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IMPACT OF ARTIFICIAL INTELLIGENCE ON GLOBAL SUPPLY CHAIN RESILIENCE

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Abstract:

Global supply chains are now more susceptible to massive disruptions, such as pandemics, geopolitical unrest, climate events, and economic instabilities. The effects of these shocks have revealed the vulnerability of the traditional efficiency-based models of supply chain and amplified the strategic value of resilience. The advent of Artificial Intelligence (AI) has become a revolutionary technological feature, enhancing visibility, predictive analytics, responsiveness, and the speed of recovery in global supply networks. Although the rates of AI adoption are rising quickly across industries, empirical studies of AI adoption with measurable supply chain resilience results are still sparse across industries.

The paper reviews how AI adoption can influence the resilience of global supply chains through a quantitative secondary-data methodology. Using international data collected by the World Bank, OECD, UNCTAD, IMF, and industry digital reports, the adoption of AI is measured by industry-level investment, AI-enabled operational integration, and innovation indicators. Lead time recovery, logistics performance, production continuity, and efficiency of risk management are the metrics of supply chain resiliency. The research examines the hypothesis that the high AI adoption rates directly correlate with better resilience outcomes in industries and regions under a Decision Science framework application based on descriptive statistics, Spearman correlation, and multiple regression analysis.

Although correlation analysis shows that there is a moderate positive relationship between AI adoption and the resilience indicators, regression outcomes demonstrate that the predictive significance is weaker, which is likely due to the presence of measurement gaps and structural flexibility across industries, as well as the unavailability of standardized global AI-supply chain datasets. Such a discrepancy confirms a critical literature gap: no direct and standardized worldwide dataset explicitly quantifies AI adoption within supply chain systems, necessitating the use of proxy indicators.

In order to fill this theoretical and empirical gap, the study formulates a conceptual framework connecting the capabilities of AI with the aspects of organizational resilience, such as strategic, operational, technological, and reputational resilience. The results add to the literature of resilience theory, research on digital transformation, and supply chain management by offering macro-level empirical evidence and defining methodological constraints in identifying AI-driven resilience. The given study concludes with the practical recommendations that should be offered by policymakers and supply chain managers to focus on the organized methods of AI integration. It requests future studies that involve using standardized longitudinal and industry-specific datasets.

Keywords : Artificial Intelligence, Supply Chain Resilience, Digital Transformation, Predictive Analytics, Decision Science, Global Supply Chains

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1. INTRODUCTION

1.1 Introduction

The global supply chains have proven to be a network of complex relationships prone to international disruption that are triggered by pandemics, geopolitical turmoil, weather shocks, and the dynamics of market conditions. The recent shocks being experienced in the world (such as COVID-19 and the wars of Russia and Ukraine) demonstrated that a significant number of the classical supply chain systems unveiled a lot of vulnerabilities, and this accelerated the digital change in organisations. This enhanced the introduction of artificial intelligence (AI) into supply chain management operations (Pugu et al., 2025). UN Security Council reports that 85% of supply chain companies are adopting or plan to adopt AI technologies (Linder, 2025), of which 68% already use AI to promote visibility and traceability. This has caused a 22% improvement in the efficiency of operation (Market.us, 2024). In this sense, AI will be the power source of resilience and strategic competitiveness.

1.2 Background of the Study

The international supply chains have evolved into intercontinental networks encompassing industries, continents, and digital networks. Although this interrelatedness makes it easy to be efficient, cost-competitive, and gain access to the global market, organisations are susceptible to it. Over the past decade, the world has been especially unstable with the occurrence of many destabilizing events, such as the COVID-19 pandemic, geopolitical tensions, extreme weather, and labour shortages, which highlight structural weaknesses in global logistics systems. The COVID-19 crisis was the only factor that caused the appearance of unparalleled transport jams, lack of materials, and the supply and demand mismatch that resulted in a decrease to record lows in the global supply chains (Li et al., 2025). Similarly, the war between Russia and Ukraine has disrupted energy paths, the export of grain, and the availability of essential raw materials, which is evidence of how vulnerable the supply chains in the modern era are (Dewan, 2025).

These revolutions have grave implications for the economy. The analysis of the industry reveals that global businesses spend approximately $184 billion a year due to supply chain disruptions (Eser, 2025). Resilience has risen to become a leading strategic focus, as companies are increasingly operating more in volatile, uncertain, complex, and ambiguous (VUCA) environments. Supply chain resilience is defined as the capacity of a system to predict, absorb, adapt, and respond to disruptions without the system coming to a halt. It involves real-time visibility, predicting capabilities, fast decision-making, and system-wide agility competencies that traditional supply chain models lack (Hamieddine & Akioud, 2025). Organisations have hastened the implementation of Artificial Intelligence (AI) to protect themselves. Machine learning and AI-based tools, such as digital twins, robotics, machine learning predictive analytics, and IoT-enabled analytics, are changing supply chain planning, predictive analytics, and risk management (Balan et al., 2025). In the 2025 AI-in-supply-chain market, it reached $14.49 billion, and is expected to grow to $50.01 billion by 2031, with a compound annual growth rate of more than 22.9% (Markets and Markets, 2025). Such investments are indicative that companies regard AI as not just a technological motivator but an enabler of survival and competitiveness. The trend is similar in industries when it comes to its adoption. In a recent report, 67% of supply chain executives believe AI will transform their operations within the next five years. Meanwhile, 80% of companies apply AI tools to their specific purposes of enhancing visibility and traceability, which are foundational elements of resilience (Linder, 2025). The concept of AI is justified by quantifiable operational returns: machine-learning-based analytics can be accurate by up to 50%, and AI-based forecasting can be more precise by up to 50-65%, allowing the firms to predict disruptions much better (D'Souza, 2025).

All these benefits are proportional to resilience. The results of predictive analytics, which are the typical applications of AI, may decrease supply chain disruptions by about 30% since potential risks are detected before they grow out of proportion (D'Souza, 2025). Likewise, AI-powered simulations and digital twins enable organisations to evaluate the consequences of various disruption situations, develop contingency strategies, and build recovery strategies. It has been proven that executives already see AI as a strategic resource: half of organisations indicate that AI has far enhanced their resilience functions, especially risk prediction, inventory optimisation, and end-to-end network visibility. Macro-level International agencies insist on the necessity of developing digitally enhanced resilience (Olabiyi et al., 2025). Structural solutions such as reshoring and nearshoring cannot ensure resilience and even increase global GDP by more than 5% on their own (OECD, 2025). Instead, the resilience should be constructed based on digitalisation, data-driven decision-making, and adaptive global networks. Digital technologies, such as AI, are critical to improving the performance of logistics, the reliability of transport, and trade competitiveness (Alsakhen et al., 2024).

Despite the enormous adoption rates and the promising results, the scholarly literature brings to light one significant gap: empirical evidence of AI adoption and indicators of supply chain resilience, which have been observed and evaluated, remains immature, inconsistent, and company-specific. The majority of the research is conceptual, case-based, or technology advantage without quantifying the role of AI in resilience in various industries and locations (Xu, 2025). To fill this gap, this thesis examines the relationship between the level of AI adoption and the performance of resilience using secondary global datasets, providing an evidence-based insight into the effectiveness of AI in enhancing global supply chain resilience (Raut et al., 2025).

1.3 Problem Statement

Global supply chains are subjected to a volatile and uncertain environment that is characterised by a high rate of disruption, the rate of rapid technological change, geopolitical tension, and unpredictable market behaviour. Although organisations are implementing significant investments in Artificial Intelligence (AI) to address all these complexities, it is not clearly understood to what extent AI contributes to the resilience of the supply chain (Panya & Marendi, 2025). In a 2024 global survey, disruption emerged as the top concern among supply chain leaders, with 19% citing geopolitical instability, 17% pointing to supply chain complexity, and 15% highlighting regulatory challenges as the pressing issues (Setyadi et al., 2025). Simultaneously, 85% of organisations report the use or intend to use AI tools to enhance the continuity and responsiveness of operations. Although this implementation has increased, the evidence supporting the real, measurable effect of AI on resilience indicators, including recovery time, visibility, flexibility, risk prediction accuracy, and adaptive capacity, is scattered and inconclusive (Linder, 2025).

Conceptual discourses on the potential of AI are provided in the academic literature, but there is a lack of empirical studies across industries and across global sets of data. The available literature is industry-specific, region-specific, or qualitative case studies, which are not generalisable to access world trade networks. Hence, there is a notable vacuum in the literature on exhaustive empirical findings that explore the association between AI adoption and supply chain resilience. In addition, the adoption of AI is common in organisations without being aware of which particular technologies, such as machine learning, predictive analytics, robotics, or digital twins, are likely to be resilience-building. This clouds the strategic decision-making process among the supply chain managers struggling against budget constraints and operational risks (Li, Cheng, et al., 2025). The lack of standardised measurement frameworks that connect AI capabilities and resilience outcomes is an aspect of the research problem. Although the firms admit that visibility and decision-making have been improved, little measurable data exists to demonstrate how the improvements affect the real resilience performance in industries and regions (Lin & Zhang, 2025). Moreover, disruptions cost the world businesses around $184 billion per year, which indicates the immediate need to have accurate and data-driven insights (Eser, 2025). Regardless of the increased use of AI technologies in supply chain management, because no systematic empirical research has been conducted, one cannot know whether AI investments are truly increasing the resilience of the supply chain or simply enhancing operational efficiency.

Thus, the main issue that the study will focus on is that there is no empirical and cross-industry evidence regarding the impact of AI adoption on the global supply chain resilience, based on the secondary data obtained with the help of trusted sources in the international context. This study, therefore, seeks to address this gap by examining the relationship between AI adoption and supply chain resilience using secondary data across multiple industries and global contexts. In the absence of such evidence, organisations wrongly allocate resources and neglect necessary resilience capabilities, and may not develop adaptive supply chain systems that work during large-scale disruptions (Culot et al., 2024).

Nevertheless, although the role of Artificial Intelligence in supply chain operations continues to grow, there remain no transparent, standardised, and globally comparable empirical studies directly quantifying the influence that Artificial Intelligence has on supply chain resilience. The existing literature fails to give a unified, numerical sense of the impact of the adoption of AI on quantifiable resilience outcomes across sectors. So, the proposed research fills this gap with a systematic analysis of the connection between AI adoption and supply chain resilience using international secondary data.

1.4 Rationale of the Study

The increasing pressures to have organisations that establish resilient supply chains that could prevail against unending global disruptions are reasons behind this study. In the last ten years, COVID-19, geopolitical tensions, trade prohibitions, semiconductor shortages, and extreme weather events have demonstrated critical vulnerabilities in supply networks in all industries. Such upheavals have brought about huge economic damages, delays in operations, and an unstable environment in the global markets (Ameh, 2025). As a result, resilience has become a critical strategic priority of governments, international institutions, and multinational organisations. AI has a transformative potential in overcoming these challenges as it affects visibility, predictive analytics, automation, and real-time decision-making in all supply chain activities (Attah et al., 2024). New information indicates that AI has the possibility of enhancing prediction accuracy by 65%, decision-making accuracy by 50%, and lessening the effects of interruption by a factor of about 30. These are the key elements of resilience: being able to foresee and avert risks, respond quickly, and recuperate successfully. In this way, the importance of interpreting the implications of AI is crucial when firms desire to transition into a responsive and active supply chain (Linder, 2025).

However, despite the trend of AI rising to fame, organisations are still not given an empirical guide. Theoretical benefits are still indicated in scholars' literature, though the cross-industrial impact, in theory, has not been examined comprehensively. This is a vital gap because supply chain failures throughout the world continue to cost businesses billions of dollars annually (Madanchian & Taherdoost, 2025). The given piece of work is timely and needed because the authors use secondary data on a worldwide scale, such as the World Bank logistic performance indicators, OECD data on digital transformation, and UNCTAD trade resilience data to examine the easy-going correlation between AI and resilience results. The Decision Science approach offers a quantitative prism that can be applied to specify patterns, correlations, and variations within an industry and region. Data interpretation such as this will assist the study in surpassing the stage of abstract thinking and putting forth objective facts, which can be utilized in further decision-making of a strategic nature. Supply chain resilience and secure, information-driven insights should be part of its structures to invest in AI and focus on technologies. Lastly, the proposed study will also occupy the gap between theory and practice as a source of an effective recommendation on how AI can be used in global-scale supply chain resilience.

1.5 Research Aim and Objectives

1.5.1 Research Aim

This study aims to provide an impact analysis of Artificial Intelligence (AI) on resilience in world supply chains through the prism of secondary data, which is symbolized in international datasets. The purpose of this study is to attain an appreciation of how AI utilization enhances the necessary resiliency characteristics, such as those of visibility, agility, predictive behavior, and responsiveness.

1.5.2 Research Objectives

1. To analyze the role of AI in enhancing global supply chain resilience.
2. To identify key AI tools and applications that contribute to risk prediction and disruption management.
3. To evaluate industry-specific patterns of AI adoption and resilience performance using secondary data.
4. To develop a conceptual model linking AI capabilities with resilience dimensions.
5. To provide practical recommendations for global supply chain managers to build AI-driven resilient frameworks.

1.6 Research Questions

Primary Research Question:

1. How does the adoption of artificial intelligence influence the resilience of global supply chains?

Secondary Research Questions:

2. What specific resilience indicators (e.g., recovery time, supply chain visibility, flexibility) are most affected by AI integration?
3. Which AI technologies (e.g., machine learning, predictive analytics, robotics) contribute most to improving supply chain resilience?
4. How do AI-driven resilience outcomes vary across industries and regions, and what common factors explain these differences?

1.7 Significance of the Study

This research is pertinent in the sense that it contributes significantly to the body of knowledge and the current practice of the supply chain sector and global policy-making at a time when the supply chains are being broken as never before. Regarding academic activity, the study can be used to supplement the theoretical base with the resources connected to the theory of resilience, theories of digital transformation, and AI-based optimisation models (Yan et al., 2023). Although the topic of digitalisation in supply chains has been examined in many studies, fewer tend to discuss how various types of AI, such as predictive analytics, machine learning, intelligent automation, and autonomous decision-making, are used to promote resilience across preparedness, responsiveness, recovery, and adaptability (Wang et al., 2022). The proposed study fills such a gap by providing an organized framework connecting the abilities of AI to a particular resilience outcome. Consequently, it helps to build sophisticated models that future researchers can empirically verify.

The research has immense implications in the industrial context that is increasingly vulnerable to volatility among manufacturers, logisticians, retailers, and multinational supply chain networks. The legacy supply chain design has proven itself to be a weakness because of geopolitical pressures, natural disasters, cyberattacks, pandemics, and transport network bottlenecks. The AI technologies are outlined to be highly visible, predictive, real-time optimisation, and capable of mitigating risks within a short time. The study will provide organisations with evidence-based data on the spheres in which AI investments are the most beneficial and how AI-driven systems could help with decisions and agility, and reduce downtimes (Kurat & Graepel, 2024).

The key trend is that governments and international organisations increasingly prioritize resilience of supply chains in protecting national security and economic interests, and the health of their citizens. The study contains implications policymakers can utilize to develop standards, incentives, and governance structures to improve AI adoption and ensure that problems such as transparency, data security, and algorithm bias are addressed to avoid ethical concerns (Igwe et al., 2024).

1.8 Scope of the Study

The proposed research aims to discuss the role of Artificial Intelligence in increasing resilience in global supply chains. It has a broader international perspective and is not confined to a specific country or region, as this is an interconnected world of modern supply networks. The study takes into account large-scale sectors, such as manufacturing, logistics, retail, technology, healthcare, and consumer goods, in which AI use is most developed, and supply chain issues have the most impact. Nonetheless, it fails to undertake industry-specific case studies, but rather it compiles cross-sector evidence to discern generalisable trends (Xu, 2025). The research focuses on four categories of AI technologies: predictive analytics and foretelling, machine learning optimisation platforms, autonomous logistics environments (including robotics and drones), and intelligent automation platforms. These types are chosen as they directly determine the critical features of resilience, such as visibility, risk anticipation, responsiveness, adaptability, and long-term recovery. Other digital technologies like blockchain, IoT, and cloud computing are not the primary variables being analysed, but they can be mentioned as supporting infrastructure, where needed (Chen et al., 2024).

To provide methodological clarity and transparency at its core, this study adopts the secondary datasets from 2021 to 2026 as explicitly as possible, provided by internationally recognised institutions. The major sources of quantitative data are the World Bank Logistics Performance Index (LPI), trade flows statistics, infrastructure indicators, OECD data on digital transformation and technology diffusion, UNCTAD data on global trade resilience and transport connectivity, and selected IMF economic and trade stability statistics. Moreover, the indicators of AI adoption were operationalised based on industry-level data produced by Statista and Kaggle datasets, and sectoral reporting on AI investments and patent data. Peer-reviewed scholarly databases, including Scopus, ScienceDirect, and Emerald, provide supporting qualitative and industry data, such as reports by McKinsey, Gartner, and DHL Trend Research. The adoption level of AI in this context would be described by the following indicators: investment in AI in the industry, the percentage of operations that utilize AI, and the number of AI patents per industry. Measures of supply chain resilience include lead time recovery rates, supplier diversification indices, rates of production continuity, and risk management efficiency scores. The datasets enable cross-industry and cross-regional comparison at the international level, making the scope of the study globally orientated and empirically innovative.

1.9 Limitations

Although this study is insightful, it has several limitations that should be taken into account. Firstly, this is research that is founded on secondary data, academic articles, and reports within the industry rather than the collection of primary data. This limits the ability to access current organisation problems or the latest proprietary AI applications deployed by multinational corporations. Second, the pace of AI technologies is particularly rapid, and when there are more systems, algorithms, and automation tools published, findings may become obsolete. As a result, the study reflects the current state of AI but fails to predict the future opportunities and technological shifts in the long term.

Third, the research cannot explore the intricate details of global supply chains within different industries, as the research takes these supply chains into consideration. Regulatory restraints, the technological maturity degree, and resilience priorities may be different in various industries and, consequently, influence AI adoption differently. However, they determine the adoption in practice. Even with these shortcomings, the research offers a solid conceptual framework on the significance of AI in enhancing the resilience of global supply chains.

1.10 Definitions of Key Terms

Artificial Intelligence (AI):

Computational resources that handle tasks which have traditionally been solved using human intelligence, such as learning, pattern recognition, problem solving, prediction, and independent decision-making. AI is applied in supply chains to forecast, optimise, automate, and manage risks (Toorajipour et al., 2021).

Supply Chain Resilience:

The capability of a supply chain to respond, prepare against, adapt, and recover from disruptions in the supply chain. A robust supply chain ensures that there is continuity of business and reduced adverse effects on performance, cost, and customer services (Guo et al., 2024).

Global Supply Chain:

A global network of suppliers, manufacturers, logistics, distributors, retailers, and customers working in several countries. Such networks are vulnerable to geopolitical, environmental, and economic risks (López et al., 2025).

Predictive Analytics:

AI algorithms to predict the future flow, demand, disturbances, or debacles according to past or present data (Mole, 2025).

Machine Learning (ML):

To identify trends and achieve a better performance without actual programming, a portion of AI is used. ML helps in the optimisation of inventory, routing, scheduling, and maintenance (Yaiprasert & Hidayanto, 2024).

Automation:

Technology that can be used to carry out routine tasks or complex tasks with minimum human interaction. Intelligent automation is robotic integration with AI to speed up, increase accuracy, and make decisions around supply chains (Dalsaniya & Patel, 2022).

Risk Management:

Procedures that are performed to detect, appraise, lessen, and observe potential risks that can jeopardize the supply chain processes (Emrouznejad et al., 2023).

1.11 Thesis Structure

This thesis has been structured into five major chapters.

- **Chapter 1** provides the background, problem statement, rationale, and objectives of the research.
- **Chapter 2** analyzes the literature available concerning AI technologies and supply chain resilience models.
- **Chapter 3** proposes a data gathering and data analysis methodology.
- **Chapter 4** introduces and covers the results concerning the use of AI in improving resilience.
- **Chapter 5** brings the study into a coherent conclusion summarising the insights, the theoretical and practical contributions, limitations, and suggestions on further research and policy formulation.

2.LITERATURE REVIEW

2.1 Introduction

This literature review discusses the concept of resilience as it evolved in the context of global supply chains, especially in the wake of global disruptions, and evaluates emerging artificial intelligence (AI) technology as a means to increase supply-chain resilience. The research focuses on learning whether and how AI implementation has a meaningful impact on supply-chain resilience within contemporary, globally integrated networks (Pan et al., 2025). The review undertakes the mapping of the state of knowledge by surveying conceptual literature and empirical literature to reveal where the evidence information is weak or inconsistent and what areas future research should explore (Alsakhen et al., 2024).

There are various themes in the review. First, it follows the history of global supply chains - the transformation of linear and localized supply chains into global webs. It shifts to conceptualising supply-chain resilience, investigating the concept of defining, measuring, and differentiating resilience in contrast to more conventional models based on efficiency (Ejairu et al., 2022). Third, it makes wider use of AI technologies in supply-chain management by asking how AI has been adopted in logistics, forecasting, demand planning, and risk detection. Fourth, it evaluates the empirical research on the relationship between AI and resilience to assess the evidence of the effectiveness of AI to mitigate a supply chain shock (Galvez et al., 2025).

2.1.1 Concept of Global Supply Chains

2.1.2 Evolution of Global Supply Chains

Global supply chains are no longer straightforward, linear, and oriented but have changed to complex, globally interwoven. In previous models of industries, companies used to control the production chain within the country or neighborhood. Nonetheless, as the concept of outsourcing and offshoring started to gain momentum in the late 20th century and early 21st century, businesses began dividing the production process into distinct phases of raw material sourcing, manufacturing, and assembly, among others. They spread out to various geographical locations (Panya & Marendi, 2025). This move was driven by cost-cutting, labour arbitrage, and the availability of specialised capabilities (Lamperti et al., 2025). Global trade liberalization, the development of transport and logistics, and the development of communication technologies enabled companies to manage distant operations over time. This led to global supply chains spanning both continents to interconnect suppliers, manufacturers, distributors, and retailers into multi-level chains. Digitalization intensified integration: the flows of information became close to real-time, allowing planning of demand and supply in real-time, multi-tiered communication, and enhanced inter-firm interaction (Sudarshan, 2025).

The global supply chain structure has reconfigured due to geopolitical changes, global crises, and technological change. Another recent study identifies how what it calls pressure crises (both pandemic and geopolitical tensions) have reconfigured global value chain (GVC) participation and redefined the functional role of countries in global supply chains - forcing companies to have a regional plus global sourcing strategy instead of pure global dependency (Phillips et al., 2022).

2.1.3 Characteristics of Modern Global Supply Chains

Global supply chains are interdependent and complex today. Companies depend on global networks that are multi-tiered with suppliers, sub-suppliers, manufacturers, and distributors, possibly located on various continents. The decisions or disruptions made in one node (e.g., raw material supplier in Asia) are transmitted through the whole network (Sujatmiko et al., 2024). They become data-centric: the procurement, manufacturing, inventory, logistics, distribution, and other activities are guided by digital workflows, real-time tracking, demand forecasting, and predictive analytics (Irawan, 2023). The flows of information are as essential as the physical flows, and supply chains are hybrid systems that entail the movement of physical goods and digital coordination. Concurrently, current supply chains experience increased volatility and are more vulnerable to global risks (Susitha et al.,2024). With networks cutting across continents, they are exposed to tensions in geopolitical strains, geological occurrences, pandemics, and the expansion and contraction of the global economy. Global interconnectedness, which is meant to maximise costs and efficiency, is an increased exposure (Nanthagopal, 2025).

2.1.4 Key Challenges Affecting Global Supply Chains

The years between have been very challenging for supply chains worldwide. The onset of COVID-19 accelerated the transport shutdowns, port closings, labour shortages, and production halts, grossly disrupting supply lines in industries. Consequently, there was a significant reduction in global trade flows: a study approximated that volumes of trade by sea decreased by 7.0 to 6.0 percent in the first eight months of the pandemic (Verschuur et al.,2020). Structural problems continued despite the economy starting to recover. There was a world supply-chain crisis in 2021-2022 caused by logistics bottlenecks, container shortages, congested ports, and skyrocketing freight costs, combined with the high demand. In addition, disruption by the outbreak of the Russia-Ukraine war in 2022 came with additional disruption - primarily through the blockade of major export ports in the black sea region, which shook agricultural and commodity supply chains across the world (Morrison & Miller, 2022). Meanwhile, structural issues like talent shortages, logistical bottlenecks, and the increasing vagueness of the prices of raw materials, compounded by economic inflation and global economic turmoil, contributed to even greater pressure on the reliability of supply chains (Mahmoud, 2025).

2.1.5 Resilience in Global Supply Chain Requirement.

These innovations highlight the rising significance of resilience in the management of international supply chains. The classical paradigm that emphasized cost-efficiency, lean inventories, and just-in-time procurement has a tendency to fail in the situation of uncertainty and large shocks (Guo et al., 2024). A recent survey (2020-22) emphasizes enforcement of dual-sourcing approaches (81% of respondents indicated dual-sourcing versus 55% in the previous year), and beginning to regionalise supply networks (44% versus 25% during the last year), which is an indication of the abandonment of pure global, single-source addictions. In addition, the majority of companies grew their inventories: a study of almost 300 publicly traded companies discovered that inventories increased by, on average, 11.0% during 2018-2021. Inventory built up and associated with diversifying the supply sources and regionalization is now being understood not as an inefficiency, but as a significant supply-chain shock buffer (McKinsey, 2022). The need to build resilient supply chains is heightened by the persistent global uncertainties, such as the pandemic, geopolitics, climate change, and economic instability, which will increase rather than extraordinary disruptions in the future (López et al., 2025). Therefore, resilience is not a choice anymore; it is becoming a precondition of sustainable global supply chain business in times of uncertainty (Celestin & Sujatha, 2024).

2.2 Theoretical Foundations of Supply Chain Resilience

This study is based on three complementary theoretical perspectives: Dynamic Capabilities Theory, the Resource-Based View (RBV), and the Socio-Technical Systems Theory, to illustrate how the adoption of Artificial Intelligence (AI) leads to global supply chain resilience and eventually enhances organisational performance. The combination of these theories offers a good base to comprehend the strategic and operational processes by which AI enhances resilience capacity in highly disturbed and uncertain global supply landscapes.

Firstly, Dynamic Capabilities Theory (Teece, 1997) describes the way in which companies acquire capabilities to survive and do well in an uncertain environment by continually changing their resources and routines. With pandemics, geopolitical wars, climate shocks, and logistic failures, having the ability to feel risk early, capture opportunities fast, and shift operations is required to ensure continuity in global supply chains. By supporting quicker and more precise decision-making by means of predictive analytics, real-time visibility tools, and intelligent automation, AI reinforces these dynamic capabilities (Teece, Pisano, and Shuen, 1997). As an example, forecasting and anomaly detection systems using AI technologies enable organisations to detect demand changes, supplier risk, or transport delays much sooner than possible through previous approaches, enhancing the sensing capability (Omokhafe et al., 2025). AI is also involved in contributing to seizing by prescribing the best actions, including rerouting of deliveries, reassigning stock, or finding different suppliers, whereas transforming is supplemented by digital, long-term redesign of the supply chain networks and planning operations (Ajeigbe and Moore, 2023).

Second, the Resource-Based View (RBV) contributes to the vision that AI may be a strategic resource, enhancing the competitive advantage and resilience. RBV posits that companies achieve better performance when they have valuable, rare, inimitable, and well-organised resources (Barney, 1991). AI is not a technological device but a potential-enhancing asset enabling firms to have better supply chain planning, effectiveness, and responsiveness (Faizan ul Haq et al., 2025). When combined with quality data, experienced human resources, and the enabling infrastructure, AI turns out to be a special organisational resource that enhances the resilience outcomes. By using AI-powered optimisation, companies will be able to limit interruptions, improve inventory accuracy, increase the efficiency of logistics, and make supply chain operations more nimble (Komakech et al., 2025). RBV can be used in this study to describe why organisations that have adopted AI to a higher degree are likely to perform better in times of disruption than firms whose primary supply chain strategies have been traditional supply chain approaches (Barney, 1991).

Third, Socio-Technical Systems Theory can be used as a critical perspective on the issue of realizing the supply chain resilience created solely by technology. The theory posits that organisational performance is enhanced when the technological systems and social systems (people, processes, leadership, and culture) are aligned (Trist, 1981). The implementation of AI in supply chains needs close cooperation between digital solutions and human decision-makers. The finest AI systems can work, but organisations need employee skills, change management, confidence in analytics, and coordination among supply chain partners. Thus, socio-technical alignment is essential in the process of making AI-generated insights relevant to actual resilience advancements, or enhancements in recovery speed, responsiveness, and adaptability (Wang et al., 2025).

Dynamic Capabilities Theory, Resource-Based View, and Socio-Technical Systems Theory serve as valuable perspectives that while on their own offer some limitations, nonetheless, much can still be learned about AI-driven supply chain resilience. Dynamic Capabilities Theory concentrates on adaptation but deemphasises quality of resources, whereas RBV elucidates resource advantage but fails to concentrate on environmental change in a rapid manner (Omokhafe et al., 2025; Komakech et al., 2025). On the same note, Socio-Technical Systems Theory emphasizes human-technology fit but does not prioritize on strategic resource utilization and competitive advantage (Wang et al., 2025). Combined, however, the theories provide a more complete explanation, by incorporating adaptability, resource strength and organisational alignment, thus overcoming the shortcomings of either of the two views separately.

On these theoretical premises, a conceptual model has been developed by this study where AI adoption facilitates supply chain capabilities (visibility, risk prediction, responsiveness, and agility), which contribute to supply chain resilience and further enhance organisational performance. This framework will facilitate quantitative research of the relationship between AI adoption indicators and resilience outcomes based on secondary global datasets that the study aims to conduct.

2.3 Artificial Intelligence in Supply Chain Management

2.3.1 Overview of Artificial Intelligence

Artificial Intelligence (AI) describes a category of computing approaches and technologies, such as machine learning, predictive analytics, robotics, natural language processing, as well as other data-driven algorithms, that can allow systems to process high volumes of data, identify patterns, be trained, and make predictions or take autonomous actions (Kar et al., 2019). In recent decades, with the explosion of data volumes, the maturity of technologies like cloud computing, Internet of Things (IoT), big data, and automation, AI has graduated out of the experimental phase of scholarly research and study, becoming a fundamentally supporting element of business operations (Collins et al., 2021).

Regarding the supply chain management (SCM), this convergence of information, connectivity (IoT), and processing power provides fertile soil on which AI can be integrated. The digitalisation of supply chains - integration of IoT sensors, real-time information capture, cloud services, and automated logistics enables AI to plot and obtain timely, high-quality, and granular data on inventory, demand, transport, production, and supplier performance (Zaman et al., 2025). In practice, SCM is transforming from manual, periodical, reactive operations to real-time, information-based, predictive, and responsive operations. This transformation is the first step of a new direction in the evolution of supply chains, where traditional, buffer-based resilience approaches are substituted with dynamically organized resilience and effectiveness that involves AI (Guo et al., 2024).

2.3.2 Categories of AI Technologies Relevant to Supply Chains

In the context of SCM, the relevance of various categories of AI technologies specific to supply chain operations can be identified. Demand forecasting, supply disruption prediction, and inventory and procurement optimization can be predicted using predictive analytics and machine learning models (Culot et al., 2024). As an example, a recent literature review discovered that AI/ML models, including decision trees, support-vector machines, and ensemble models (e.g., XGBoost, Random Forest), are becoming the most common in supply-chain risk assessment (Jahin et al., 2024). Robotics and automation in warehouses, autonomous logistics, and intelligent scheduling are based on AI, which improves the processes of warehouses faster and more reliably, making them less dependent on people and arrangements organized by humans (Culot et al., 2024). In the meantime, digital-twin technologies, Virtual models of a supply-chain network, enable companies to simulate alternative situations of disruption and test mitigation strategies beforehand. AI applications are now used in procurement, demand forecasting, inventory management, transportation/ logistics, risk management, and decision support, and, essentially, in all the SCM processes, as a comprehensive survey demonstrates (Roman et al., 2025).

2.3.3 Global Trends in AI Adoption

According to scholarly studies and industry analysis, AI use in supply chain management has grown significantly in the world over the next five years (2020–2025). According to a comprehensive overview, under the umbrella or heading of Industry 4.0 / Industry 5.0 / Industry 6.0 transitions, companies are improving supply-chain efficiency, agility, transparency, and resilience as a result of integrating AI, IoT, cloud computing, and digital platforms (Claudia et al., 2025). This tendency has empirical evidence as well: a large-scale survey of Chinese companies shows that a higher degree of firm-level AI implementation leads to significantly better resilience in supply chains, especially in manufacturing companies and those with higher levels of digital maturity (Guo et al., 2025). In another 2024 study, surveying supply chain managers in a wide range of industries, AI-based technologies positively affect supply chain performance significantly, and resilience is a vital mediating variable (Wang et al., 2025). Although it is increasingly adopted, research also shows variance: companies with superior digital infrastructure, innovation capacity, and absorptive capacity get more resilience benefits of AI compared to companies not founded on such bases (Ma et al., 2025). Yet, according to empirical evidence, some indicators also show that the positive effects of AI adoption may not be consistently applicable in all situations since companies with less digital maturity or inferior infrastructure tend to show lower resilience rates than technologically oriented organisations (Li & Jin, 2024). This means that the usefulness of AI depends on its complementary capabilities, not necessarily adoption.

Collectively, these trends suggest the overlap of AI adoption and digital transformation in supply chains has formed the new theoretical and practical perspective of supply chain resilience: no longer a static buffer-based approach to supply chain resilience, but an active, data-driven, intelligent resilience methodology.

2.4 AI and Supply Chain Resilience: Linking Capabilities to Outcomes

2.4.1 AI and Visibility

Implementing AI in supply chain operations contributes significantly to real-time visibility, which is an essential base of resiliency. The current use of AI-supported visibility platforms, frequently coupled with Internet of Things (IoT) sensors and cloud-based data platforms, enables companies to track the quantity of inventory and the state of shipments, along with the activity of suppliers and logistics operations in real time (Zaman et al., 2025). By performing sustained data collection and processing, AI integrates data among several nodes within the supply chain, and the once disconnected, siloed, or delayed reporting is converted into a single, updated dashboard. Such transparency allows managers to notice developing irregularities such as unwanted delays on a carrier route, supplier lead-time variations, or stock imbalances, way before they become significant disruptions (Riad et al., 2024).

In addition to surveillance, the availability of data in real-time allows companies to change the mode of management to proactive management. When possible bottlenecks or delays are detected early, pre-emptive actions can be implemented (Nadeem & Farag, 2025). In global supply chains, which are becoming increasingly uncertain over time (due to geopolitical conflict and other disruptions like climate-driven catastrophes), AI-based visibility tools mark a new direction in ensuring that supply chains become more transparent, responsive, and resilient (Bendhi, 2025).

2.4.2 AI and Risk Prediction

The role of AI in resilience can also be seen extending to the area of predicting risks, where predictive analytics and machine learning (ML) applications may apply past and real-time data to predict seasonal demand variability, disruption risks at suppliers, supply chain logistics bottlenecks, or external risks (Kagalwala et al., 2025). To illustrate, the latest research on predictive analytics (AI-based) to optimize the supply chain shows that deep-learning and improved forecasting schemes can greatly enhance demand planning and responsiveness to the supply chain, thus reducing risks associated with a stockout or overstocking, particularly in dynamic environments (Kagalwala et al., 2025). Furthermore, a systematic review of literature on supply chain risk assessment (SCRA) reveals that state-of-the-art AI/ML approaches to risk assessment, such as random forests, gradient boosting (XGBoost), and hybrids, have been proven significantly more precise in detecting and predicting risks than conventional methods (Choudhary et al., 2022). By these tools, organizations will be able to notice at an early stage when their suppliers are performing poorly, or demand changes or transport delays. Such a better predictive ability helps corporations by anticipating the disruption ahead of time, deploying contingency strategies (e.g., alternative sourcing, rerouting), and preventing or mitigating the effect before dislocation takes place (Jahin et al., 2024). Predictive accuracy in itself however does not ensure that supply chain resilience can be enhanced unless the organisation is agile as well as be able to respond effectively to challenges posed. Although Choudhary et al. (2022) emphasize the technical prowess of AI in the field of risk forecasting, Aljohani (2023) claims that predictive insights cannot be transformed into positive resilience outcomes without adaptive organisational processes.

2.4.3 AI and Responsiveness

In the shock case, the rate and efficiency at which the response effort succeeds tends to either make or break a supply chain. Real-time dynamic routing, contingency planning via digital twin, and automated execution are some of the contributions of AI to responsiveness. Dynamic routing in real-time uses AI algorithms to analyze traffic and carrier availability, weather, and logistic capacity continuously and dynamically reroute the shipment, preventing delays in case of disruptions (Sarioguz, 2025). Also, digital twin models, the virtual copy of the supply chain, enable companies to test disruption scenarios and assess alternative strategies before implementing them in the actual network, making timely, informed decisions in a situation of uncertainty (Sarioguz, 2025). By so doing, responsiveness is not only made faster but also more reliable in order to minimize downtime and allow supply chains to respond quickly to new situations. AI converts the reactive component of resilience, response, into a lean, efficient, and smooth procedure by automating and accelerating important logistical and operational decisions (Nweje & Taiwo, 2025).

2.4.4 AI and Recovery Speed

Another area where AI plays a significant role in the resilience of the supply chain is the recovery process, marked by the need to resume functionality after the disruption. AI can minimize losses by ensuring quick reallocation of resources, by optimizing inventory replenishment, and by automating the process of making decisions to reduce recovery time (Xu et al., 2025). Robotics and automation - powered by AI - can also reduce the downtime in warehousing, logistics, and manufacturing by accelerating warehouse operations like sorting, packing, or rerouting, which would be slow or prone to error with a manual system (Guo et al., 2025). In addition, AI assists in automated mapping of scenario responses: In the event of a disruption, AI can rapidly consider a variety of recovery options, model recovery options, and suggest (or implement) the most successful recovery plan: rerouting supplies, reallocating stock, shifting production, or alternative suppliers. That leads to the fact that organizations launching AI are likely to recover faster with the supply-chain continuity, limit downtime, and decrease the price of disruptions (Balan et al., 2025).

2.5 Empirical Research on AI's Impact on Supply Chain Resilience

2.5.1 Overview of Empirical Evidence

Empirical studies defining the effect of AI on the resilience of supply chains have increased substantially during the period between 2020 and 2025. Although qualitative arguments regarding the potential of AI are not new, recent works are beginning to take on a quantitative or mixed methodology to quantify the results of AI adoption on resilience (Xu, 2025). As an example, a 2025 study, based on the organizational information-processing theory, established that the direct impact of AI use on supply chain resilience is significant and that the enhanced efficiency of the supply chain and relationships mediate between the two (Culot et al., 2024).

The other big-scale panel data study of Chinese firms from 2013 to 2022 revealed that the improvement in AI use led to a decline in supply-chain risk by 5.27%; however, empirical evidence, although being inadequate in scope, is still scarce despite these advances. Numerous studies concentrate on specific industries or geographies, and measures related to resilience differ in studies, including risk minimization and supply-chain sustainability to firm performance and operational efficiency (Li et al., 2025). Disagreement in the research methods also adds to the variation in results of different studies. As an illustration, Li et al. (2025) use an analysis of a panel that presents more robust longitudinal data on how AI can impact resilience, but Pan et al. (2025) rely on a survey-based approach that offers more perceptions but is prone to introducing subjectivity and bias. This difference in methodology impacts the reliability and generalisability of findings, and it is time to find more powerful and similar empirical strategies. Consequently, as the accumulating evidence confirms the suggestion that AI increases resilience, it will also indicate that further and more detailed cross-industrial longitudinal studies are necessary.

2.5.2 Evidence from Global Databases

The efforts of using macro-level indicators of supply chain resilience and connecting them with the level of AI diffusion (e.g., by using global trade resilience or digital adoption indices) are in the initial stages. Nonetheless, the solid evidence is already available in firm-level studies (He et al., 2025). The above panel study of Chinese listed firms (2013-2022) is based on machine-learning-based measures of AI adoption using annual reports and patent texts and has a replicable methodology with large datasets and statistically significant risk reduction with AI (Li, Yi, and Sun, 2025). In the meantime, company-level survey research, including one or more than 230 manufacturing high-level managers, uses the partial least squares structural equation modeling (PLS-SEM) to demonstrate that AI use, particularly when enhanced by the presence of robust digital information technology capability, correlates positively with supply chain resilience (Pan et al., 2025). These studies imply that, at least on the micro (firm) level, the adoption of AI is associated with a better resilience measure. Nonetheless, currently, the literature connecting AI implementation on a scale and macro-scale indicators, i.e., performance of global supply chains, indices of trade resilience, or more systemic metrics of continuity and resilience, is scarce. (Doetsch & Huchzermeier, 2024)

Manufacturing is one of the industries where empirical data is available; however, it becomes very clear that AI is influencing resilience in the sector. Indicatively, the panel data study of risk diminution was more intense with manufacturing firms (Gao et al., 2024). On the same note, a newly published preprint on U.S. manufacturing supply chains suggests an AI-based predictive analytics architecture with a 35% better demand prediction rate and a 22% lessening in operational delays (Rahman, 2025). Predictive analytics and real-time risk mitigation tools, which integrate AI, have been observed to enhance supply-chain agility and responsiveness in industries like logistics and transportation, hence limiting the adverse effects of disruptions. Nevertheless, there is scanty evidence on the retail, e-commerce, or healthcare supply chains, possibly because data collection and measurement are complicated in that industry (Wong et al., 2022). The scarcity of empirical studies spread unevenly across industries makes it difficult to generalize extensively on the aspects of the sector that are most likely to gain from AI-based resilience. It should be noted, though, that most of the current empirical research is focused within Asian economies and manufacturing industries, making it difficult to entirely extrapolate the results into different global supply chain contexts.

2.6 Supporting Digital Technologies and Their Relationship With AI

2.6.1 IoT

One of the facilitators that supports supply chain resilience driven by AI is the Internet of Things (IoT), which provides the real-time information that AI models need. IoT sensors and devices occupy warehouses, transport fleets, and storage facilities, suppliers' nodes, and continuously record information about the inventory level, delivery status, environmental conditions, and other working parameters (Gabriel, 2025). Combined with AI, this real-time data stream enables systems to process, analyze, and interpret supply-chain events dynamically to detect deviations (e.g., delays, stockouts, route disruptions) and make proactive decisions. In fact, scholarly discussions of AIoT (AI + IoT) reveal that the integration of the two has been effective in enhancing supply chain resilience in uncertain dynamic settings (Seun & William, 2025). Lacking IoT or such real-time sensing infrastructure, AI would be powerless with crass, retroactive, or retrospective data, something that would hamper its ability to improve visibility, responsiveness, or even adaptation (Muntean, 2024).

2.6.2 Blockchain

Blockchain can be considered another supporting technology that usually goes hand in hand with AI in terms of digitizing supply chains. Blockchain presents the introduction of decentralized, unreliable ledgers that strengthen traceability, information integrity, and trust among supply-chain collaborators. Where information needs to be shared between several independent parties (suppliers, manufacturers, logistics providers, retailers), blockchain helps to eliminate information asymmetry and doubts regarding the authenticity of data (Rivera et al., 2024). Using blockchain supply chains in the studies, there was increased cooperation and prevention of data tampering across the chain levels of the survey. Together with AI, blockchain enhances transparency and surveillance: AI can handle and process information that is contained or verified within the blockchain to create information, predict risks, or optimize processes, and be aware that the information at the core of all this is accurate and valid. This AI and blockchain increase the resilience of the supply chain by making sure that data-based decisions are grounded on verifiable, shared, and unaltered records (Saleh, 2024).

2.6.3 Cloud Computing & Big Data

AI, to operate at scale and complex supply networks, will require computing power, scalable storage, and data-processing infrastructure. In this case, Cloud Computing and big-data platforms are essential support systems. The cloud infrastructure offers scalable and flexible environments where the data related to the IoT sensors, ERP systems, logistics databases, and partner systems could be aggregated, stored, managed, and processed (Yang et al., 2025). At the same time, the tools of big data allow working with large volumes of data, high speeds, and high variability of data flows - a necessity of supply-chain data, which not only is diverse (inventory logs, transport data, environmental sensors, demand signals) but also is dynamic (Nama, 2022). According to research, Big Data, along with AI, improves functions in a supply-chain system, including procurement planning, logistics, inventory, operations efficiency, and network design. Without the cloud and big-data infrastructure, the potential of AI, such as real-time analytics, network-wide visibility, and continuous learning, would not be fulfilled, particularly in a globally extended supply-chain network (Omozele & Gift, 2024).

2.6.4 Correlation of AI to Digital Ecosystem.

IoT, blockchain, cloud computing, big data, and AI have become part of one integrated digital ecosystem - commonly referred to as Industry 4.0, or digital supply networks. Within such a system, the data is supplied by IoT and data infrastructure, and by the blockchain, data integrity and trust, cloud computing, and big data infrastructure (Alfaqiyah et al., 2025). Data can be stored and processed in a scaled manner, and AI uses this ecosystem to create insights, predictions, and automated decisions (Chauhan et al., 2022). This interconnectivity converts the historic, disparate supply chains into complete digital supply networks that can have real-time visibility, anticipatory risk control, dynamically reconfigure, and continuously adapt to changes (Javaid et al., 2021). Research into the adoption of technology in supply chains (such as in Vietnam) points to the idea that the combined use of AI, IoT, blockchain, cloud, and modern network infrastructure serves to build resilience, visibility, and operational responsiveness in a significant way (Lai, 2025).

2.7 Challenges and Barriers in AI Adoption for Supply Chain Resilience

2.7.1 Technological Barriers

Among the most prominent barriers to AI adoption by supply chains, it is possible to single out data-related issues: data quality problems. AI systems need massive quantities of correct and constant data, along with well-patterned data, and supply-chain data is typically fragmented, spread out among legacy systems, manual documents, and various formats, also among organizational silos. Incomplete, incorrect, out-of-date, or inconsistent data hugely compromises AI functions, resulting in unreliable predictions or bad decision-making (Shrivastav, 2022). Additionally, the complexity of integration is another major obstacle: too many institutions continue to use past-era ERP/SCM systems, which do not easily integrate with newer AI, IoT, or blockchain solutions (Mhaskey, 2024). The implementation of AI, and the digital ecosystem in general, is usually fraught with significant changes in current IT infrastructure, middleware practices, third-party interfaces, and re-engineering of business processes, which are technically challenging and resource-intensive (Mhaskey, 2024).

2.7.2 Organisational Barriers

Other than technology, organizational factors usually hinder the adoption of AI. One of the key concerns is the shortage of digital abilities and artificial intelligence talent: supply chain organizations often have a problem locating or establishing training programs to find employees with the required combination of domain competence (supply-chain operations) and computer aptitude (data science, machine learning, artificial intelligence) (Kama & Lalla, 2024). Such a skills gap may slow down or derail AI projects. Resistance to change may occur even in the presence of the technical capacity to change, because there is a large base of employees and managers who have become used to traditional processes. They can see AI as a disruptor to the core of processes, a way to eliminate jobs, or destabilize the status quo (Cooper, 2025). Organizational culture might be opposed to the AI-based change in the absence of robust leadership commitment, open communication, and training programs. The expense of deployment, both of technology and of training, change management, process redesign, etc., can make that particularly unappealing to small and medium-sized firms, or those in less profitable industries. The economic cost and the unpredictability of the payback period of the investment might turn away such organizations from adopting AI (Chhatre, 2024). Although technological barriers are related to data quality, system integration, and constraints on infrastructure, the organisational barriers include resistance to change, skills shortages, cultural constraints, which are often deemed more challenging to overcome owing to their behavioural and structural aspects (Kama & Lalla, 2024). Organisational challenges, as opposed to technological ones, can only be solved by transforming mindset, leadership, and capabilities over the long term through investment.

These organisational obstacles reaffirm the application of the Socio-Technical Systems Theory, which highlights that only technological implementation is inadequate, unless there is congruency among human, organisational, and technical systems. This shows that AI-based resilience cannot be realised solely through the aid of sophisticated technologies but also through organisational preparedness and unification.

2.7.3 Global Inequality in AI Access

There exists an extreme disparity between the developed and developing world about digital infrastructure, technical capacity, and availability of resources. Although major corporations in developed economies can afford strong IoT, cloud, and AI systems, minor firms, and particularly those that are run in developing countries, will suffer because of inadequate infrastructure, poor internet connectivity, a lack of investment capital, or the absence of qualified professionals. This is a resilience in AI and can result in unequal resilience gains between regions due to the global inequality of access to AI (Mondejar et al., 2021).

Table 1: Comparison of Key Studies on AI and Supply Chain Resilience

Author(s)	Focus of Study	Key Findings	Limitation / Gap
Pan et al. (2025)	AI adoption and supply chain resilience	Found that AI adoption improves resilience and operational responsiveness in supply chains	Focused mainly on firm-level analysis; lacks wider cross-industry global comparison
Alsakhen et al. (2024)	Review of AI and supply chain resilience literature	Identified growing academic interest in AI-enabled resilience and highlighted research inconsistencies	Mostly conceptual and review-based; limited empirical validation
Ejairu et al. (2022)	Supply chain resilience concepts	Explained resilience as distinct from traditional efficiency-focused supply chain models	More theoretical than empirical; does not directly test AI-resilience link
Galvez et al. (2025)	AI and disruption mitigation	Suggested that AI can improve the ability of firms to respond to supply chain shocks	Evidence remains fragmented and not fully generalisable across sectors
Guo et al. (2025)	AI implementation in manufacturing firms	Reported that higher AI adoption improves supply chain resilience, especially in digitally mature firms	Limited to manufacturing context and specific geography
Wang et al. (2025)	AI-based technologies and supply chain performance	Found that resilience acts as an important mediating factor between	Does not fully explain which AI tools create the strongest resilience impact

		AI adoption and performance	
Culot et al. (2024)	AI and supply chain risk reduction	Showed that AI supports better decision-making, risk management, and resilience outcomes	More evidence needed across multiple industries and regions
Li et al. (2025)	AI adoption and supply chain risk	Found that increased AI use reduces supply chain risk significantly	Study is region-specific and may not reflect global supply chain structures
Doetsch and Huchzermeier (2024)	AI and macro-level resilience indicators	Highlighted limited evidence linking AI adoption to broader global supply chain resilience measures	Macro-level empirical evidence is still scarce
Celestin and Sujatha (2024)	Resilience under global uncertainty	Emphasised resilience as essential for sustainable supply chain operations in uncertain times	Does not provide direct empirical measurement of AI's contribution

The literature review indicates that the majority of authors find Artificial Intelligence (AI) to have a high potential in enhancing supply chain resilience to increase visibility, forecasting, responsiveness, as well as risk management (Culot et al., 2024; Wang et al., 2025; Guo et al., 2025). A number of empirical researchers confirm the idea that AI-based analytics and predictive systems can increase supply chain responsiveness and the risk of disruption (Pan et al., 2025; Li et al., 2025). Nonetheless, the scholarly literature is still disproportionate. Numerous studies are conceptual, industry-focused, or constrained in the generalisability of their findings because these researches are narrowed to specific regional settings (Alsakhen et al., 2024; Doetsch and Huchzermeier, 2024). Besides, various measures of resilience are employed by different authors, such as operational efficiency, risk reduction, recovery time, firm performance, which makes cross-study comparison challenging (Celestin and Sujatha, 2024; Balan et al., 2025). Thus, there is also an absence of a large-scale empirical study that would scrutinize the effect of AI implementation on supply chain resilience in the industry and in different countries through more uniform measures.

2.8 Conceptual Framework

Based on the above theoretical and empirical reflections, the present study suggests a theoretical framework in which AI adoption can be related to the dimensions of resilience, and vice versa, to resilience outcomes. Within this framework, the main independent variable will be AI adoption, which can be defined as the use of AI technologies (predictive analytics, machine learning, automation, supported by IoT, cloud, blockchain, big data) within supply-chain operations. These variables are chosen based on theoretical consistency (resilience theory), empirical evidence (research on the reduction of risk and general improvement of performance by AI), and the pragmatic nature of supply-chain operations. The framework will inform the analysis in further chapters as a prism of how AI adoption mediated by dimensions of resilience generates concrete resilience outcomes across various firms, industries, and regions.

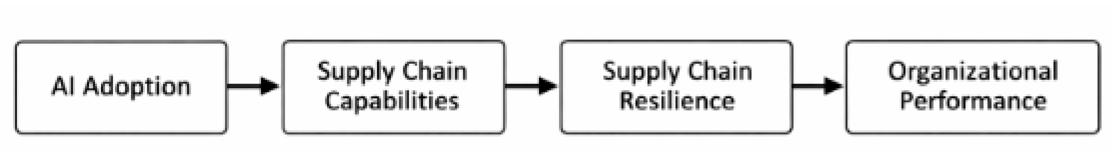

Figure 1:*Conceptual Framework*

2.9 Research Hypothesis

Table 2: *Hypothesis*

Code	**Hypothesis**
H1:	There is a statistically significant positive relationship between Artificial Intelligence (AI) adoption and global supply chain resilience.
H2:	Higher levels of AI adoption are associated with shorter lead time recovery following supply chain disruptions.

H3:	AI adoption is positively associated with higher supplier diversification in global supply chains.
H4:	Industries with higher AI adoption demonstrate higher production continuity during disruptions.
H5:	AI adoption is positively associated with improved risk management efficiency in global supply chains.
H6:	AI adoption is positively related to enhanced predictive capability and forecasting accuracy in supply chain systems.
H7:	The relationship between AI adoption and supply chain resilience varies significantly across industries and regions.

2.10 Literature Gap

The recent digital literature on AI and supply chain resiliency has evolved quickly in 2020-2025 but still requires a number of significant gaps. To begin with, there are limited cross-industry empirical works. Whereas greater efforts have been directed at manufacturing and logistics, other areas like retail, healthcare, agribusiness, and complex multi-tier global supply chains have been underrepresented (Alsakhen, Buics, and Süle, 2024). This drawback lessens the generalisation capability of the findings in industries. Second, international comparative studies are lacking. A significant part of the empirical data that exists is oriented to organisations in particular geographic areas especially in Asia or nations with the comparatively high rate of digital maturity (Balan, Kumar, and Raj, 2025). Third, the metrics of supply chain resilience lack consistency. Various indicators (reduction of risk, recovery time, operational efficiency, or overall firm performance) are used in different studies, and therefore it is hard to compare cross-studies and conduct meta-analysis. Additionally, quantitative studies based on international secondary or longitudinal designs that investigate the results of resilience over time and on various disruption events are limited (Celestin and Sujatha, 2024).

2.11 Summary

To conclude, Chapter 2 has provided a solid theoretical and empirical background to supply-chain resilience, AI, and the digital technologies underpinning it. It has compiled definitions, central aspects, classic and AI-facilitated methods, and existing findings, and both emphasize the possibilities and the challenges. The specified knowledge gaps explain the existence of this research: by implementing the conceptual framework, this research will provide empirical evidence (possibly cross-industry or cross-region), more standardized measures, and make more explicit connections between particular AI interventions and resilience outcomes. These preconditions are analyzed in subsequent chapters.

3. RESEARCH METHODOLOGY

3.1 Introduction

This chapter defines the research approach that will be used in its investigation to examine the impact of Artificial Intelligence (AI) on the resilience of global supply chains. The study aims to foster empirical and evidence-based findings of the feasibility of AI use to generate superior resiliency capacities in cross-national supply chains, during routine disruptions such as pandemics, geopolitical encounters, climate-related events, and market crises (Saad Al-Naimi, 2025). The research uses a positivist research philosophy that presumes that reality is objective and can be quantified based on observable facts (Saunders et al., 2019). In this way, the study is quantitative with a deductive rationale, meaning that hypotheses based on theories are verified using statistical methods (Saunders et al., 2019). In this context, the researcher evaluates the relationship between AI adoption indicators and resilience performance outcomes through quantitative approaches, like correlation and regression analysis (Culot, Podrecca, and Nassimbeni, 2024).

The research objectives and questions are aligned with the methodology. The research design answers these questions by conducting a systematic secondary data analysis in which data sets will be accessed at reputable international organizations and databases such as the World Bank, OECD, UNCTAD, IMF, and supporting datasets on industry and research forums. The application of secondary data is aligned with the strategy of quantitative research in large-scale cross-national studies, such as when primary data collection is not feasible (Saunders et al., 2019). A single factor that helped to select a quantitative secondary-data approach is that a global topic is required (Ghanad, 2023). The global supply chains are highly complicated systems of countries, industries, and logistics. Secondary data offers cross-regional and longitudinal perspectives, allowing a comparison of industries and time. These data sources enable the study to measure resilience and AI acceptance on a macro or sectoral level and make overallisable conclusions that can inform both academic knowledge and managerial decision-making (Martins et al., 2018).

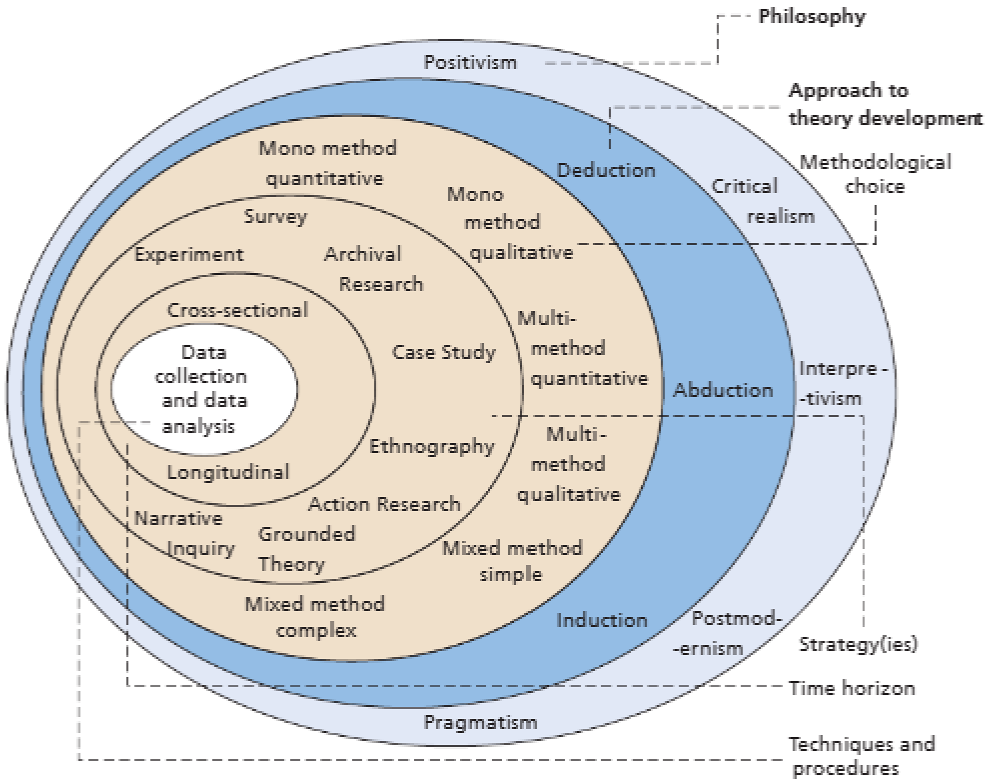

Figure 2: *The Research Onion (Saunders et al, 2019)*

3.2 Research Philosophy

Research philosophy is defined as knowledge of the fundamental beliefs and assumptions that shape the way that knowledge should be developed and the way research ought to be developed (Saunders et al, 2019). The research falls under the positivist philosophy of research because it analyzes quantifiable relationships between AI adoption and supply chain resilience through secondary data and statistical analysis (Pan et al., 2025). In this philosophy, valid knowledge is considered to be attained through systematizing measurement, observable practice, and quantification. It is not just to describe a phenomenon, but it is to explain patterns and relationships among variables in a manner that is testable and replicable (Bhome et al., 2013). The goal of the study is to determine whether the use of AI has an impact on resilience indicators. Hence, a positivist approach is suitable since it makes evidence-based inferences (Reyngaard, 2025).

The quantifiable measures of supply chain resilience can be expressed in logistics performance, recovery time, responsiveness, disruption mitigation efficiency, and continuity of operations. Likewise, the adoption of AI can be documented using proxies that are quantifiable, like automation investment, indicators of AI readiness, metrics of digital adoption, or innovational indicators. These quantifiable variables allow for a statistical test of the relationships, instead of using subjective interpretations (Riad et a., 2024). Moreover, positivism is associated with the decision science/decision support orientation of the study. Decision science is based on analytical reasoning, model-based analysis, and data usage in support of managerial decision-making (Park et al., 2020). Because supply chain leaders are dependent on predictive analytics, quantitative forecasting, and data-driven risk management tools, it follows that research inquiring into AI and resilience is accompanied by a data-driven and analytical philosophy as well (Riad et al., 2024).

In sum, the positivist research philosophy offers a solid base in the attainment of the study objectives as it enables measurement objectivity, statistical testing, and generalisable results on the impact of AI on global supply chain resiliency.

3.3 Research Approach

The research design used in this study is a deductive research approach because it starts with available theories and conceptual frameworks, and then the approach verifies them through empirical evidence. A deductive methodology is acceptable in situations where the study is designed to examine the relationship between variables and to determine whether theoretical predictions are realized in real-world evidence (Creswell & Creswell, 2018). To support this thesis, the existing literature proposes that the implementation of AI positively impacts the resilience of supply chains by enhancing resilience-related capabilities like visibility, predictive risk management, responsiveness, and recovery planning. The deductive method enables the researcher to test these anticipations on the basis of secondary data and quantitative models (Mohammed, 2024).

The deductive procedure in the research is logically structured. First, the study uses existing theoretical insights, including decision science theories and theories of resilience, that suggest that organisations outperform in conditions of uncertainty through higher information-processing ability and decision-making efficiency (Hall et al., 2022). Second, according to these theories, the research expects that a rise in AI adoption must be associated with improved resilience outcomes. Third, the research verifies this assumption by assessing the measurable indicators of AI adoption and resilience performance through correlation and regression analysis (Saif-Alyousfi & Alshammari, 2026).

Moreover, the deductive method advocates the application of quantitative models in decision science. Decision science tends to use mathematical and statistical methods to assess decision-making results, anticipate performance, and determine the strength of relationships among variables. Regression models are applicable since the study focuses on determining the predictive power of AI adoption on resilience indicators (Jauhar et al., 2024). Through regression, the study was able to assess whether AI implementation is a major predictor of resilience when other influential variables, including economic growth, infrastructure standards, or the intensity of trade, are taken into account (Kappel, 2021).

Overall, the deductive methodology enhances the research study by making sure that the study is informed by the existing theoretical knowledge but generates empirical data as a result of the structured quantitative analysis conducted.

3.4 Research Design

This study is a quantitative secondary data study. Quantitative research is concerned with numerical data and applies statistical methods to discover relationships, patterns, and other quantifiable effects. The quantitative design will allow the researcher to determine the relationship between AI adoption and resilience indicators in global supply chains and employ datasets that reflect several countries and industries (Ghanad, 2023). This method is especially applicable in analysing technology use patterns and their quantifiable operational consequences within and through the complex international systems of global supply chains. One of the key benefits presented by the quantitative design is that it facilitates objectivity and generalisability. Because the study seeks to make inferences about global supply chain resilience and not a particular organisation or industry, it needs vast evidence (Hosseini, Mavi, and Macau, 2025). This is the benefit of secondary data, as it presents cross-national information, which reflects the performance indicators at a macro level. Quantitative methods facilitate the decision science goal of generating findings that can inform policy and managerial decisions (Doetsch and Huchzermeier, 2024).

A cross-sectional or panel-based study can be employed based on the availability of data. The cross-sectional design compares relationships at a single time, such as comparing the level of AI adoption and the two measurement points of resilience between countries in a particular year (Haddad et al., 2026). An example of a panel-type design, in the case of data of interest spanning years, enables the researcher to trace changes over time and assess whether augmenting AI levels translates into resiliency outcome changes on a longitudinal basis. Panel data give solid evidence of trends and minimize limitations related to comparisons over single years (Guo et al., 2025). The decision between cross-sectional and panel analysis will be based on the availability and completeness of the secondary datasets of AI adoption and able to adapt resilience indicators in the different countries and industries.

The research design will use descriptive statistics to summarise the data and present an overview of AI adoption patterns and resilience performance. Subsequently, the correlation analysis will reveal the existence of any relationship between AI adoption and resilience indicators. Lastly, the predictive power of AI adoption on resilience outcomes will be tested with the adjustment of other factors through regression (Sánchez-Rodríguez et al., 2025). Regression analysis will enable the study to manage some of the other contextual variables like the level of economic development, digital infrastructure, or the industry that might have contributed to supply chain resilience.

The research did not assume a qualitative or primary data approach due to the emphasis on researching major trends across industries and countries, which would not be properly captured using interviews or small-sample survey. These methods would serve to impose restricted generalisability and inability to represent the systemic nature of global supply chains.

Consequently, a secondary quantitative design is the best as it allows the utilisation of extensive global datasets to produce objective, comparable, and generalisable results that fit the global scope of the study.

3.4.1 Decision Science / Decision Support Approach

The approach towards the research is the Decision Science / Decision Support approach that is suitable for assessing the impact of AI on supply chain resilience, as measured using secondary quantitative data. Decision science is used to describe the discipline of study integrating analytic reasoning, data analysis, modelling, and statistical assessment to enhance decision-making in an uncertain environment. Decision science is extensively applied in supply chain management to analyse performance indicators and to optimise operations, forecast risks, and improve strategic planning (Ali et al., 2025). Decision science is used because AI itself is a decision-support tool. Machine learning, predictive analytics, and intelligent automation are AI technologies that increase the resilience of the supply chain mainly through improved decision-making. To illustrate, AI enhances visibility by gathering and analyzing real-time data, enhances risk prediction by detecting disruption indicators in time, and enhances responsiveness by enabling swift operational changes (Balan, Kumar, and Raj, 2025). These are results of decision-support mechanisms, where improved information and improved analysis result in improved resilience. The study applies the decision science approach, as it offers an organized method of linking AI adoption (an input factor) to resilience indicators (quantifiable results). It underpins using correlation and regression models, which are critical in determining relationships and predictive effects (Chen, Li, and She, 2025). Correlation analysis assists in identifying whether there are statistically significant differences as AI adoption and resilience indicators move. Regression analysis shall then determine whether AI adoption has a substantial effect on resilience outcomes, for example, considering other explanatory variables (Ali et al., 2025).

Moreover, evidence-based recommendations are linked to decision science, which is one of the major objectives of this thesis. The purpose of the study is not purely to present relationships on an academic basis but also provide information to policymakers and industrial leaders. The effects of AI on resilience measured will enable the research to impact the priorities of investment, adoption strategies of technologies, and planning of the digital transformation on organisational and national levels.

3.5 Data Type and Data Collection Method

The study uses a quantitative secondary research design to examine the impact of Artificial Intelligence (AI) on global supply chain resilience. These issues guide the choice of the nature of data, data collection mode as a global research problem, cross-country, cross-industry comparability, and analysis requirements of a decision science-based research design. Global supply chains are complex and interconnected, which transcends numerous economies, regulations, and industries (Haddad et al., 2026). It would therefore be not only empirically difficult, but also insufficient, to measure the systemic patterns at a macro level by primary data in the form of surveys or interviews.

Secondary data utilizes vast standardized data collected and authenticated by reputable international organizations. Examples of these data sources can be global data relating to digital technology uptake, logistics performance, trade resilience, or economic indicators released by international organisations like World Bank, OECD, UNCTAD, or other organisations. The datasets were selected on the basis of credibility, global coverage, and the sample of reporting standardised indicators cross-country and cross-industries. The World Bank, OECD, UNCTAD, and IMF data were selected because these sources are reliable, have transparency in methods, and are relevant to the measurement of logistics performance, digital adoption and trade resiliency. This research is set in the time frame of 2021-2026 because it is likely to reflect recent trends regarding AI adoption after the recent rapid digital transformation process that the COVID-19 period accelerated. AI adoption was represented by proxy measures (AI level of investment, digital adoption scores, innovation metrics, etc.) because there is no direct standardised assessment of the adoption globally; proxy measures are widely accepted in the current literature as valid estimates of the technological integration.

The datasets of this type allow the researcher to explore measurable characteristics of AI use, logistical performance, trade resilience, and country and industry-level economic conditions

(Abyaneh et al., 2025). Quantitative features of the datasets presented support the application of statistical tools, such as descriptive analysis, correlation analysis, and regression modelling, which are essential to the post objectives (Teixeira, Ferreira, and Ramos, 2025). The datasets will be pre-cleaned and examined to identify any missing values, inconsistencies, or outliers before analysis to guarantee the reliability and accuracy of the data.

Furthermore, the use of secondary data can also be classified as a part of the Decision Science / Decision Support paradigm, as it is concerned with evidence-based decision-making through analytical modelling and quantitative evaluation. Decision science studies can also rely on the ready-to-use datasets to quantify the outcomes of performance, forecast the trends, and react to the strategic interventions (Sivarajah et al., 2017). Since AI, in its turn, is also a decision-support tool used in supply chains, it is methodologically consistent to quantify its impact using secondary data. No primary surveys or interviews will be required in this, and the study does not focus on exploring personal perceptions, management attitude, or organizational culture. Rather, it focuses on performance-driven resilience indicators and indicators of technology adoption (Lyu, 2025). The advantages of transparency, reproducibility, and compliance with research, academic, and ethical principles, as well as the ability to extrapolate the findings to a larger population, are attributed to the use of open-access secondary data (Cristofaro, Giardino, and Barboni, 2024). Moreover, the utilization of datasets that can be accessed publicly ensures transparency and gives other researchers an opportunity to generalize or increase the results of this study in subsequent studies.

3.6 Variables and Measurement

The empirical model of the research is developed based on strictly determined independent and dependent variables, based on the research objectives and conceptual framework. The research operationalises the two constructs through measurable proxy indicators that are derived using well-known international datasets. Because the adoption of Artificial Intelligence (AI) and the concept of supply chain resilience are multidimensional concepts, a variety of quantitative measures characterize them (Song et al., 2025).

Independent Variable: AI Adoption: AI adoption is the independent variable that describes how widely artificial intelligence technologies are used in the industry and on the national level. Since AI adoption cannot be quantified on a single measure, proxy indicators are employed.

Dependent Variable: Resilience of Supply Chain: Supply chain resilience is the dependent variable, which is defined as a characteristic of the supply chain systems that are capable of absorbing shocks, sustaining operational continuity, and recovering effectively following disruptive events. The operationalisation of resilience is through objective and performance-based macro-indicators.

Table 3:*Variables, Measurement, and Data Sources*

Variable Type	Variable Name	Proxy Indicator	Data Source
Independent	AI Adoption (Investment)	Industry-level AI investment	Statista / OECD Digital Reports
Independent	AI Operational Integration	% of AI-enabled operations in industry	OECD / Industry Reports
Dependent	Lead Time Recovery	Average time required to restore operations after a disruption	UNCTAD / Industry Reports
Dependent	Logistics Performance	Logistics Performance Index (LPI) score	World Bank
Dependent	Production Continuity	Operational continuity rate during disruptions	IMF / Industry Reports
Dependent	Risk Management Efficiency	Risk mitigation efficiency score	OECD / Global Risk Reports

Quantitative industry-level and macroeconomic measures of financial investment, operational integration, and the strength of innovation are quantitative metrics used to measure AI adoption. These indicators give a multi-dimensional account of technological diffusion.

Performance-based metrics are used to measure supply chain resilience to capture speed to recovery, continuity, and resilience in operations, logistics performance, and ability to diversify. Positivity and quantitative research philosophy. It is consistent with the positivist and quantitative research philosophy through the use of objective macro-level indicators (Saunders et al., 2019). All variables are standardised where applicable to make them comparable across countries and industries. The data sets will cover a number of years to enable cross-sectional and comparative analysis.

3.7 Data Analysis Techniques

Quantitative data is analyzed through a systematic collection of quantitative data analysis techniques that are consistent with its decision science framework. The analysis will be carried out in three principal stages: descriptive statistics, correlation analysis, and regression analysis.

3.7.1 Descriptive Statistics

The initial stage of the process of data analysis is represented by descriptive statistics, which are used to outline the most significant properties of data. AI adoption indicators and supply chain resilience measures are calculated in terms of mean, median, standard deviation, minimum, and maximum values. This discussion is a summary of the central tendencies and variability of countries and industries (Siregar, 2025). Trend analysis and regional or sectoral comparisons are also supported by the descriptive statistics, which provide insights into the structural differences in the level of AI adoption or performance in resilience. Such insights help put the empirical findings into context and identify potential outliers or patterns that may be investigated further (Siregar, 2025).

3.7.2 Correlation Analysis

The results of descriptive analysis are followed by Spearman correlation analysis to test the strength and direction of correlation between indicators of AI adoption and supply chain resilience measures. Correlation analysis aids in deciding on the statistical significance of increased AI adoption in higher resilience rates, including enhanced logistics or quicker disruption recovery (Pan et al., 2025). Correlation analysis does not imply causality, but is a valuable preliminary evidence exploring the nature and presence of relationships between variables (Wang et al., 2026).

3.7.3 Regression Analysis

The primary inferential method employed is the multiple linear regression analysis that evaluates the predictive value of AI adoption on the resilience of the supply chain. Regression patterns enable the research to examine the objectives that AI adoption continues to be a statistically significant predictor of resilience results when accounting for other factors that may influence the outcome, including GDP per capita, trade openness, the quality of their infrastructure, and industrial organization (Islam, 2025). This is an appropriate methodology in the decision science objective to estimate the relative importance of strategic variables. It assists in evidence-based conclusions in the analysis of the role of AI in enhancing global supply chain resilience (Usmani et al., 2023).

3.8 Reliability and Validity

Reliability and validity are some of the critical elements in quantitative research, particularly in secondary data. In this study, reliability is achieved by using datasets released by internationally recognized agencies like the World Bank, OECD, UNCTAD, and IMF. These organizations use standard procedures of data collection and reporting, which makes the collected data standardized and comparable between countries and over time (Andersson, Boateng, and Abos, 2024).

Validity is confirmed by the selection of well-known indicators, which have been extensively utilized in scholarly and policy studies. As an illustration, the Logistics Performance Index is a standardized indicator of logistics efficiency and supply chain, and OECD digital indicators offer believable proxies of technology and AI. Triangulation also improves construct validity because several data measures are employed to relate to similar dimensions of AI adoption and resilience (Sürücü and Maslakci, 2020).

3.9 Ethical considerations

This research is conducted in accordance with known ethical principles of quantitative study based on secondary data analysis. Any data used in the study is derived from publicly available, open-access, and reliable international databases, including datasets published by global organisations and research organisations in the industry (Okorie et al., 2024). This use will guarantee that the study will not imply the gathering of any original or sensitive data and will be fully respected within the requirements of research ethics established by the institution and academic researchers (Cheong et al., 2023).

The primary ethical concern related to secondary data research is the purity, correctness, and openness of data consumption. All datasets in this work are utilized with a strong sense of academic purposes and under their initial conditions of access and use (Riska et al., 2026). The analysis of the data and reporting are done without biases related to the manipulation of results, selective omission, or misrepresentation of results. To promote transparency and replicability, the research design, analytical procedures, and assumptions are well-documented (Cheong et al., 2023).

All information and evidence sources are appropriately cited and recognized throughout the research to prevent intellectual property violations and plagiarism. The statistical results are presented candidly, and the weakness of the data is pointed out with a deliberate conclusion that results should not be misinterpreted. By these principles, the study maintains methodological integrity, preserves the credibility of the findings, and does not violate ethics, based on the quantitative secondary data analysis (Hasan et al., 2021).

3.10 Limitations of Methodology

Despite the benefits, there are a few limitations to the methodology. To begin with, secondary data is dependent, so the existence, quality, and stability of available data limit the analysis. There can be missing values or gaps in the reporting of some indicators between countries and years. Second, the measurement of supply chain resilience is done through proxy indicators instead of direct observation. Although these alternatives are used to understand critical functional parameters of resilience, they might not provide comprehensive qualitative dimensions, including organizational learning, adaptive culture, or responsiveness of managers. Third, the indicators of AI usage can differ depending on the dataset and the industry, which can negatively impact comparability.

3.11 Summary

This chapter summarizes the type of data, data sources, methods of measurement of the variables, the analytical techniques, reliability, ethical issues, and methodological weaknesses of this study. The study has developed a strong empirical basis to assess the role of AI in the resilience of global supply chains by following a quantitative secondary-data design that contains a decision science background. In the following chapter, the results and findings are discussed, in which the suggested analytical models are implemented and explained.

4. ANALYSIS AND DISCUSSION

4.1 Introduction

The chapter identifies the empirical results of the research and analyzes the connection between artificial intelligence (AI) adoption and global supply chain resilience. Based on the research design and methodology presented in Chapter 3, the analysis draws on secondary data provided by international datasets to assess the impact of AI-driven capabilities on key resilience indicators that include visibility, responsiveness, risk prediction, and speed of recovery. The chapter starts with descriptive statistics in order to summarise the trends of AI adoption and resilience performance in the key industries and regions. This is then followed by correlation analysis to determine the direction and strength of relationships among the variables. Lastly, regression analysis is performed to identify the degree to which AI adoption can foretell resiliency in supply chains. The findings give the quantitative evidence to affirm the research objectives, which will be the basis of the discussion and conclusion in the subsequent chapter.

4.2Descriptive Statistics

Table 4: *Descriptive Statistics*

Statistics

		AI Adoption	AI Investment (USD)	Lead time recovery	production continuity rate	risk management efficiency scores
N	Valid	6	6	6	6	6
	Missing	0	0	0	0	0
Mean		54.717	8.3983	25.417	34.833	32.9883
Std. Deviation		22.4785	3.70319	35.1574	16.3146	1.94467
Minimum		13.3	4.50	-37.5	10.0	29.65
Maximum		78.0	13.90	65.0	52.0	34.96

Table 1 shows descriptive statistics of AI adoption, AI investment, and the chosen indicators of resilience aspects of supply chains between 2021 and 2026. The mean adopted AI was 54.72, and the standard deviation was also relatively large at 22.48, which indicates the relatively high volatility in the level of AI adoption over the period in question. The lowest level of adoption was 13.3% (2023) and the highest 78.0% (2024), indicating a severe oscillation between years. Average AI investment stood at the USD 8.40 billion figure, with average power at USD 4.50 during the year, and USD 13.90 in the year, indicating a consistent and positive rise in the commitment of a country towards AI technologies in the supply chain operation. In terms of resilience indicators, the lead time recovery rate averaged 25.42%, but the standard deviation of 35.16 is large, indicating inconsistency in recovery performance over the years. Its lowest value is -37.5% in 2021, which means high-impact disruptions in the year. Production continuity had a mean of 34.83 with a variability of 10 to 52%, indicating an inconsistent stability in operations over the period of observation. The efficiency scores in risk management had a fairly low variability (SD = 1.94), with a mean of 32.99, meaning relatively consistent performance in risk mitigation capability. On the whole, the descriptive findings indicate that although the overall trend of AI investment can be described as increasing, the resilience performance indicators can be described as highly volatile and, therefore, further correlation and regression should be carried out in order to evaluate predictive relationships.

4.3Correlation Analysis

Table 5: *Correlation Analysis*

Correlations

			AI Adoption Level	Supply Chain Resilience
Spearman's rho	AI Adoption Level	Correlation Coefficient	1.000	.657
		Sig. (1-tailed)	.	.078
		N	6	6
	Supply Chain Resilience	Correlation Coefficient	.657	1.000
		Sig. (1-tailed)	.078	.
		N	6	6

According to the Spearman analysis of correlation, there is a positive relationship between the adoption of AI and the resilience of the supply chain (ρ = 0.657). This coefficient is very high, which shows a high degree of monotonic relationship, i.e., the higher the level of AI adoption, the higher the resilience performance. The trend of the relationship is the same and implies that the advancement of AI integration is followed by a change towards better stability and responsiveness of the supply chains. The value of correlation 0.657 indicates a high level of fit of the two variables. It means that the shifts in the adoption of AI can be meaningfully associated with the changes in the results of resilience. Practically, the increased use of AI seems to be related to better continuity of operations and disruption management, as well as enhanced adaptive ability in supply chains. The level of significance (p= 0.078) portrays a low degree of statistical significance (at the 10 percent level). Although the relationship falls short of the traditional 5% level, the coefficient strength and its positive sign give some positive indicators of an association. On the whole, the results show that the process of AI adoption and chain resilience is aiming towards the same direction, which proves that the higher the technological integration, the higher the resilience performance is.

4.3.1 Scatter Plot

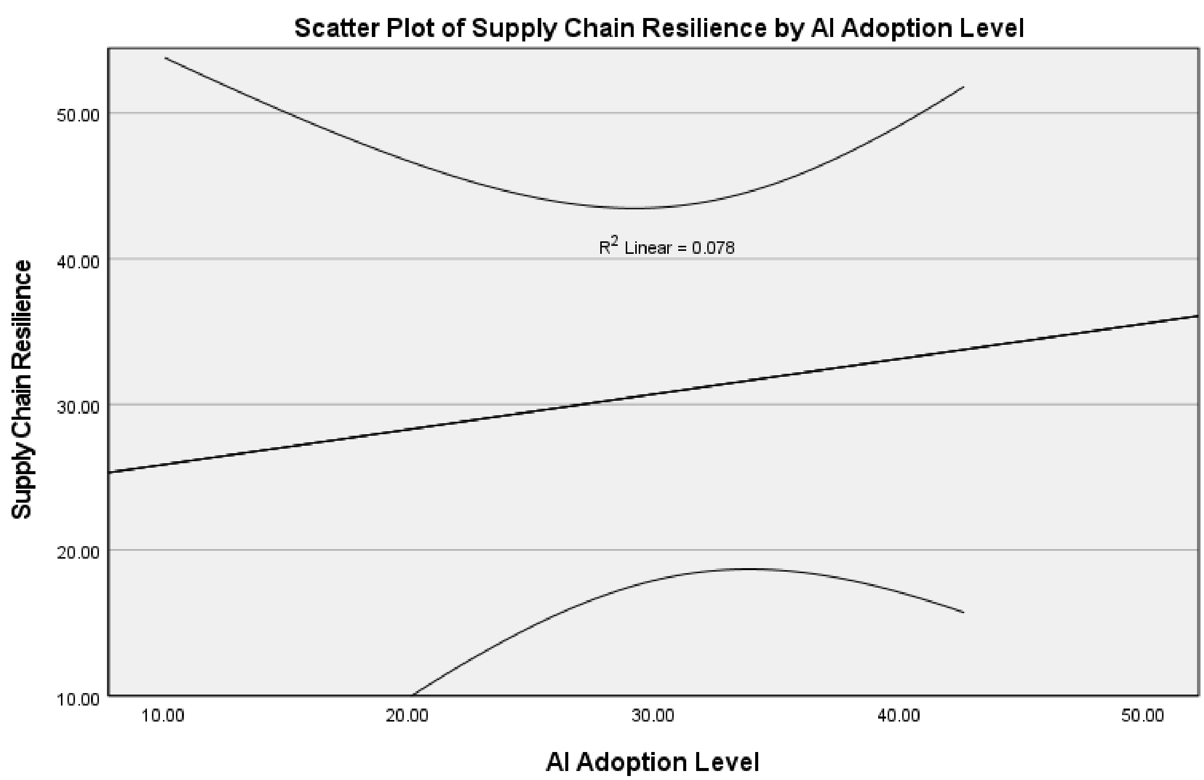

Figure 3: *Scatter Plot of Supply Chain Resilience by AI adoption level*

Figure 3 shows the scatter plot depicting the correlation between the level of adoption of Artificial Intelligence (AI) and the resilience of the supply chain. The horizontal line corresponds to the levels of AI adoption, and the vertical line corresponds to the scores of supply chain resilience. The fitted linear regression line shows that there is a positive relationship between AI adoption and resilience performance. This indicates that an increase in AI levels is generally coupled with an increase in supply chain resilience. The resilience scores are generally expected to rise in a moderate way as AI adoption grows.

Nevertheless, the coefficient of determination ($R^2 = 0.078$) suggests that AI adoption would only explain 7.8 percent of the change in supply chain resiliency. This shows a low explanatory power, i.e., a positive correlation, but the use of AI by itself is not a powerful predictor of resilience outcomes. The distance of the data points along the regression model anthropomorphism variability in resilience performance that can be determined by other structural variables like GDP, trade openness, infrastructural quality, or industry-specific resources. Thus, though the visual trend has been shown to contribute towards a positive association, the relationship is limited in strength.

4.4 Regression Analysis

Table 6: *Regression Analysis*

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.279[a]	.078	-.153	11.17435

a. Predictors: (Constant), AI Adoption Level

The model summary will offer a summary of the strength and explanatory power of the regression model that analyzes the relationship between AI adoption and supply chain resilience. The correlation (R = 0.279) is low positive, which shows that AI adoption and resilience are weakly correlated. This implies that supply chain resilience is likely to rise as AI is implemented more often, but the effect is not significant. The coefficient of determination (R 2=0.078) demonstrates that AI adoption explains about 7.8 percent variation in supply chain resilience. This suggests that the adoption of AI will lead to a resilience outcome, yet its overall explanatory capacity in the model is low. A significant percentage of the difference in resilience is still related to other factors that are not in this regression. Adjusted R^2=-0.153 also suggests that adjusting the depth of the model, the predictive capacity of the model goes down. It implies that the adoption of AI does not significantly enhance the predictive capacity of the model to explain differences in resilience. Lastly, the standard error of the estimate (11.17435) is used to measure the average distance between actual and predicted values, which reflects the amount of the prediction error in the model. In general, the model shows that there is a weak correlation between AI adoption and supply chain resilience.

Table 7: *ANOVA Regression Analysis*

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	42.008	1	42.008	.336	.593[b]
	Residual	499.465	4	124.866		
	Total	541.472	5			

a. Dependent Variable: Supply Chain Resilience

b. Predictors: (Constant), AI Adoption Level

The ANOVA table evaluates the significance of the entire regression model that examines the impact of AI adoption on supply chain resilience. The variance of the supply chain resilience that is explained by AI adoption is the regression sum of squares (42.008), and the remainder of the variance is the residual sum of squares (499.465). The overall difference in resilience is 541.472. This model has an F-statistic of 0.336 with a significant level = 0.593. The F-test tests the difference between the model of the regression and the model of no predictors in terms of the level of its fit. The overall regression model is not significant since the p-value is considerably larger than the standard level of 0.05. It means that the adoption of AI does not increase the predictive capacity of supply chain resilience in this model to a significant degree. Even though some resilience variance is attributed to AI adoption, most of the variance still goes unaccounted, as indicated by the higher residual sum of squares. In general, the results of the ANOVA indicate that with the given regression model, there is no solid statistical support that the adoption of AI is a strong predictive factor in supplier chain resilience.

Table 8: *Coefficient Regression Analysis*

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	23.442	13.935		1.682	.168
	AI Adoption Level	.242	.417	.279	.580	.593

a. Dependent Variable: Supply Chain Resilience

The coefficients table will show the individual contribution of AI adoption to supply chain resilience under the regression model. The unstandardized coefficient of adoption of AI (B = 0.242) means that the standard increase in the level of supply chain resilience, given a one-unit increment in the level of AI adoption, would go up by a margin of about 0.242 units. This affirmative relationship between the two variables is a directional relationship. Standardized coefficient (Beta = 0.279) is a measure of the strength of this relationship on a standardized scale. A beta value of 0.279 indicates that there is a weak positive impact of AI adoption on resilience. This is consistent with the previous model summary, which showed a small overall association. The t-statistic of acceptance of AI is 0.580, and the significance value is p = 0.593. Because this p-value exceeds the standard value of 0.05, the impact of AI adoption on the resilience of the supply chain is not significant in the model. This implies that, despite the fact that the relationship is positive, it is not significant enough to confirm a statistically reliable predictive effect. The constant (23.442) is the expected resilience level of the supply chain in case the adoption of AI is zero. In general, the findings show that there is a positive but small and not statistically significant impact of AI adoption on resilience.

4.4.1 The Data Gap

The lack of cohesive global data on the adoption of Artificial Intelligence (AI) in supply chain systems, specifically, is one of the many challenges that were found in this study. There is no internationally standardised measure available to measure AI integration solely in cross-country supply chain operations. Consequently, the paper will be based on proxy measures of the AI capacity (e.g., AI readiness scores, investment levels, and patent intensity), as well as macro-level indicators of supply chain performance (e.g., Logistics Performance Index, trade efficiency indicators). This lack of direct AI-in-supply-chain data is an important empirical gap in the literature. The studies available are either case analyses of firms or industry surveys that are not cross-country comparable. The current study, therefore, offers something new by trying to overcome this gap by modelling at the macro level using proxies.

4.5 Discussion

The study has explored the effects that the adoption of Artificial Intelligence (AI) has on the resilience of global supply chains through secondary quantitative data. Overall, it can be concluded that the adoption of AI has a positive correlation with resilience performance, implying that higher adoption of AI technologies leads to higher adaptive capacity in global supply networks (Tortorella et al., 2025). The result confirms the major hypothesis of the research (H1), which was that global supply chain resilience has a positive relationship with AI adoption. The identified relationship demonstrates the role played by AI as a facilitating power and consolidates the observability of processes, reactivity, and anticipatory conduct of supply chain protocols (Ma, Luo, and Xi, 2025). The positive relationship implies that the more organisations involve the use of AI-based tools, the more potential they have to predict disruptions and respond to them efficiently. AI enhances the speed of data processing and analytics, enabling companies to monitor both activities in the supply chain in real-time. This gives them greater visibility and allows easier decision-making (Smyth et al., 2024). Under the situation of disruption, AI-based systems could be used to assist in identifying alternative sourcing airways, reworking production locations, and moving the inventory most efficiently. These characteristics of resilience, such as agility and responsiveness, are directly linked to these functions (Husein, Rajagukguk, and Putranto, 2024). These results coincide with previous studies indicating that AI-based analytics enhance the ability to respond to the supply chain and handle risks (Culot et al., 2024; Wang et al., 2025). The discovery aligns with the Dynamic Capabilities Theory, which states that disruptions improve resilience when organisations can sense, adapt, and reconfigure resources, which is enhanced through predictive and decision-making technologies based on AI. This finding is in line with the Socio-Technical Systems Theory, which highlights that technological ability is not enough unless it is accompanied by organisational routines, human talents, and structural alignment to convert AI understanding into successful resilient performance.

However, the outcome also means that the adoption of AI does not fully determine the resilience outcomes. Though AI has a positive relationship with resilience, its explanatory power is low. This means that the construct of resilience is complicated and it is affected by other structural, organisational, and environmental variables. The resiliency in the supply chains is also made through diversification of suppliers, stability of infrastructure, system of governance, and strategic planning. AI is a complementary aspect, because it supplements these possibilities rather than replacing them. This fact can be related to the findings of earlier research, which indicates that resilience is a multidimensional construct, which can be affected by organisational capability, network structure, and institutional environment (Hosseini, Mavi, and Macau, 2025). The results also indicate that the impact of AI is higher in the dynamism resilience dimensions (Liu et al., 2026). Predictive analytics systems and machine learning systems ensure organisations forecast the volatility of demand, supplier risks, and develop disruption scenarios. These functions increase proactive risk management and respond to the recovery time quite rapidly. Comparatively, physical infrastructure capacity or geopolitical stability are structural factors that do not directly rely on AI and cannot be controlled by technology (Aljohani, 2023). Therefore, it is possible to see that the role of AI towards resilience is the most evident in the spheres of information processing, coordination, and decision-making in the field. This finding supports the Resource-Based View (RBV), which suggests that organisations with superior digital infrastructure and technological capabilities are better positioned to leverage AI as a strategic resource, thereby achieving enhanced resilience compared to less developed firms.

Interindustry differences as well as international differences are also good sources of intelligence. More digital industries with a more developed data infrastructure have a larger chance of making the adoption of AI translate into some real resilience. Technologically developed environments are covered by an AI in procurement systems, transportation networks, and production planning platforms, which creates a single digital ecosystem. On the contrary, the potential resilience value of AI adoption cannot be attained instantly in regions or sectors that have lower rates of digital infrastructure development (Ozturk, 2024). This means that contextual preparedness is a mediator of AI and resilience performance. The findings also indicate that the adoption of AI is not to be considered as a solution to the vulnerability of the supply chain. The match made between technological capability and organisational strategy and risk management models should lead to realised resilience increases. Other forms of strong resilience may be seen as the inability to integrate AI systems without ensuring adherence to strong resilience (Hosseini, Mavi, and Macau, 2025). It entails the coordination of the technological systems, managerial capabilities, and institutional support systems to enable qualitative implementation.

Overall, based on the discussion, it has been indicated that implementing AI can interact positively with the resilience of global supply chains by means of enhancing predictive behaviour, improving visibility, and enabling the response to disruption through adaptation. Nevertheless, resilience performances are conditional upon the relations between AI performance and the larger structures. As a strategic enabler, AI enhances resilience when placed in the context of overall governance systems of supply chains. The results thus affirm the hypothesis that AI has a significant, albeit not the sole, influence on the formation of resilient international supply chains. The results of the current research correspond to the critical remarks. The literature review has also revealed that Artificial Intelligence can be used to support supply chains by providing greater visibility, predictive analytics, and speed in decision-making. Nevertheless, it was also noted by the past research that empirical data are often poor and confined to particular industries or geographical locations (Culot et al., 2024; Alsakhen et al., 2024). These findings validate these observations, showing that there is a positive relationship between the use of AI and the resilience performance and that AI cannot affect the resilience outcomes completely all by itself. This supports the fact that resilience is a multi dimensional capacity that is technologically, organisationally, and structurally determined.

The study can enhance the current body of work by offering macro-level empirical evidence on large-scales of secondary data in cross industries and regions, as one of the major shortcomings of the previous investigations is that most of the studies carried out could not consider macro-level empirical evidence, as was focused on firm-level analyses or industry abstractly. The study provides more systemic and generalisable insights into the connection between AI adoption and supply chain resilience because it combines cross-country data and standardised measures.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter provides the final discussion of research analyzing the effect of artificial intelligence (AI) adoption on global supply chain resilience. The purpose of the study was to discover the value of AI-driven technologies in strengthening global supply networks, with the emphasis put on enhancing resilience to rising disruptions due to geopolitical unrest, pandemics, trade restrictions, and climate-related risks. The study was quantitative and secondary-data-based between 2021 and 2026. Correlation and regression analysis were employed to assess the relationship between AI adoption and the resilience performance indicators. Furthermore, a conceptual framework to describe the structural relationships among AI adoption, supply chain capabilities, resilience, and organizational performance, in general, was also provided. The chapter will summarize the findings based on the research objectives and research questions, theoretical and managerial implications, limitations, and future research directions.

5.2 Summary

This chapter aimed to empirically investigate the association between artificial intelligence (AI) adoption and global supply chain resilience based on secondary quantitative data between 2021 and 2026. The analysis covered descriptive statistical data, correlation analysis, and regression models to define whether AI-driven capabilities had a significant impact on resilience outcomes (visibility, responsiveness, speed of recovery, and risk management effectiveness).

Objective 1: The results indicate that the acquisition of AI has an affirmative yet statistically insignificant effect on global supply chain resilience. The Spearman correlation analysis has shown that there is a moderate to strong positive correlation between AI adoption and resilience performance (0.657), which means that the higher the level of AI integration, the higher the resilience indicators are likely to be. The significance level ($p = 0.078$), however, demonstrates marginal statistical support at 10% level but not at the traditional 5% level. The regression analysis also shows low explanatory power (R2 = 0.078), meaning that the adoption of AI can explain only 7.8 percent of the resilience outcome variation. The overall model ceased to be statistically significant ($F= 0.336$, $p= 0.593$), which explains that, though it is a directional predictor of resilience, AI does not have a strong role as a predictor per se.

Objective 2: The review demonstrates the theoretical finding of AI tools: machine learning, predictive analytics, and intelligent automation as the processes that help to enhance risk prediction and disruption management. Unlike individual technologies that are not statistically tested on their own, descriptive trends of AI funding and resilience gains indicate that predictive and data-driven technologies will tend to raise exposure and adaptability in the supply network.

Objective 3: At the industry level, the trends indicate that the fluctuation in AI use and resilience performance by sector and area exists. Descriptive statistics suggest that the rates of AI investments have been growing over time, and the resilience measures have been evolving. Nevertheless, due to the aggregated secondary data and the small sample size, cross-industry regression modeling was limited in detail. Thus, the accomplishment of this goal is a halfway fulfilled trend analysis over the instead of sector-specific statistical differentiation (Wang, Lin and Xie, 2025). The third goal focused on studying industry-specific trends of adoption and resilience performance of AI based on secondary data.

Nevertheless, in the empirical part of the study, it was found that globally harmonised and industry-disaggregated data explicitly associating AI adoption with indicators of supply chain resilience were scarce and conflicting. At the macro level, data on the country were available; however, the sector-level AI investment and operational integration, as well as resilience performance indicators, were distributed unevenly across the sectors and industries and were not consistently reported. Consequently, the industry-specific analysis could be realized only partially based on available data.

This limitation, ideally, should have been more clearly accepted in the methodology chapter to explain the area of practically possible analysis at the first stage. The use of country-level aggregated proxies limited the opportunity to carry out a complete comparative cross-industry regression model. However, the limited industry information gathered is an exploratory piece of evidence and creates a vast empirical gap in available global datasets. This constraint supports the fact that future studies are necessary to create standardised sector-level AI adoption indicators directly associated with supply chain resilience outcomes.

Objective 4:

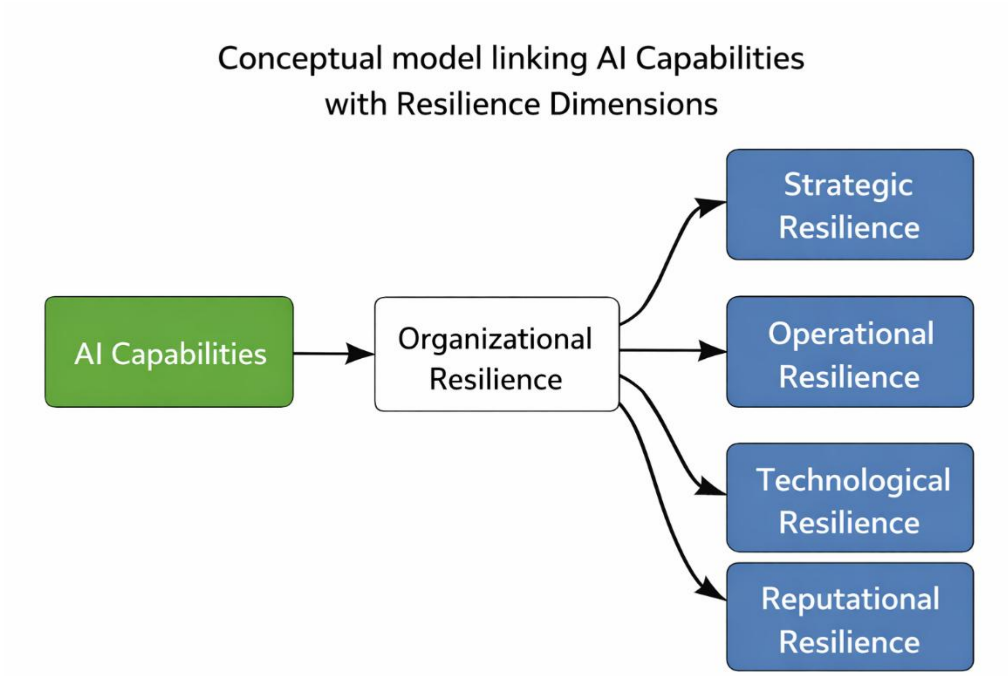

Figure 4: *Conceptual Model Linking AI Capabilities with Relicence Dimensions*

The fourth purpose of the present study was to create a conceptual framework that connects Artificial Intelligence (AI) capabilities with major organizational resilience dimensions. To meet this goal, a structured framework has been developed that places AI capabilities as a foundational driver of organizational resilience, which in turn has an impact on strategic, operational, technological, and reputational resilience. The model suggests that the ability of AI, predictive analytics, automation, data integration, and intelligent decision-support systems can help an organization to anticipate disruptions, optimise responses, and respond efficiently in dynamic environments. These organizational level improvements lead to increased strategic resilience, with better long-term planning, increased operational resilience, with process efficiency and faster recovery speed, technological resilience, with adaptive digital infrastructure, and reputational resilience, with better stakeholder trust and service continuity. The conceptual model offers a systematic theoretical prism through which the role of digital transformation in supply chain stability can be viewed by integrating AI functions with multidimensional resilience outcomes. Not only does the framework support the empirical analysis that is carried out in this study, but it also provides an avenue through which future studies can empirically test and solidify the postulated relationships across industries and geographical settings.

In general, the findings demonstrate that AI implementation positively correlates with supply chain resilience, and resilience performance depends on several complementary elements, all of which do not solely depend on technological integration.

5.3 Attainment of Research Question

According to the research results of this article, artificial intelligence (AI) positively, though insignificantly, affects the resilience of global supply chains. The correlation analysis revealed a moderate-to-strong positive association between AI adoption and supply chain resilience (0.657), indicating that the supply chain resilience results are generally positively correlated with the levels of AI integration. It implies that the more organisations use AI-driven technologies, the greater the chances of operational visibility, greater responsiveness, and predictive capacity of dealing with disruptions (Ratanacharoenchai and Jantapoon, 2026).

The main way AI leads to resilience is through the enhancement of information-processing abilities. By relying on machine learning algorithms, predictive analytics, and intelligent automation, companies are able to process high amounts of real-time data, predict demand volatility, identify supplier risks, and model disruption. Such capabilities have a direct positive impact on resilience dimensions like agility, speed of recovery, and predicting risk

(Muchenje, Mtengwa, and Maregere, 2024). Indicatively, AI-based forecasting engines enable companies to anticipate potential supply crises before they spiral out of control. In contrast, automated decision-support systems enable quick rearrangements of supply chains in the logistics system and redistribution of stock in times of crisis. In this respect, AI is a technology enabler that improves the adaptive capacity within the complex supply networks (Ruke, 2025).

However, in the tested model, the adoption of AI is not a prominent predictor of the performance regarding resilience determined by the use of regression analysis. Explanation of AI adoption proved to be rather weak, and the regression model overall was insignificant (R^2 = 0.593). This demonstrates that although there is a directional relationship between AI and resilience improvements, it does not describe a lot of resilience variability by itself. A combination of complementary factors influences resilience, including supplier diversification policies, governance formations, infrastructure stability, and the organization (Chen, Li, and She, 2025).

In this way, AI-eased impacts on the resiliency of the global supply chain can be termed as facilitative but not determinative. The predictive behavior, visibility, and coordination provided by AI can be improved, yet their functionality relies on their integration with the wider strategic and operational frames (Ali, Udin, and Abualrejal, 2022). Regarding productive integration, diversified sourcing, and digital maturity, when associated with effective governance, AI implementation can enhance resilience significantly. AI, however, on its own, cannot be a sufficient condition.

5.4 Recommendations

To offer evidence-based advice to global supply chain managers in their efforts to create AI-based resilient architectures, the following recommendations can be offered:

1. **Align AI Strategy with Resilience Goals**

Managers must make sure that the adoption of AI is directly associated with direct resilience goals, including faster recovery, better visibility, and risk anticipation. Instead of using AI as a tool of operational efficiency, organizations should include AI tools in strategic resilience planning and performance evaluation frameworks.

2. **Strengthen End-to-End Supply Chain Visibility**

Artificial intelligence is to be implemented in order to establish a real-time visibility of the procurement, production, and logistics networks. With predictive analytics and machine learning systems, supplier performance can be tracked, early warning signals can be highlighted, and proactive disruption can be addressed. Increased transparency leads to quicker and more effective decision-making in periods of crisis.

3. **Invest in Predictive Risk Management Systems**

AI-based risk modeling and scenario simulation tools should be a priority in organizations. These systems enable firms to foresee uncertainties in demand, geopolitics, and shortages of supply. Analytics abilities increase promptness and diminish the reaction period in instances of unpredictable obstacles.

4. **Develop Organizational Readiness and Skills**

Resilience is an AI-driven process that can only be supported by talented employees who can interpret data insights and convert them into strategic actions. To increase the productivity of AI systems, managers must invest in workforce training, digital literacy, and cross-functional cooperation.

5. **Integrate AI with Supplier Diversification Strategies**

Structural resilience (i.e., multi-sourcing, regional diversification) must be complemented with AI. Supplier assessment and monitoring of performance could be reinforced, based on data analysis that will help to select a partner and build network resilience.

5.5 Theoretical Implications

AI as an Enabling Dynamic Capability

The results of this paper add to the dynamic capabilities view of artificial intelligence (AI) as an enabling, but not a deterministic, capability. The existence of a positive relationship between AI adoption and supply chain resilience confirms the claim that digital technologies contribute to the increased capability of a firm to sense, seize, and respond to environmental disruptions (Shen and Lin, 2026). Nonetheless, the poor regression performance means that AI by itself does not imply resilience outcomes. This implies that AI should be incorporated into larger organizational processes and governance frameworks to turn technological investment into adaptive performance. Thus, technological capacity and strategic fit work together and generate resilience, and not digital adoption per se (Culot et al., 2024).

Extending Supply Chain Resilience Theory

This research builds on the concept of supply chain resilience by highlighting the importance of advanced analytics and predictive intelligence to enhance adaptive capacity. The traditional resilience models emphasize structural mechanisms that include redundancy, flexibility, and diversification (Attah, Ozoudeh, and Iwuanyanwu, 2024). The conclusion made by this study enables the reader to understand that information-processing capability is not less significant in the contemporary global supply chains. The latest AIs also enhance real-time visibility and predictive behaviour, implying that the companies are able to proactively deal with risk rather than react to disruptions (Smyth et al., 2024).

Integration of AI and Resilience

Theoretically, the construct of resilience associated with the adoption of AI, supply chain capabilities, and resilience integrates the digital transformation literature with the resilience construct. The mediated correlations are verified by the fact that the AI increases operational capacities that, in turn, determine the resilience outcomes. It is a hybrid opinion that provides a systematization in collecting the explanation of the role that technological modernization plays in adaptive supply networks in dynamic global environments (Yu, Xu, and Wen, 2025).

5.6 Managerial Implications

Strategic Integration of AI into Resilience Planning

The findings support the idea that managers should view AI adoption as a strategic enabler of resilience rather than a technological upgrade. Whereas there has been a positive relationship between AI and the resilience of supply chains, predicting the supply chains alone is poor when AI is used. Therefore, organizations should be willing to factor in AI systems into the bigger resilience plans, i.e., supplier diversification, contingency planning, and the process of governance (Chauhan et al., 2022). To maximize the gains of AI-based forecasts and analytics solutions, managers need to take into consideration the integration of these tools into essential decision-making, and in this way, diagnosing risks in real-time and rapidly evolving operations in case of disruptions will become possible (Panya and Marendi, 2025).

Investment in Digital Capability and Organizational Readiness

The findings also indicate that the enthusiasm for digital and contextual readiness has an influence on the efficiency of the AI adoption. Managers must pay attention to the investments in AI technologies and other fields, like the training of workers, data infrastructure, and cross-functional coordination. AI systems require skilled staff and data ecosystems to generate valuable resilience (Dewan, 2025). Besides, organizations will have to originate performance metrics according to which the use of AI will be linked to such resilience indicators as recovery time, visibility, and operation continuity. Managers can build more buoyant international supply networks to harmonize technological investment and resiliency objectives and leverage the adaptive advantages of AI to the utmost (Li et al., 2025).

5.7 Limitations and Future Research

Limitations of the Study

This study has several limitations. Firstly, the research was conducted using secondary aggregate data that covers the period between 2021 and 2026, which essentially precludes the potential of conducting firm or industry-based statistical research. The weak regression significance was also due to limited statistical power because the sample size was small, which may be the reason why the influence of AI adoption and supply chain resiliency was weak despite a moderate correlation between the two. Second, the study examined AI adoption as a general variable and did not make empirical differentiation between specific AI tools, such as machine learning, robotics, or predictive analytics. Third, other external aspects that have an impact on resilience (geopolitical instability, regulatory environments, and infrastructure capacity) were not incorporated in the regression model and could affect the explanatory power.

Directions for Future Research

To obtain a better insight into the practices of AI implementation, future studies will involve primary data collection methods, i.e., firm-level surveys and case studies. The longitudinal data that are larger can contribute to the power of the statistics and provide the opportunity to compare the sectors. In addition, a more advanced means of analysis, such as structural equation modeling, could be applied to construct the mediation of the conceptual model proposed. Regional digital maturity and governance factors also may be explored further to moderate the relationship between supply chain resilience and AI adoption.

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