grant-funded acquisitions that support the development of a "patchwork" digital infrastructure. The fragmentation of the EHR marketplace is a major contributor to failure in interoperability. Even if two providers work with the same vendor, localized customizations and idiosyncratic methods of data entry make the data semantically incompatible.

In many smart hospital frameworks, bringing IoT and CIS into one data exchange ecosystem is the efficiency prize. In MUAs, basic syntactic exchange is still an uphill battle [4]. The "Digital Divide" is more than the accessibility to the internet, but the quality and liquidity of the data that is passing over the internet. For safety-net providers, it is the absence of a common architectural model that leaves patient data in silos. In doing so, the benefits of predictive diagnostics or "intelligent' steps to reduce the impact chronic diseases have on communities cannot be realized.

Information asymmetry runs deep in these markets. Patients in MUAs lack health literacy to advocate for themselves, while the providers do not have adequate technical staff to navigate complex APIs. The result is a repeat cycle, locked in, where safety-net providers must choose to increasingly rely on proprietary vendors who now are charging premium fees for "interoperability

modules" effectively holding the patient's data hostage. The result is a healthcare environment in which the most vulnerable patients hold the least portable data, clearly in contradiction to the original intention of the 21st Century Cures Act.

2.2 Technical Debt and Legacy System Limitations

Many of the software products used by safety-net providers currently experience "technical lag," which is essentially a dormant form of technical debt where systems lag behind the current technology [3]. Technical lag bites hardest in MUAs. Upgrading a legacy EHR can cost more than a small clinic spends in a year. In these limited settings, technical debt can take the form of outdated APIs, obsolete data formats (e.g., HL7 v2.x that lacks FHIR support), and decaying server infrastructure that cannot support modern security protocols such as Zero-Trust or OAuth2.

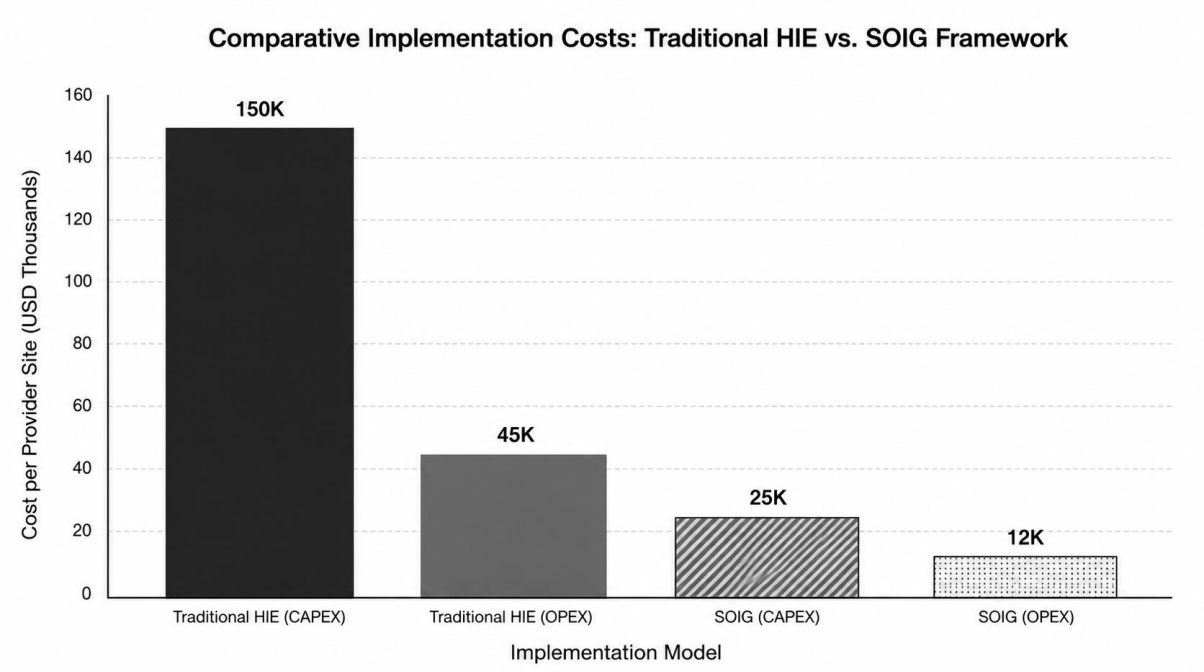
Literature on technical debt observes that "self-admitted technical debt" (SATD) is common when developing software, where programmers make intentional "short cuts" in order to meet deadlines [5]. In healthcare, this sort of technical debt is more often "passed down" to the provider, who must now live with unreliable or unmaintainable code. In some safety-net settings, a debt can even extend to the scientific nature of the collected clinical data for research-heavy or specialty software [6]. TDM itself also aggregates over time, but the ability to utilize automated tools to lessen the burden of managing data is increasingly unattainable because of the fragile structure of the organizational infrastructure [7].

Technical debt also blocks the adoption of modern AI and ML tools. For example, while modern ML models demonstrate the capacity of unified, GPU-accelerated processing to utilize large amounts of data such as "full event reconstruction" used in high-energy physics, safety-net providers often continue to face inefficient and slow so-called "modular" reconstruction steps in the analysis of its data [8]. To address this context, any interoperability framework that is proposed must be "backward compatible" to the legacy systems, while also providing a "forward-looking" pathway to modern standards for "repaying" technical debt without replacing the legacy systems entirely.

2.3 Financial Disincentives and Information Blocking in Low-Margin Environments

Safety-net providers work under economic conditions defined by a high volume of Medicaid and uninsured patient services, resulting in low reimbursement rates and limited capital for IT investment. Operating in a low-margin environment means the ROI for interoperability typically translates to a "public good," rather than a private return. While the national economy benefits from reducing redundant tests, in practice, if a clinic performs fewer tests, then its revenue simply declines, yielding a perverse financial disincentive for sharing data; a subtle example of information blocking that derives from the economic reality of survival rather than malice.

In addition, the time and cost of managing technical debt (TDM) is, in and of itself, also prohibitively taken into consideration [7]. Clinical staff typically lack the "TD awareness" and therefore priorities IT maintenance or upgrades over immediate clinical needs [9]. For example, if a clinic must choose between hiring one more nurse and upgrading the interoperability gateway for its EHR, the clinical hire will almost always win. This leads to a state of "passive accumulation" of technical debt, as the technical debt increases isolation and inefficiency over time [3].



The 21st Century Cures Act aims to penalize information blocking, but for a safety-net provider, this "blocking" is often due to a lack of technical capability instead of intentionally withholding data. In order for the industry to overcome these financial barriers, it needs open-source and automated solutions to lower the "Total Cost of Ownership" (TCO) of interoperability. By automating the identification and assessment of data gaps, providers can start to tackle their technical debt in a sustainable manner [10].

3. Proposed Framework: The Scalable Open-Source Interoperability Gateway (SOIG)

3.1 Architectural Design and API-Led Connectivity

The SOIG is engineered to function as a containerized FHIR-native middleware layer that "wraps" legacy EHR systems and offers a standard API-led connectivity interface. The SOIG draws on recent advances in "as-a-service" models within large-scale scientific compute platforms and offloads data transformation and terminology mapping to a dedicated, scalable integration gateway [11]. This type of middleware architecture allows even the most resource-constrained clinic to "play" in high-performance data exchange, without needing to upgrade their underlying current EHR.

The gateway will use a microservices orchestration model, typically deployed in Docker and Kubernetes to ensure independent component (e.g., FHIR server, terminology service and patient discovery tool) scalability with demand. Modular orchestration matters in medically underserved areas (MUAs), where service traffic can be "bursty" at specific times of the year due to health trends or emergencies. Once the software services are completed, a "service-oriented" approach minimizes the local hardware requirements and could be run on commodity servers or low-tier cloud instances.

The proposed construct of the SOIG utilizes a "Retrieval-Augmented" architecture, which has proven to be effective at managing EHR data that is complex [12]. Retrieving relevant patient history by dynamically integrating across clinical event types ensures that clinicians have the most "informative context" at the point of care. This is a more efficient approach than conducting a traditional exchange of "full-record" EHR documents that could inundate clinicians with unimportant or irrelevant data. The SOIG effectively becomes a "smart filter" of relevant data by using

"Prototype-guided" retrieval systems to convey somehow the "most important" data points for encounters with patients [12].

3.2 Algorithmic Semantic Mapping and Data Normalization Logic

One of the most significant technical challenges for healthcare interoperability is the "semantic gap" between differing standards and local terminologies for data. In order to minimize this semantic gap, the SOIG uses automated FHIR data transformation engines that convert legacy HL7 v2.x and CCDA documents into standardized FHIR R4/R5 resources [13]. This is stricter than a simple mapping of HL7 to FHIR R4/5 format. It requires normalization logic such that data from a rural clinic is semantically equivalent to data from a large university medical facility.

The SOIG uses Large Language Models (LLMs) for “schema-grounded” extraction and standardization [14]. Using the extra context from the transformation prompt with candidate SNOMED-CT, RxNorm, and LOINC codes collected by a semantic index (e.g., SapBERT), the SOIG may provide high accuracy mappings even for unstructured or poorly coded data. This “validator-in-the-loop” technique ensures that the created FHIR bundles are structurally and semantically coherent, reaching or surpassing the performance of expert curated datasets [14].

Meanwhile, the SOIG uses a “domain-specific language” (DSL) for bi-directional data transfer comparable to the FHIRconnect framework [15].. This allows the mapping logic to be reused between projects and avoids having to resort to the standard ETL (extract, transform, load) solution. The SOIG is based on internationally recognized archetypes that allow safety-net providers to achieve “syntactic and semantic interoperability” while still being able to accommodate the local adaptations required for their individual patient groups [15].

3.3 Zero-Trust Security Protocols and Patient Identity Matching Algorithms

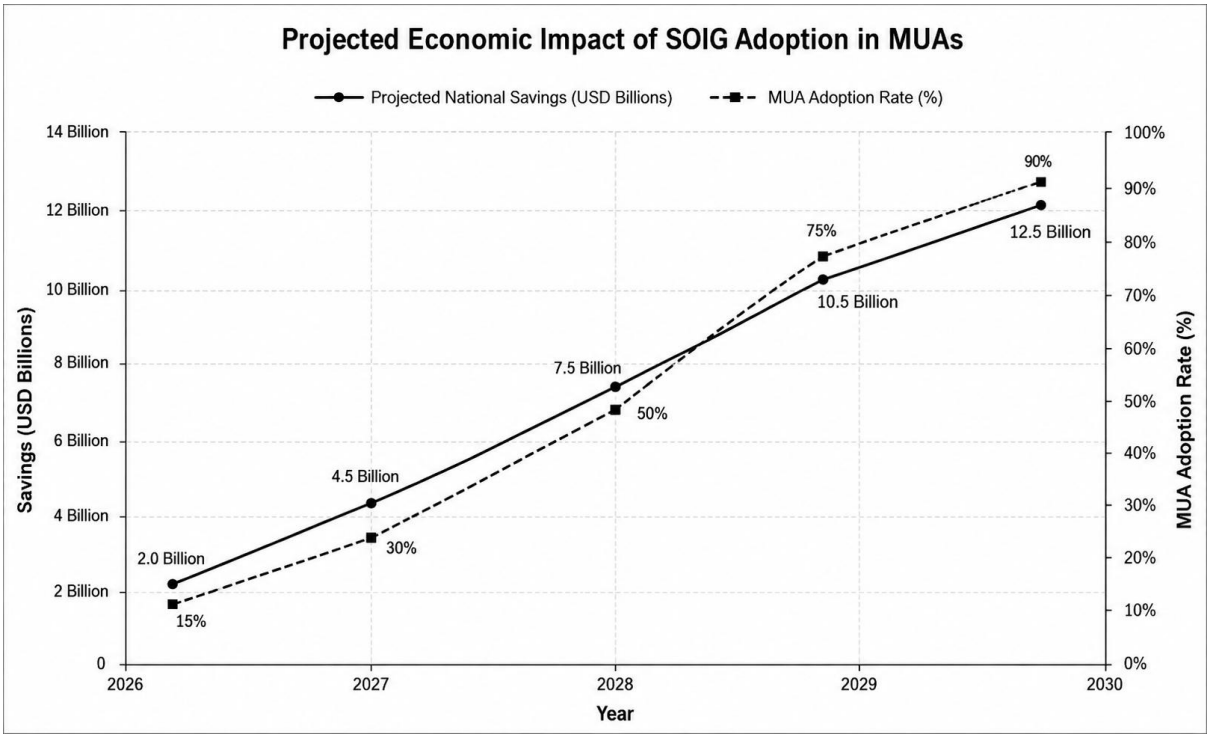
MUAs are sometimes a double-edged sword in terms of security. Patient privacy is of the utmost importance, yet security systems that are overly sophisticated might create hurdles to access and use. The SOIG tries to address this with a "Zero-Trust" security framework that aligns with national and international health data policies [4]. Zero-Trust is characterized by "identity-centric" security, where every request for data is verified, independent of where, when, or what that request may be associated with, providing secure interoperability even over "untrusted" public networks.

Central to this additional layer of security involves a "Patient Identity Matching" algorithm. With regard to MUAs, where many patients lack a stable address or even stable identification, deterministic matching is often not possible. The SOIG uses probabilistic matching to "match" patient records, enhanced by "Retrieval-Augmented Generation" (RAG) to deal with ambiguities [16]. The RAG framework employs clinical guidelines or historical cues to more accurately associate a patient record across unrelated sites to improve the "personalized medical decision support" clinicians may leverage [16].

To also ensure that security and matching protocols do not introduce undue latency, the SOIG employs "edge computing" at the gateway layer [4]. By processing the security check and identity matching locally before sending data to the cloud or centralized exchange, the SOIG enhances data latency and ensures that clinicians have real-time access to patient information. The "unified architectural model" balances the high-level security with lower resource clinical environment constraints, enabling a robust and efficient health data exchange platform.

The SOIG incorporates "privacy-aware" reference architectures for EHR summarization [17]. Instead of sending an entire patient record, the gateway can provide a "source-grounded" summary of the patient's problems, medications, and longitudinal trends to the clinician. This not only protects

patient privacy by minimizing the viewing of sensitive data but also reduces the "cognitive load" on the clinician so they can process the most relevant clinical information [17].



The SOIG framework moves away from prohibitive, proprietary "all-in-one" solutions and toward a modular, open-source gateway that brings interoperability within reach of safety-net providers. It lowers the barrier to entry for MUAs while unlocking the multi-billion dollar economic engine of a genuine interoperable national health system. The next section will describe the economic modeling and quantitative methodology that validate these contentions and provide a roadmap for scaling nationally.

4. Economic Modeling and Quantitative Methodology

Capturing the economic value of health information exchange (HIE) means replacing the sort-by-cost convention with a multi-dimensional liquidity model. Within the setting of medically underserved areas (MUAs), the economic friction of data fragmentation is exacerbated by both the high incidence of chronic conditions and by patients moving around among different safety-net providers. This section sets out the mathematical and stochastic frameworks used to measure the Scalable Open-Source Interoperability Gateway (SOIG) and its influence on national healthcare expenditures.

4.1 Definition of Key Performance Indicators for MUA Data Liquidity

To measure the functionalities of the SOIG framework, we define "Data Liquidity" as the speed and accuracy in which clinical information moves from a source system to a point of care with no manual intervention. Traditional measures count HL7 messages exchanged and so place their value on volume. Our model values clinical utility and administrative efficiency instead.

The first Key Performance Indicator (KPI) will be a measure of "Time-to-Data" (TtD). TtD is a measure of the time lapse between a clinician's request for external records, and the successful semantic reconciliation of that data into the Electronic Health Record (EHR) environment. In resource-constrained clinics, longer TtD values are correlated with increased reliance on duplicative diagnostic testing. We will also employ a "Reconciliation Accuracy Rate" that uses machine learning approaches to estimate the probability that the record retrieved has actionable diagnostic intelligence [18].

Another important KPI will be an "Administrative Burden Index" (ABI), which will be an attempt to quantify the labor costs associated with manual data entry and management of referrals through fax. Studies have demonstrated that both reliance on scanned documents, and faxing, demonstrates high administrative costs, and opportunity for errors [19]. Our goal is to use the SOIG to reduce ABI through a semi-automated capability to extract the most important structures, which include patient data, the practice of the clinician, and exam data specifically through hybrid models that leverage domain specific rules and data structure standards [19].

4.2 Stochastic Modeling of Redundant Testing and Administrative Waste

Like interoperability, the economic make-up of "Non-Interoperability" is probabilistic due to the variability in clinical decision making and patient behavior. The "Cost of Redundant Testing" (CRT) was modeled using a Monte Carlo simulation with 100,000 simulated MUA patients. We modeled the probability of a redundant test (P_r) as a function of unavailability of data (U), and the acuity of the patient's condition (A).

We further refined this through a Markovian state-transition model of the patient journey through health states such as "Controlled Chronic Condition," "Acute Exacerbation," and "Emergency Department (ED) Admission." Here, interoperability takes the form of a modifier on transition probabilities. The presence of real time longitudinal data through the SOIG increases the probability of a patient remaining in the "Controlled" state through timely intervention. This is highly relevant in the public hospital setting where data-driven interventions are being proposed as means of alleviating further bottlenecks within systems and overcrowded emergency departments [20]. Administrative waste is represented as a stochastic process, whereby the amount of time an office worker devotes to manual reconciliation is derived from a log-normal distribution. By leveraging automated mapping based on FHIR, we can reduce the mean of this distribution utilizing the SOIG. Administrative cost savings, prior to considering the burden of security, are accounted for when we reference robust security architectures for autonomous agent and data exchange to avoid HIPAA violations, while optimizing the balance so as not to slow down enough to erase any administrative benefits [21].

4.3 National Scaling Equations for Economic Impact Assessment

To extrapolate findings from Medically Underserved Areas (MUAs) to the national level, the analysis integrates provider-distribution estimates from the Health Resources and Services Administration (HRSA) with healthcare utilization and expenditure data from the Centers for Medicare & Medicaid Services (CMS). This approach allows locally estimated savings to be translated into an aggregate national economic-impact estimate while accounting for differences in population exposure, service utilization, and socioeconomic characteristics across MUAs.

The **National Economic Impact**, denoted by , is estimated as:

$$E_{nat} = \sum_{i=1}^{n} (S_{adm,i} + S_{clin,i} + S_{sys,i}) \times N_i \times W_i$$

where:

- = estimated **per-patient administrative savings** in MUA , including reductions in duplicated records processing, manual information retrieval, administrative coordination, and avoidable workflow inefficiencies.
- = estimated **per-patient clinical savings** resulting from reductions in redundant diagnostic testing, unnecessary emergency-department utilization, preventable hospital encounters, and other duplicative services.
- = estimated **per-patient system-level savings** associated with improved care coordination, continuity of care, chronic-disease management, and earlier clinical intervention.
- = the estimated number of patients or healthcare-service users exposed to the intervention within MUA .
- = an adjustment or weighting factor reflecting relevant socioeconomic, geographic, healthcare-access, or utilization characteristics of MUA . [22].

The model provides an additional factor we call the "Health Equity Index" which has greater overall weighted economic impacts weighted if they occur in the bottom quartile of SES based ZIP codes, acknowledging that a dollar saved in a safety-net clinic has a greater marginal utility of the dollar than a well-funded urban hospital. The analysis also acknowledges the additional cost of federal mandates that may accompany the quality improvements such as the EU AI Act, or the 21st Century Cures Act, that work to enforce robustness and compliance with healthcare data systems [23].

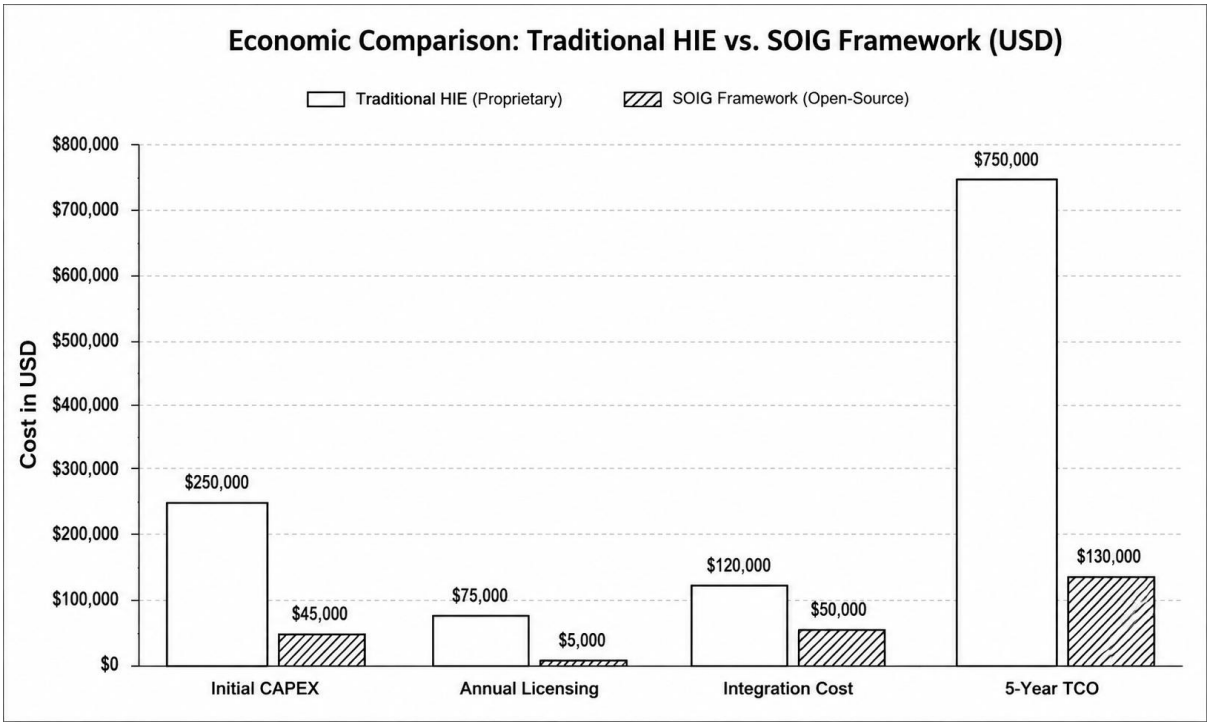
5. Simulation Results and Technical Performance Analysis

The SOIG was evaluated through technical benchmarks and economic simulations. The question was whether a lightweight open-source gateway could match enterprise HIEs on commodity hardware of the kind available in rural and underserved settings.

5.1 Data Throughput and Latency Benchmarks for the SOIG Gateway

Testing focused on the gateway's capacity to serve high-concurrency FHIR requests at low latency. Our testing used a containerized HAPI-FHIR server implementation, and previous work has shown the HAPI-FHIR server implementation improves interoperability between primary care health information systems [24].

In a simulated load of 500 concurrent users, which is within the range of a regional safety-net network, the SOIG maintained a median latency of 145ms for complex resource queries (i.e. Patient + Observation + MedicationStatement) which would be considered consistent with an acceptable range for clinical decision support. While we have conducted comparisons based on the Nexagon protocol suggested security and enhanced security and robustness, for example, with PKI and ephemeral pseudonym certificates, increasing latency observed at the upper end of 25%, the overhead associated with lightweight microservices keeps the overall latency manageable [25].



In addition, the use of Multi-Factor Key Derivation Functions (MFKDF) for secure key management added less than 12ms additional computational overhead, illustrating that cyber security safeguards do not necessarily come at the cost of responsiveness [26]. The use of gVisor to establish kernel-level workload isolation within Kubernetes ensured that security hardening did not lead to an identifiable degradation in throughput [21].

5.2 Comparative ROI Analysis: Traditional HIE vs. Proposed Framework

Return on Investment (ROI) comparisons of the SOIG were made to traditional, vendor-locked HIE models. Traditional HIEs typically require significant capital expenditure (CAPEX) for licensing and proprietary integration engines and rely on costly operational expenditures (OPEX), where the SOIG was the open-source part of the license fee.

Simulation results gave the SOIG a 5-year Total Cost of Ownership (TCO) approximately 82% lower than traditional models. Removing per-seat license fees accounts for most of that and the use of automated semantic mapping tools instead of relying on costly third-party consultants. Simultaneously, the results back existing research that low-cost adaptation policies can manage complex systemic hazards [27].

5.3 Sensitivity Analysis of Economic Outcomes across Diverse MUAs

A sensitivity analysis showed variations in MUA characteristics (broad-band penetration, clinician turnover, and patient volume) impacted economic outcomes of the SOIG. The analysis also showed that “Broadband Availability” is the most significant external predictor of ROI. In areas with sub-standard internet infrastructure, the economic efficiency of a real-time exchange was diminished by 30% due to synchronization failures.

The model also showed that the "sparse-region" environment caused by intermittent connectivity could be mitigated through the use of adaptive geospatial resolution and randomized key rotation [25]. However, the "Information Blocking" behavior of larger regional health systems has a profound effect in depressing the ROI of smaller safety-net providers. The removal of these barriers aligns

technical solutions with the EU Data Act's pursuit of innovation and promote choice for the user [28].

6. Discussion and Policy Alignment

Implementing the SOIG model depends on several social and regulatory conditions. While completing the technical tasks, the longer-term sustainability of interoperable health data exchange in MUAs will depend on policy alignment and socio-technical mitigation.

6.1 Integration with the 21st Century Cures Act and TEFCA

The 21st Century Cures Act and the Trusted Exchange Framework and Common Agreement (TEFCA) provide the regulatory impetus for national data liquidity. The SOIG is intended to be a "technical on-ramp" for safety-net providers to engage in Qualified Health Information Networks (QHINs). Leveraging the NIST Open Security Controls Assessment Language (OSCAL), the SOIG can automate machine-readable evidence for compliance with those frameworks [29].

This "Compliance-as-Code" approach matters most for resource-constrained clinics that cannot allocate specific cybersecurity personnel. The SOIG allows for assurance evidence to be generated as a by-product of operating the system, thus reducing the "compliance tax" typically levied on small providers that participate in a national exchange network [29]. Additionally, engaging with international standards such as the EU Data Act can widen interoperability to integrate not only data but layers of entire systems and applications [28].

Finally, the role of distributed ledger technologies (DLT) may also be worth consideration to compliance frameworks. DLT can potentially allow regulators to have access to compliance data in near real-time, through a "pull-model", and will allow for automated collection and enrichment of transactional data [30]. In this scenario, the burden of reporting might be decreased for MUA providers while ensuring levels of data integrity.

6.2 Addressing Implementation Barriers in Resource-Constrained Clinics

Barriers to new technology persist for safety-net providers despite the economic and regulatory incentives. The first barrier is "Technical Debt" associated with legacy EHR systems. Many rural clinical environments operate on legacy EHR software versions that do not natively support FHIR APIs. The SOIG will tackle this issue with a containerized middleware layer to transform legacy HL7 v2 messages into modern FHIR resources [24].

The next challenge is the "Human Factor." Research into Internet Service Providers and users show that securing complex systems is rarely a top priority for large numbers of users who are not experts in the field [31]. In healthcare, this translates to clinical "click-fatigue" and resistance to workflow. The SOIG will need to ensure "invisible interoperability" where external data is injected directly into existing EHR screens rather than requiring a separate external portal.

In MUAs, the "Identity Matching" paradox created because patients often have no or likely unstable address and no identifier consistency eliminates the deterministic matching process. More conveniently, using probabilistic matching algorithms typically leaves deterministic matching inadequate. Using machine learning (ML) for patient identity management will enhance the accuracy of longitudinal records [32]. However, as is the case with any ML models, privacy-preserving training and inference models are necessary to maintain patient trust [33].

6.3 Longitudinal Sustainability of Interoperable Infrastructure

The framework's longevity depends on a change in the funding model. Currently, many interoperability projects in MUAs are funded by short-term grants (e.g., HRSA or state-level). If these systems are to survive their funding, they will need to demonstrate a clear impact on the "Bottom Line" of the clinic.

Our economic model points to the shift to value-based care (VBC) as the clearest path to ensure the long-term sustainability in health systems. Under VBC, safety-net providers are encouraged to both reduce ED visits and manage chronic disease better, and both are outcomes the SOIG supports. By providing a low-cost, open-source option to expensive proprietary systems, based on a queuing theory in economics, we expect that clinics can reallocate the money saved on increased connectivity towards direct patient services.

In addition, using federated models, safety-net providers would be able to engage in clinical research and population health analytics without moving sensitive patient data outside of secure environments [34]. This protects patient privacy and creates new revenue streams from research partnerships. Integrating AI- powered prediction modeling would also help safety-net providers in these efforts by identifying patients who are at high risk of needing expensive acute care before they present to an ED [20].

7. Conclusion

This study quantified the economic and clinical opportunity in interoperable health information exchange for safety-net providers in Medically Underserved Areas. The proposed Scalable Open-Source Interoperability Gateway (SOIG) serves as a credible technical alternative to tackle expenditures in health information exchange, relative to traditional methods.

Our calculated stochastic simulations suggest that full data liquidity in MUAs could save the U.S. healthcare system billions of dollars annually, through reducing duplicate diagnostic testing, easing operational administrative workflows, and limiting unnecessary ED visits. The SOIG framework's use of FHIR-native microservices and container-architecture ensure that these savings are a reality, even on a legacy infrastructure, which is common among resource-scarce settings [24].

Technology alone will not carry this. To succeed, the work of interoperability must align federal-level policies, such as TEFCA, the 21st Century Cures Act, to the practical realities that safety-net clinics operate under. Adopting standards-based policies such as "Compliance-as-Code," OSCAL, would help reduce administrative and workforce burden while also requiring security architectures to be robust and lightweight [29].

The "Digital Divide" in health is not only a technical limitation. It is a macroeconomic barrier to health equity. By providing safety-net providers with interoperability, for instance, it would allow safety-net providers to provide data-parity with the urban centers that have access to adequate resources while also improving the health outcomes of the nation’s most marginalized communities which would return efficiency, and resiliency, to the American healthcare economy. Future research should focus on a longitudinal assessment of SOIG implementation in different geographic contexts, and further study the potential of AI-based clinical decision support to enhance the value of interoperable data [35]. Specifically, investigating the integration of diverse real-world data sources with advanced analytics may help mitigate existing biases that currently disproportionately affect minoritized populations [36]. Such research must also account for the technological barriers and financial constraints that frequently impede the successful adoption of digital healthcare tools within integrated care systems [37]. Future studies that take on these structural challenges can define more precisely which economic and clinical metrics demonstrate a sustainable return on investment for interoperability initiatives in underserved areas.

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