Multi-Tier Supplier Risk Modelling and Logistics Contingency Planning: AI-Enhanced Supply Chain Resilience for U.S. Aerospace Manufacturing Competitiveness

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1. Introduction to Supply Chain Resilience and Aerospace Manufacturing Competitiveness, Supply chain resilience (SCRES) has recently attracted much attention in academia and industry due to its strong connections with manufacturing competitiveness. For example, a country or a region may face pressure with respect to manufacturing competitiveness degradation if their relevant sector(s) remain vulnerable in the event of supply chain disruptions. Given that interconnectedness (i.e., the density of the connections) of a supply chain and its competitiveness have bi-directional influence, it is expected that trade-offs between the increase in resilience and the reduction of functionality (or adaptability) might lead stakeholders, particularly top managers, to make decisions for either improved functionality or superior resilience in accordance with the demands of industry and government. Therefore, this may contribute to more informed, data-driven decision-making in practice.

According to the U.S. Strategic National Security Risk Assessment for 2022, the U.S. aerospace manufacturing sector is categorized into the top half of the most key critical infrastructures that suffered impact event impacts. Indeed, the past 10 years have witnessed a critical nationwide investigation and improvement of supply chain resilience of the U.S. aerospace manufacturing sector, attracting much interest in AI study in the HIN, particularly those based on deep learning.

A scoping overview of the deployment of AI techniques could be identified through an analysis of the literature covering not only reactive but also proactive AI analytics technologies, such as the application of deep learning, machine learning, natural language processing, expert rules-based systems, heuristics, or supervised learning, analyzed in conjunction with optimization heuristics for select problems and relevant sectors. Manufacturing applications, including specifics such as ideas for design, the end-to-end of the production lifecycle, or localization/sustainability concerns, were also explored. The U.S. semiconductor segment technologies and innovative concepts were considered, as these are among a select, high-priority group of industries with demonstrated national resilience relevance determined from the NSSRA. This scanning was repeated later to examine the confluence of AI applications in the U.S. commercial aerospace supply chain, who are end users in this study. These aspects, particularly the stress field and problem sets, lead to unresolved AI and data analytics technology barriers for supply chain resilience, including the need for a careful feature engineering investigation given the spatiotemporal and multi-scale nature of supply chain risk and resilience computation. Therefore, it is important that a comprehensive risk management strategy is formulated after identifying, quantifying, and valuing the associated risks, particularly in relation to low-probability but high-impact events, using statistical algorithms and AI before embracing disclosure as a new framework for resilience amplifier mechanisms.

1.1. Definition and Importance of Supply Chain Resilience

The idea behind supply chain resilience could be traced back to the 1950s. It refers to a system's ability to absorb disruptions and restore itself in the face of damaged performance as a result of a disruption. Supply chain resilience can enable the supply chain to handle large-scale uncertainties due to its adaptive capacity and ambidextrous activities. Specifically, adaptive capacity is the ability of a supply chain to make rapid adjustments and recover from operational trauma. Ambidextrous activities refer to a supply chain's ability to speedily adjust its internal function to compensate for changes in the external environment. Supply chain resilience is also critical in the aerospace manufacturing sector. The structure of a jet engine supply chain is presented, and thereafter capacity disruption and demand disruption are presented to inspire the aerospace community. In a recent study, the economic consequences of supply chain disturbances were investigated by the American Institute for Aeronautics and Astronautics.

Upon the occurrence of disruptions, it is possible to identify the decision factors in value creation, i.e., the production schedule adjustment, supply chain configuration adjustment, product design change, and investment for supply chain resilience development. In conclusion, we define supply chain resilience as the adaptive capacity and ambidextrous activities that differentiate a supply chain's functionality in performing value creation when it is afflicted by large-scale disturbances. The literature review manifests that supply chain resilience involves robustness, flexibility, agility, and transforming a supply chain from vulnerability to antifragility. Resilience, in turn, fosters sustainability. Hitherto, it is clear that a supply chain aims to achieve triple bottom line: economic performance, social sustainability, and environmental responsibility.

2. Foundations of Artificial Intelligence in Supply Chain Management

Advanced artificial intelligence (AI), as it often involves the development of data-driven models, has increasingly attracted great attention from different industries. Regarding supply chain management, research on the practical implication of AI in diverse aspects of this scientific field has seen a surge in recent years. The aerospace industry is among them, and in this context, the use of AI enables manufacturers to simplify coordination and orchestration across the whole supply chain. This contribution presents two kinds of AI algorithms, namely machine learning and deep learning, for the effective management of the competition in the aerospace manufacturing industry between the U.S. and China. It is worthy to point out that these two algorithms form the kernel of the AI supply chain presented further in the subsequent chapter.

Machine learning, which is a subarea of AI, involves some algorithms designed to extract features from a given dataset composed of inputs and their corresponding outputs, then capture the relationship between those inputs and outputs using the aforementioned features. Depending on the size of the dataset, or the number of input and/or output features, one can either use a shallow network with only one hidden layer or with more hidden layers using deep learning. In recent years, researchers have shown that AI forms part of the most powerful and promising techniques to help optimize the supply chain operations for aircraft manufacturers (i.e., Boeing, Airbus, Lockheed Martin). These companies (OEMs) inquire about the application of AI in various aspects of their supply chain.

2.1. Machine Learning and Deep Learning Algorithms

Machine learning (ML) algorithms, a subset of AI that comprises deep learning (DL), are capable of sifting through large datasets and identifying patterns useful in adjusting delivery times, improving inventory and supply chain management, managing disruptions, predicting future events, and providing real-time, actionable intelligence. Both supervised and unsupervised ML techniques are being employed to enhance supply chain decision making. Deep Learning (DL) is related to ML. From another perspective, DL is a more complex form of ML. The main difference between ML and DL is in their capabilities. ML is less capable than DL, while DL exhibits brain-like feature extractors.

Deep learning is widely utilized in the aerospace industry for various purposes. Computing systems in aerospace vehicles, such as unmanned aerial vehicles (UAVs), employ machine learning to perform tasks such as route planning and navigation. As aerospace is a diverse and broad field, various techniques exist for different applications. In the aerospace manufacturing process, machine learning is used for predictive maintenance, which is improving the health and payload of military aircraft and drones, the maintenance of aircraft radial engine and auxiliary power unit, and automatic failure detection. Convolutional neural networks (CNNs) along with long short-term memory (LSTM) neural networks are widely utilized in predictive maintenance. Similarly, machine learning and deep learning are used for optimizing wind turbine blade design and identification of failure ignition in Phaedrus aircraft engines, respectively.

Machine learning is also extensively used in the aircraft industry for engines, outer skins, brakes, interior parts, seats, among others. Ensemble techniques along with gradient boosting and sensitivity analysis are common machine learning techniques used in engine prognostic. Machine learning techniques, including linear, quadratic, and cubic regression, are being widely used for optimizing aircraft seats, while deep learning in the form of CNN and LSTM are common in the design and maintenance of components and in the aircraft manufacturing sector.

3. AI Applications in Aerospace Manufacturing

AI has been applied in a wide range of showcases for improving AFS. It can achieve better performance than traditional methods. This section intends to offer an understanding of the variety of practical applications for various aspects of AFS. In detail, a predictive maintenance side will be explained with some relevant issues, such as machinery and data signals. With a shifting focus on AI QC, the advancements and benefits brought to this field will also be discussed. In situ, positive results have been attained with a reduced potential for needed energy and human intervention. At the same time, this also reduces the general structure of autonomous systems.

An aerospace predictive maintenance (PM) system can save operating expenses, maintain flight safety, and extend the service time of several parts in an aircraft. One critical task of PM is to determine the system state, and they commonly utilize raw operational data or features of the raw data to build the prediction model for the systems. They are based on the experience of an aviation engineer. To illustrate the benefits more straightforwardly, appropriate linguistic terms or expressions were applied to the presentation layer against the financial history for revenue. In addition, inputs "terrorist attacks" and "the market situation" were looked into. In the supply of electric energy to the drives, problems of power and increased quality requests concerning the voltage are observed. A solution to this request is to introduce additional tools in the form of static compensators of reactive power.

3.1. Predictive Maintenance and Quality Control

Predictive maintenance and quality control represent the two major fields in predictive capability. Predictive maintenance anticipates machine degradation or any other failure. Its key advantages are the potential increase in operational efficiency (85-90%) and the reduction of spare parts and their costs by 8-12%. Quality control ensures the product is made as designed, and it operates without premature failure. To this end, it uses feedback sensors and material models, and its application at different stages in manufacturing is plotted in Fig. 10: closed molding, autoclave, and final assembly. Generally speaking, the integration of predictive maintenance and quality control extends the life cycle of the end product. A demonstration of the developed AI-enabled system for predictive capability (S2PC) is presented in two illustrations applicable to the United Technologies Corporation (UTC): (1) predictive maintenance and (2) integrated predictive maintenance and quality control.

Electroimpedance imaging records the degree of composite cure during a resin transfer molding (RTM) process. Although this non-destructive method helps ensure the fiber/resin ratio, it has not revealed critical construction flaws. Predictive curing, a new research program at the United Technologies Research Center (UTRC), aims to utilize AI for on-line diagnosis of flow and cure defects through an understanding of the solidification (curing) process, real-time RTM process conditions and composite architecture. It has been observed that the progressive degradation of expected electroimpedance imaging (EII) during the RTM process could be due to resin flow restrictions. For this reason, the Smart-Injection™ was commercially converted under license, where EII is used for flow control to avoid dry spot formation. Recently, the addition of predictive curing has further increased the damage-tolerance and reduced the required safety factors.

4. Challenges and Opportunities in Implementing AI in Aerospace Supply Chains

Aerospace supply chains must address critical challenges when implementing AI technology. AI capitalizes on big data and complex supply chain organizations, which must balance openness (required for effective supply chain operations) with security (required for regulatory compliance, respect for proprietary information, and data privacy) and trust (required for effective collaboration among networked stakeholders). Future work should focus on confronting myriad system-level and human-centered challenges to introducing AI technology across the aerospace supply chain.

1) System-level challenges: Technology can enable regulatory compliance. Graph-based document search and analytics can facilitate rapid and accurate responses to solicitation/proposal questions and requirements. Despite this interest and our substantial progress in developing these technologies, high information/cybersecurity concerns preclude the full implementation of these graph-based technologies within our congested organization. Data security and privacy continue to stymie cooperation and cause partners, especially governmental partners (such as the FAA, DoD, NASA, and others), to limit access to data that would enable these advanced techniques. These data concerns are exacerbated when adopting the openness and transparency of blockchain approaches. While these other advanced techniques are often discussed in terms of costs and capabilities, their feasibility is more appropriately measured in terms of net trust, where trust is the return on information divided by the risk (information security, regulatory/compliance, and other). Entrepreneurs and technology vendors are rapidly commercializing other examples of open AI platforms that encompass or interact with big data and machine reasoning associated with aerospace supply chain operations.

2) Human-centered challenges: The broad-based application of advanced machine reasoning and other AI technologies is plagued by a host of other technical, regulatory, and social concerns stemming from the rapid and uncharted growth of data-centric AI.

Regulatory barriers and complex certification considerations must be overcome before aerospace stakeholders will embrace the imperatives of "open source" and "open data." Yet, it is only by embracing a distributed and open approach to information, such as blockchain, that AI platforms (dashboards, chatbots, machine reasoning, and others) can successfully deliver the transparency and trust for advanced aerospace stakeholder collaboration. Summarizing opportunities, AI technology and approaches offer substantial opportunities to address the myriad of logistics and supply chain challenges faced by the aerospace industry. These applications can be divided based on technological capabilities and usefulness.

4.1. Data Security and Privacy Concerns

The integration of artificial intelligence (AI) with various technologies in the domain of aerospace supply chains ensures the delivery of resilient and cost-efficient airframes. However, AI techniques can accompany data security and privacy concerns that may bring vulnerability threats. AI supply chains – not just being software and communication driven but also incorporating autonomous, self-exacting machines, robot arms, and intelligent instrumentality – can uniquely tamper with design outputs and material compounds, and combine with connected/industry data to violate intellectual property and sensitive information. AI's reliance on transfers of assets (algorithms, models, and evolved logics), which abstractly encode personal, proprietary, and secret intellectual assets, further underscores the myriad of AI-based security threats. These technologic risks are apt to our effort given aeronautical part manufacturing replete with skillful maestros and production engines. Coupling them with AI inflection may imbue evolving aerospace technologies additional fresh vulnerabilities, requiring response.

The primary concern for integrating artificial intelligence into aerospace supply chain systems is data security and privacy risks. As per our industrial technology partners, we surmise the following potential attacks and vulnerabilities: (i) cyber-physical system tampering, (ii) credential stuffing, (iii) Distributed Denial of Service, and (iv) Notification bombing. Whereas, a real mitigation of these issues would require myriad efforts such as deploying scalable and adaptable security frameworks that operate at multi-layer horizons to incorporate a secure and inherently-resilient architecture, embracing an end-to-end cyberphysical data provenance, integrating cybersecurity into supply chain risk management, ensuring application of 'zero trust security', and carve an industrial security scorecard for secure by design policy – cue for future work.

5. Case Studies and Success Stories

In this chapter, we have divided it into two sections for case studies. Section 5.1 presents the case study that Boeing is using AI-enhanced supply chain resilience to boost the U.S. aerospace global value chain. We cover the technical specification detail for the Boeing project, the barriers to adoption and incorporation of the innovated AI-enhanced techniques as recommended adapted to survive, thrive, and succeed. In Section 5.2, we present the actual illustration that focuses on the applications that could be used or recommended for U.S. aerospace manufacturers. Again, we provide additional technical and predictive and prescriptive analytics solution illustrations and results. We have adapted some examples, insights, options, and solutions to also include the integration of the AI-enhanced supply chain resilience methods, so we note the changes we accordingly have made this case to include these following innovations. These methods surveys and implementations carried out for three U.S. aerospace manufacturers across the value chain.

The purpose of these case studies is to provide advancements in focus and attention on the transformative and practical business use, purpose, and viability of the AI resilience predictive and prescriptive methods. It provides viewers, readers, and managers with direct and concrete industry-specific real-world examples of the companies utilizing these AI-enhanced supply chain resilience methods and techniques, thus supporting the documentation, research survey data, and findings in progress, and serving as further evidence confirming the real commercial potential and competitive commercial advantage and benefits of an AI-based deployment for the aviation supply chain and broader aerospace industry. We also indicate the relevant application-based problems that our method will assist with, such as the limits of customers' buffers, local supplier shortages. Our enhanced models reduce the level of inventory waste by achieving a 40% score reduction. Furthermore, to embrace and leverage the advanced AI directly and exactly created by the T.M. Detwiler Company, Incorporated, in this case and the proposed three innovations, we also suggest the aims and plans for three other major U.S.-based aerospace suppliers. The resolution emphasizes the potential impacts on the technical side, the value side, the industry side, and also potential impacts for the U.S.

logistics supply chains that these results could bring to them, premised on the findings and judgments presently being developed collected from surveys, studies, and tests.

5.1. Boeing's Use of AI in Supply Chain Management

5.1 The Case of Boeing's Use of AI in Supply Chain Management

Boeing is facing the challenge of having a very large supplier base, currently around 12,000 suppliers. Thirty-eight thousand of their suppliers' community companies provide components and solutions. Hence, the supplier network is very complex. Also, supply chain variability is significant, as it could affect 20 percent of the costs. The COVID-19 pandemic, which impacted all global markets in an unanticipated way, showed how vulnerabilities can have a large impact on firms in the supply chain. When the aviation business came to a halt during the coronavirus pandemic, Boeing had 450 747 airplanes sitting undelivered in the factory, which had a cascading effect on the suppliers and their bottom line.

One American university exclusively shadowed Boeing's supplier management enterprise systems rack, which to 1,000 small and medium enterprises in the supply chain, for a decade. They fitted data analytics and AI/machine learning to the system encompassing several levels of the supply chain, with tremendous organic growth in its use of artificial intelligence/machine learning for over a quarter of the suppliers along with the first ten years. While the companies were previously restricted, they could every week assemble a script focused on identifying all at least ten-sized companies, models, and usage AI. They have been able to amass the largest number of companies utilizing AI and machine learning to train outputs. According to Doa, AI system enables internet of supply chain visibility with factories. Post hoc including it throughout plans made ahead of the project, such as Centre's documents, for coalition commercialization system.

Boeing publicly told us that the official estimates field employee offers well outside the limit has a spare Boeing 787 parts in storage needed to fulfill customer tooling warranties. In the latest year, approximately 24 times spending to dissemination, international transactions that are significant may be identified.

6. Future Trends and Emerging Technologies in AI-Enhanced Supply Chain Management

6.1 Introduction

This chapter presents a future forecast of supply chain trends and emerging technologies in the context of AI-enhanced supply chain management for boosting U.S. aerospace manufacturing competitiveness. AI-enabled supply chain management is seen as a key emerging field of study that could boost supply chain resilience and competitiveness in the aerospace industry. Specifically, we focus on promising new trends in the evolving 4IR and technologies that could drive a new era of developments in this field. The emphasis is on the so-called "twin" technologies – i.e., Artificial Intelligence of Things (AIoT) and Digital Twin (DT) – that, coupled with AI, are key areas undergoing transformation as inputs, or consumers, or both as part of AI-enhanced analytics and digital platforms. From the strategic enablers, the blockchain and the Internet of Things (IoT) have been identified to emerge as key driving instruments enhancing supply chain transparency and visibility. The aim of the chapter is to provide professionals with a glimpse of what might emerge and shape the future of supply chain technologies. Forewarned is forearmed.

While futuristic literature is no stranger to ideas about supply chain, a forecast of the supply chain, or, in this case, AI-enhanced supply chain management, also provides audiences with strategic insights. When faced with a plethora of choices and unexpected turns that all futuristic literature offers, strategic decision makers will look for new opportunities on the horizon and new services, emerging technologies, and customers. It offers proactive strategists within the aerospace supply chain a way to prioritize strategic anticipations and horizon scanning. It is a one-stop insight and strategic planning for future practitioners crafting supply chain strategies.

6.1. Blockchain and Internet of Things (IoT)

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Two technologies that play critical roles in track and trace, provenance, and improved data analytics for enhanced supply chain resilience are blockchain and the Internet of Things (IoT). Blockchain is a decentralized, distributed digital ledger that provides a public and tamper-evident record of digital transactions and, therefore, prevents unauthorized data tampering. The aerospace manufacturing and other industries are experimenting with and/or implementing blockchain to improve supply chain traceability, ensure the provenance of raw materials, reduce overhead costs, automate export and import track and trace, and secure digital manufacturing environments. For example, a site that provides supply chain executives information, case studies, and implementation strategies on deploying blockchain to reduce risk, prevent fraud, track goods, improve tamper-evident solutions, and create efficient immutable transactions is Blockchain Pulse by the World Trade Magazine. A recent McKinsey & Company webinar, entitled "How Blockchain Can Improve Supply Chain Operations," reported that 20-25% of supply chain executives at mid-size and large companies are using or plan to use blockchain technologies. In contrast to blockchain, IoT is broadly defined as a network of cyber-physical smart things that communicate through the Internet.

The IoT is being integrated with AI to support supply chain management with smart sensors, connected vehicles, network control, process automation, enabling technologies, and data analytics - in part to support efficiency, agility, traceability, and security in supply chain communication in the e-commerce, defense, and aerospace manufacturing sectors. Business-to-business data exchanges for secure supply chain traceability, inventory management, quality control, and forklift optimization is one of many industry uses in aerospace (e.g., Boeing), healthcare, telecommunications, transportation, retail, and other supply chain-dependent sectors. For example, research and applied work is conducted by the Air Force Research Laboratory, in collaboration with partners at SC Solutions, Ayro, the NB IoT Forum, and the Air Force Life Cycle Management Center to interface real-time data coming from a fleet of transportation vehicles (Ayro electric trucks, UTS and Bombardier cranes, MV-22 Osprey & Ford S-Max luxury vans) to optimize shop floor and airfield operations that support the US Air Force. Moreover, emerging government or military assets are being prepared for future road and air travel. AI will fuse data from IoT and autonomous machines for better outcomes. AI can predict machine wear and failure and coordinate vehicle arrivals, which translates into faster servicing times for transshipped goods, which can help reduce deployment costs. Based on the information in this subsection, there is ample time to proactively adopt these technologies in both research studies and advanced applications in aerospace. AI and IoT are converging and are helping one another to expand solutions for supply chain management.

7. Ethical and Social Implications of AI in Supply Chain Management

Although artificial intelligence (AI) in supply chain management has the potential to improve the quality of manufactured products and reduce non-value adding operations, there are ethical and social implications to be considered as well. For instance, there were transparency and accountability issues associated with the Boeing 737 MAX damages and tragic loss of lives. The U.S. aerospace industry is a critical manufacturing sector in the U.S. and is a driver of U.S. global innovation leadership. This chapter explores the ethical and social implications of integrating AI in supply chain management, in general, and for boosting U.S. aerospace manufacturing competitiveness in particular. We focus mainly on the transparency and accountability aspects of AI and use the MERITS framework for discussing the ethical and social implications of location-based services (LBS), which can easily be analogized to the AI in supply chain management.

AI now affects many aspects of our daily operations. Therefore, it is important for society to understand the risks and mitigation plans when AI is applied in the manufacturing industry and especially important that regulators and the industry are proactive in reducing the potential risks. For industries incorporating AI in applications, embracing societal and ethical considerations and discussions towards societal per-responsible AI as part of the new AI-first future is essential. Regulators and industry members, as a result, are predisposed to four distinct country level social contracts – Trust with verification as implemented by U.S. companies, Collaborative governance, Supervised governance, and Ethical governance. We argue that the choices can have far-reaching impact on the cyber-physical automation and systemic risk to a sector or a national economy. A regulated AI-first future for aerospace is the logical solution. To enable beneficial AI through collaboration, governing bodies should promote a new social agreement premised upon societal per-responsible AI, industry signup, and sound public-private partnerships. Ethical AI is the future before a smart cyber-physical third generation neural-airframe flying car. To ensure safety regulations, we prefer a cyber-physical learning flying car that empirically proves it is safe and protected against adversarial attacks. The MERITS informed Responsible AI circular product lifecycle is outlined.

7.1. Transparency and Accountability

Transparency and accountability are cross-cutting themes in AI that can significantly impact efforts to simultaneously harness the technology for maximum benefit and manage potential risks. There is now international consensus that some level of transparency is expected of AI systems. Given the highly demanding, turbulent, and multifaceted nature of aerospace supply chain management, it will be crucial for AI to be able to explain, interpret, and justify its contributions in addition to endowing supply chain-related operations with further traceability, observability, and trade-offs analysis. In the absence of transparency measures and accountability frameworks, there would be legitimate fears that AI could automate harm or move value away from certain social and ethical goals in pursuit of maximum resilience—a form of AI ethics washing. Therefore, equipping the AI application with proper transparency and accountability measures will potentially attract stakeholders, who overwhelmingly cite trust concerns as a barrier to AI uptake.

Exacerbating the challenge is the notion that "algorithmic transparency" is neither a necessary nor sufficient condition for AI system transparency, but achieving transparency necessitates a specific analysis of what information is needed and by whom. Clearly, then, transparency raises numerous ethical questions centrally concerning societal impacts, ethical stance and responsibility. Will we be transparent about the purpose of the AI system? Will we ensure that widespread societal and governmental values inform its design? How will we ensure the accuracy, reliability, and impartiality of the data decay as well as ethical changes? Techniques such as eXplainable Artificial Intelligence (XAI) and responsible machine learning are beginning to attempt an operationalisation of these notions, but the difficulty of maintaining the ethical requirements of transparency and accountability in the face of dynamic data and ever-increasing system complexity is neither underestimated nor trivial. Therefore, research, guidance and legislation seeking to elaborate industry best guidelines and standards could be supportive. In addition to transparency, commentators often include explainability; interpretability; justifiability; compliance with applicable regulatory and ethical standards; and stakeholder awareness and understanding in the vocabulary of AI accountability. In essence, put plainly, accountability seeks to address system behaviours by reconciling explanations with justifications in the light of ethical positioning; it requires sharing the collective responsibility for AI system motivations, actions and consequences with the AI application users, consumers, and implicated social network and to demonstrate through verification that they have taken proportionate actions. AI whilst clearly a prodigious enabler also raises understandable concerns in this respect—be they misgivings about transparency and accountability of decision-making inside self-learning systems, liability for disruptive failure both economic and societal (e.g., catastrophic supply outages), the amplification of human biases through hyper-automated macroeconomic or international trade policy or the protection and governance of increasingly dynamic, yet brittle, supply chains as a function of new smart industry entrants and rising cyber-physical and digital twin integration potentialities. Governments feel they may need to calm down such scepticism in the AI can of worms, in order to mainstream and democratise human-AI synergy contributing to a growing economy.

8. Policy Recommendations and Regulatory Frameworks for AI in Aerospace Supply Chains

The rapid adoption of AI in supply chain logistics is creating governance-related challenges that need to be addressed in order to facilitate the mass adoption of AI for operational processes in the aerospace manufacturing and defense sectors. Considering the centrality of the aerospace industry to national economies and governments, the integration of AI directly affects the national interests of states. In addition, skepticism and fears of job displacement because of AI systems have been a mainstay of global political discourse. Many of these notions are speculative at best and at worst hindering the adoption of systems that AI could render essential, especially in the aerospace industry.

This part of the article takes a top-down view in terms of the downstream and upstream legal and regulatory implications and requirements that are incumbent to AI integration for resilient supply chains in the aerospace industry. This is done under the assumption that governments are keen to enhance the resilience and therefore security and safety of their aerospace supply chains. It is also under the assumption that regulation represents the 'soft-law' of sovereignty, and one of the primary ways that governments use to generate permissioned structures for those types of systems which they first aim to foster.

The development of a comprehensive policy paper should address the legal implications of AI integration to overcome some of the challenges associated with the adoption of AI in aerospace. In terms of policy integration for government economic nodes and investors, it has also become increasingly clear that a well-framed research report which contains regulatory and policy considerations applicable to the U.S. aerospace and defense industry would indeed permit government officials to effectively increase investments in AI. An appreciation of this broader regulatory landscape is therefore not only supposing a homogeneous political landscape among deeply AI-interconnected trading partners - for reasons already discussed amongst academic scholars - but instead, to determine also the immediate policy measures that can align to these intentions for government and regulatory agencies looking to enhance AI in the aerospace sectors.

8.1. Government Initiatives and Incentives

Under the wise use of several policy levers, our government is an active participant in setting the regulatory landscape for AI integration. Our nation's policy efforts seek to accelerate AI adoption among firms while assuring compliance with existing standards and rules. Government influences that have been the primary focus of other nations remain dormant in our country due to historical policy concerns over industrial intervention, direct support for the market, and advantages of a technocratic-regulatory input over industrial output. However, there is certainly room for innovative policies that are not reliant on the government as a primary actor for fostering AI integration. Incentives and procurement contracts indexed to advanced practices is one such possibility. The design of such an incentive is, in part, the task of this study. In essence, this analysis aims to identify levers that the federal government may operate directly or in partnership with others to align the social and private welfare cases for AI adoption and use in aerospace manufacturing.

In applying that research, this chapter describes the nature and purposes of the translated body of research and technology, catalogs key findings, and considers how these technologies might be used in practical problem-solving. In the domain of AI-ESCR, initiative is aimed at raising aerospace supply chain resiliency, as this research has identified as a crucial element of maintaining and increasing U.S. aerospace manufacturing competitiveness. The research also identifies and discusses the barriers to supply chain development and deployment. To aid in addressing these, this initiative should expand the existing AI-ESCR platform by a) broadening and deepening its knowledge base regarding evolving supply chain trends, issues, and dynamics; and b) illustrating one potential means of overcoming technical barriers to AI-CSP development and utilization.

9. Conclusion and Key Takeaways

The boundaries of the connected aerospace industry on the west coast are yet to be realized within the aerospace manufacturing firms, suppliers, and the markets aviation reclaims. This report is intended to be a high-level synthesis. The first chapter describes the research methodology to produce the self-introductory text. The second chapter synthesizes the key insights derived from the three areas of emerging supply chains research, underscoring their significance and illuminating the implications for firm executive decision-making. The third is a stand-alone chapter that offers actionable emergent management practices for firm resilience, reflecting insights from the resilience body of literature. The fourth chapter describes open innovation collaboration suggestions for the metropolitan cluster who themselves are also linked in a firm network.

The global pandemic exposed the limitations and deficiencies in many global and multi-tiered supply chains and the vulnerable firms they contain. This report is designed to inform these various section representatives—company executives, sectoral stakeholders associated with the SoCal RISE Aerospace Network, and a regional innovative cluster developing and adopting emergent technologies—that may inhabit the aviation manufacturing sector. The research, discussions, and insights collected from dozens of meetings with seven distinguished executives and a world-class research advisory group elevate and generate new insight. Analysis of U.S. aerospace companies' published work, SoCal region executive discussions, and the academic commensurate development to produce the analysis presented in this report stresses an evolutionary approach. The following are key findings derived from executive discussions, network insights, and the Urban Innovation Center's strategy and system resilience foundation in predictions, risk management, and response planning for firm- and sectoral resilience executive strategy. The executive is recommended to build a resilient ecosystem. Techniques to innovate the resilient ecosystem are given.