SYSTEMATIC REVIEW OF ARTIFICIAL INTELLIGENCE APPLICATIONS AND THEIR IMPACT ON SUPPLY CHAIN DECISION-MAKING AND OPERATIONAL AGILITY

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ABSTRACT

Modern global supply chains face a state of endemic volatility, characterized by geopolitical conflicts, sudden disasters, and systemic disruptions that create significant demand-supply imbalances. This systematic literature review analyzes and synthesizes the academic literature from 2020 to 2024 to understand how Artificial Intelligence (AI) applications are being leveraged to transform supply chain decision-making and enhance operational agility. Following a rigorous SLR methodology, 41 peer-reviewed articles were selected from the Scopus and Web of Science databases. The synthesis reveals that AI is not a singular technology but a convergent ecosystem, primarily involving machine learning for predictive analytics, intelligent automation, and enabling technologies like the Internet of Things (IoT). The findings indicate that AI's primary impact is the facilitation of a paradigm shift in decision-making, moving from a reactive and historical-based model to a proactive, anticipatory, and data-driven one. This transformation is the central mechanism enabling a new level of operational agility, allowing firms to develop not only defensive resilience to mitigate disruptions but also offensive agility to improve innovation performance and competitive advantage. The review concludes that the realization of AI's full potential is significantly moderated by socio-technical challenges, including data quality, integration complexity, and the critical need for an organizational culture that fosters digital skills and human-AI trust.

Keywords: **AI, Decision-Making, Digital Transformation, Operational Agility, Supply Chain**

1. INTRODUCTION

1.1. Background: The 'New Normal' of Supply Chain Volatility

The contemporary global supply chain environment is defined by unprecedented volatility and complexity. In recent years, the linear and often fragile links of global networks have been profoundly stressed, exposing deep-seated vulnerabilities (Acar & Uzun, 2022). The COVID-19 pandemic, in particular, served as a catalyst, triggering systemic disruptions that resulted in severe demand-supply imbalances, halted sales, and significant operational risks for businesses worldwide (Acar & Uzun, 2022; Akhtar et al., 2021). These challenges were not isolated; they compounded existing pressures from geopolitical conflicts, trade disputes, and sudden natural disasters (Acar & Uzun, 2022; Al Zoubi & Gharaibeh, 2021). This has led to a consensus in the literature that disruption is no longer an intermittent event to be managed but a constant, structural condition of the modern business landscape. The resulting "enigma of professionalism" suggests that traditional management approaches, which often rely on theoretical models and historical data, are increasingly ill-equipped to handle the speed and scale of real-world demand fluctuations and supply-side uncertainties (Asif et al., 2024; Arma, 2022; Mardhiyah, 2022; Tan, 2022; Winata, 2022). For many firms, this environment has led to dire economic consequences, including supplier bankruptcies and corporate insolvencies, particularly for those with limited contingency plans (Akhtar et al., 2021).

1.2. The Imperative for Operational Agility

In response to this volatile 'new normal', the strategic focus of operations and supply chain management has converged on the imperative for operational agility (Barney & Hesterley, 2023; Blome & Schoenherr, 2021). Agility, broadly defined as the capability to effectively sense, respond to, and exploit market changes, is increasingly positioned as the critical determinant of firm survival and competitive advantage (Blome & Schoenherr, 2021). The literature demonstrates that organizations are under immense pressure to reduce delivery lead times and manage demand shocks at extreme speeds, giving rise to the concept of "supply chain hyperagility" (Cohen & Kouvelis, 2021; Rolando, Chandra, et al., 2025; Rolando, Widjaja, et al., 2025; Widjaja, 2025). This hyperagile capability is not merely about speed; it represents a fundamental shift in operational strategy. It involves sophisticated scenario planning (Daugherty, 2021), diversifying supplier bases to reduce single-source dependency (Daugherty, 2021), and possessing the data-analytic capabilities to reconfigure assets in real-time. A frequently cited example is Nike's use of predictive-demand analytics and RFID technology during the pandemic to reroute inventory from closed physical stores to burgeoning digital sales channels, thereby minimizing the disruption's impact (Dwivedi et al., 2021; Putri, 2022; Rolando et al., 2022; Setiawan, 2022; Wijaya, 2022). This demonstrates that agility has evolved from a static organizational attribute to a dynamic capability. It is a demonstrable performance outcome (Guerra et al., 2022) that mediates higher-level firm success, such as fostering innovation performance (Habibi, 2024) and sustaining a competitive edge (Blome & Schoenherr, 2021; He et al., 2023). However, a significant gap often exists between recognizing the need for agility and the ability to define, measure, and successfully implement it (Cohen & Kouvelis, 2021; Khan et al., 2023; Ingriana et al., 2024; Mulyono, 2024; Rolando & Mulyono, 2025a, 2025b).

1.3. The Research Gap: Synthesizing the Role of AI

The literature overwhelmingly posits that the primary enabler for achieving this requisite level of agility is the integration of digital technologies, particularly Artificial Intelligence (AI) (Acar & Uzun, 2022; Kim et al., 2022; Kumar & Mallipeddi, 2022). AI applications are presented as transformative tools capable of enhancing operational efficiency, optimizing logistics, and, most critically, predicting demand patterns to mitigate risks (Kim et al., 2022). While numerous studies have reviewed the concept of supply chain agility (Blome & Schoenherr, 2021; Layode, 2024) and others have reviewed the applications of AI in supply chain management (SCM) (Kim et al., 2022; Lim, 2022), a clear research gap exists. There is a lack of a recent, systematic synthesis that explicitly excavates the mechanism connecting specific AI applications to the transformation of managerial decision-making and the subsequent measurable impact on operational agility. The implicit hypothesis across the literature suggests a causal chain: AI implementation leads to improved data analytics, which transforms decision-making processes, ultimately enhancing operational agility. This systematic review is essential to validate and structure the evidence for this causal pathway, synthesizing disparate findings into a coherent framework (Maha et al., 2025; Mulyono et al., 2025; Rahardja et al., 2025; Rolando, 2024; Rolando & Ingriana, 2024).

1.4. Research Objectives and Questions (RQ)

The primary objective of this systematic literature review is to analyze and synthesize the empirical and conceptual literature published between 2020 and 2024. The aim is to develop a comprehensive understanding of the specific applications of Artificial Intelligence in supply chain management and to critically evaluate their impact on decision-making processes and the enhancement of operational agility.

To achieve this objective, the review addresses the following research questions (RQ):

- RQ1: What are the primary AI applications and technologies (e.g., machine learning, autonomous robotics, digital twins) being implemented in supply chain management according to the recent literature?
- RQ2: How does the integration of these AI applications transform supply chain decision-making processes?
- RQ3: What is the documented impact of AI-driven decision-making on operational agility and firm performance?

2. RESEARCH METHOD

2.1. SLR Design

This study employed a Systematic Literature Review (SLR) methodology. The process was guided by established rigorous frameworks (e.g., Kitchenham) and structured around three distinct phases: Planning, Conducting, and Reporting. The *Planning* phase involved the precise definition of the research scope using the Population, Intervention, Context, Outcome (PICO) framework. This framework defined the Population (global supply chains), Intervention (AI applications), Context (2020-2024), and Outcomes (transformed decision-making and operational agility), which directly informed the three research questions. The *Conducting* phase, detailed below, involved the systematic search, screening, and data extraction from relevant literature. The final *Reporting* phase consists of the thematic synthesis and discussion of findings presented in this article.

2.2. Search Strategy and Data Sources

A comprehensive search strategy was executed on two primary, high-impact academic databases renowned for their coverage of engineering, technology, and management literature: Scopus and Web of Science. The search string was developed to capture the core concepts of the research questions, combining keywords for the intervention (AI) with the domain (SCM) and the specified outcomes (decision-making and agility). The following Boolean search string was adapted for each database's syntax:

($"Artificial Intelligence"$ OR $"Machine Learning"$ OR $"Predictive Analytics"$) AND ($"Supply Chain"$ OR $"Supply Chain Management"$ OR $"Logistics"$) AND ($"Decision-Making"$ OR $"Strategic Planning"$) AND ($"Agility"$ OR $"Operational Agility"$ OR $"Resilience"$ OR $"Responsiveness"$)

2.3. Inclusion and Exclusion Criteria

To ensure the relevance, timeliness, and quality of the reviewed literature, a strict set of inclusion and exclusion criteria was applied during the screening process.

Inclusion criteria were:

(1). Articles published in English-language, peer-reviewed journals or high-impact conference proceedings;
(2). Publication date between 2020 and 2024 (inclusive), a period selected to capture the most recent technological advancements and the accelerated digital transformation following the onset of the COVID-19 pandemic (Acar & Uzun, 2022);
(3). Studies that explicitly discuss AI, machine learning, or related sub-fields as a central theme within the SCM context; and
(4). Studies that explicitly analyze the relationship between these technologies and supply chain decision-making and/or operational agility.

Exclusion criteria were:

(1). Studies published before 2020 or after 2024;
(2). Non-English language articles;
(3). Grey literature, including magazines, dissertations, theses, textbooks, and unpublished working papers; and

(4). Articles where AI was mentioned only in passing (e.g., in a keyword list) without being a substantive focus of the research.

The initial search yielded a large corpus of articles, which was systematically screened by title and abstract, followed by a full-text review by the research team to assess eligibility. This process resulted in a final selection of 41 key studies that form the evidence base for this review.

2.4. Data Extraction and Thematic Synthesis

A structured data extraction form was developed to capture salient information from each of the 41 selected articles. The extracted data points included: Author(s) and Year, AI Application(s) Studied, Research Method (e.g., empirical, case study, conceptual, SLR), Industry/Context, Key Findings related to Decision-Making, and Key Findings related to Operational Agility/Performance.

To analyze and synthesize the findings from these diverse studies, a narrative-based thematic synthesis approach was employed. This method involved coding the extracted data and organizing it according to the three predefined research questions. This qualitative synthesis approach is particularly effective for an SLR as it allows for the integration of findings from studies with heterogeneous methodologies (e.g., empirical quantitative studies (Cohen & Kouvelis, 2021; Guerra et al., 2022), case studies (Dwivedi et al., 2021; Liu et al., 2021), and conceptual reviews (Blome & Schoenherr, 2021; Kim et al., 2022)), enabling the construction of a comprehensive and interpretive model of the phenomenon. The results of the data extraction from the 41 selected studies are presented narratively in the following section.

3. RESULTS AND DISCUSSION

3.1. Overview of Selected Studies

The final corpus of 41 studies reflects a rapidly expanding research interest in the AI-agility nexus, particularly in the years following 2020. The literature is methodologically diverse. A significant portion consists of conceptual papers and systematic reviews that work to establish the theoretical foundations and frameworks linking digital transformation, AI, and supply chain capabilities (Blome & Schoenherr, 2021; Kim et al., 2022; Layode, 2024; Manana & Mawela, 2022). A second strong contingent of research focuses on specific AI sub-fields, most notably the application of machine learning (ML) for demand forecasting and predictive risk analytics (He et al., 2023; Lim, 2022; Müller et al., 2022; Park et al., 2021). A third group presents empirical evidence, sourced from both qualitative case studies of industry leaders (Dwivedi et al., 2021; Liu et al., 2021) and quantitative structural equation modeling (SEM) or surveys (Cohen & Kouvelis, 2021; Guerra et al., 2022; Habibi, 2024). This empirical work seeks to validate the proposed links between technology adoption and measurable performance outcomes. The reviewed studies cover a wide range of contexts, including challenges in global supply chains (Acar & Uzun, 2022; Al Zoubi & Gharaibeh, 2021), specific regional investigations in emerging economies (Habibi, 2024; Qu & Kim, 2024), and various industries such as manufacturing (Khan et al., 2023), retail (Liu et al., 2021; Sadikoglu & Demirkesen, 2022), and logistics (Sayudin, 2023; Singh et al., 2023).

3.2. RQ1: The Landscape of AI Applications in Supply Chain Management

The synthesis of the 41 studies reveals that "AI" in the context of SCM is not a monolithic technology but rather a convergent technological ecosystem. The primary applications identified, which directly address RQ1, fall into several key categories:

Predictive Analytics and Machine Learning (ML): This is, by a significant margin, the most frequently cited application of AI in the reviewed literature. ML models are extensively used for demand forecasting (Kim et al., 2022; Lim, 2022; Park et al., 2021). These models represent a significant leap over traditional statistical methods by allowing firms to move beyond analyzing historical sales data. AI-based models can integrate a wide array of external, real-time parameters—such as weather patterns, competitor actions, macroeconomic indicators, and consumer sentiment—to adjust forecasts dynamically (Park et al., 2021; Sodhi et al., 2023).

Intelligent and Autonomous Systems: This category includes the application of AI to physical and digital processes. It encompasses intelligent automation (Sodhi et al., 2023; Tamtam & Tourabi, 2025), autonomous robotics for logistics and warehousing (Sayudin, 2023), and AI-driven process automation (Tavana et al., 2023). These applications are primarily focused on streamlining operations, reducing human error, and eliminating operational bottlenecks.

Digital Supply Chain (DSC) Enablers: A critical finding is that AI rarely functions in isolation. Its power is unlocked when integrated within a broader Digital Supply Chain (DSC) (Habibi, 2024; Tiwari et al., 2024). AI acts as the system's analytic brain, but it is functionally dependent on other technologies to act as the sensory nerves. These enabling technologies include the Internet of Things (IoT) and RFID sensors for real-time data collection (Dwivedi et al., 2021; Tiwari et al., 2024; Tsao et al., 2024; Vo et al., 2024), Big Data analytics platforms for processing volume and velocity (Tiwari et al., 2024; Tsao et al., 2024), blockchain for enhancing security and transparency (Qu & Kim, 2024; Vo et al., 2024), and Business Intelligence (BI) platforms for visualization and reporting (Wulandari & Hadi, 2023).

AI-Driven Risk Management: Moving beyond simple forecasting, AI and ML models are increasingly used to identify patterns, anomalies, and imminent dangers. This enables a proactive risk reduction strategy, shifting the paradigm from post-event analysis to real-time, predictive risk mitigation (Lim, 2022; Müller et al., 2022).

Emerging Technologies: The most recent literature (2023-2024) highlights the nascent but significant potential of next-generation AI. This includes Quantum AI (QAI) for solving highly complex combinatorial problems, such as optimizing multi-variable routing and emissions management (Wulandari & Hadi, 2023), and Generative AI (GenAI) for optimizing digital SCM performance and strategic frameworks (Acar & Uzun, 2022).

In summary, the answer to RQ1 is that AI in SCM is a synergistic ecosystem where AI's predictive and optimizing intelligence is fused with an IoT-driven sensory layer, all operating within a digital-physical infrastructure (Tsao et al., 2024).

3.3. RQ2: The Transformation of Supply Chain Decision-Making

The integration of the AI applications identified in RQ1 fundamentally transforms how, when, and by whom managerial decisions are made. The synthesis identified four primary transformations, directly addressing RQ2.

From Reactive to Proactive/Anticipatory: The most significant transformation is the shift from a reactive, experience-based decision-making model to a proactive, data-driven, and anticipatory one (Liu et al., 2021; Müller et al., 2022). Traditionally, managers would react to a disruption or a demand surge after it occurred. In contrast, AI-driven "demand sensing" (Sodhi et al., 2023) uses real-time data to anticipate market fluctuations before they manifest. This allows planning models to adapt quickly (Park et al., 2021) and enables firms to engage in proactive risk prevention rather than "post-event analysis" (Müller et al., 2022). This effectively changes the temporality of supply chain management, moving the decision point from after a problem to before it.

Enhanced Granularity and Real-Time Capability: The convergence of AI, IoT, and BI platforms (Tiwari et al., 2024; Tsao et al., 2024) provides decision-makers with real-time, granular insights into end-to-end operations (Tavana et al., 2023). This capability allows managers to move away from high-level, periodic reviews (e.g., quarterly or monthly) and toward continuous, granular optimization of sourcing, production, and logistics (Al Zoubi & Gharaibeh, 2021; Dwivedi et al., 2021).

Optimization of Complexity: AI, and its future quantum iteration (Wulandari & Hadi, 2023), can process and optimize complex, multi-variable problems that are intractable for human decision-makers alone. This includes complex location-inventory-routing problems (Tsao et al., 2024) and dynamic, strategic decision-making (Tavana et al., 2023; Akhtar et al., 2021), allowing firms to achieve a level of operational efficiency and strategic alignment previously unattainable (Al Zoubi & Gharaibeh, 2021).

Rise of Autonomous Decision-Making: The literature points to the emergence of autonomous systems where AI agents and intelligent automation platforms (Tamtam & Tourabi, 2025; Wulandari & Hadi, 2023) are empowered to make and execute operational decisions without human delay. This includes triggering predefined response workflows (Sodhi et al., 2023) and optimizing routine processes like inventory management, as seen in Amazon's use of ML to enhance predictability and performance (Liu et al., 2021).

The central mechanism underpinning these transformations is uncertainty reduction. By processing vast, diverse, and high-velocity data (Park et al., 2021; Sodhi et al., 2023), AI provides a level of enhanced cognition (Asif et al., 2024) and predictive accuracy that human managers cannot achieve alone. This augmented cognition is the direct enabler of operational agility.

3.4. RQ3: The Impact of AI-Driven Decision-Making on Operational Agility

The synthesized literature provides robust evidence that the AI-driven transformation in decision-making (RQ2) has a direct, positive, and multi-faceted impact on operational agility (RQ3).

Direct Enhancement of Agility: Numerous studies explicitly link digital transformation and AI adoption to enhanced operational agility and adaptability (Habibi, 2024; Barney & Hesterley, 2023). AI-driven analytics contribute to "more agile and adaptive business processes" by streamlining operations, reducing human error, and minimizing operational bottlenecks (Tavana et al., 2023). This provides the firm with the capability to respond to changes with greater speed and precision.

Agility as a Mediator for Firm Performance: The review reveals that agility is not merely an internal operational goal but a critical mediator for high-level, strategic firm performance. For instance, one empirical study found that digital supply chain dimensions (such as information technology and digital performance measurement) significantly enhance supply chain agility, which in turn strongly boosts innovation performance (Habibi, 2024). Other studies confirm this, linking AI-driven supply chain agility directly to a sustainable competitive advantage (He et al., 2023).

Empirical Validation: This link is validated by concrete, real-world examples. The case of Nike (Dwivedi et al., 2021) demonstrates how its use of predictive analytics and RFID technology enabled a tangible display of agility: rerouting inventory from closed stores to digital channels, thus mitigating the impact of mass shutdowns. Similarly, Amazon's (Liu et al., 2021) extensive use of data analytics and ML for predictability and data-driven decision-making is identified as a key factor in its "ability to respond quickly to changing market conditions."

This synthesis reveals that the impact of AI on agility is twofold, allowing for a distinction between two forms of agility. First, AI enables Defensive Agility, which is synonymous with resilience. This involves using predictive analytics for risk management (Lim, 2022; Müller et al., 2022) and real-time monitoring to effectively mitigate disruptions (Blome & Schoenherr, 2021). This is the baseline capability of using AI to survive volatility. Second, and more strategically important, AI enables Offensive Agility. This is a value-creating capability. By using AI not just to anticipate the future but to act upon it, firms move beyond survival. They leverage AI-driven insights to improve innovation (Habibi, 2024) and strengthen their market positioning (Tavana et al., 2023). In this sense, AI transforms agility from a purely defensive shield into an offensive weapon for capturing market share.

3.5. Discussion and Synthesis: The Socio-Technical Challenge

Synthesizing the findings across all three research questions, a clear framework emerges: The convergence of AI, IoT, and Big Data (RQ1) enables a proactive and anticipatory decision-making paradigm (RQ2), which in turn builds both defensive (resilience) and offensive (competitive) operational agility (RQ3).

However, the literature is unequivocal that realizing this framework is not a simple technical implementation. The impact of AI is significantly moderated by a host of socio-technical challenges that can impede or even nullify its potential benefits.

First, technical barriers exist, including persistent issues with data quality, the high cost and complexity of integrating AI with legacy systems (Lim, 2022), and challenges related to scalability (Sadikoglu & Demirkesen, 2022).

Second, and more critically, the literature identifies managerial and organizational barriers as the most significant hurdles. A primary issue is the "black box" problem, or the lack of explainability in many AI models (Sadikoglu & Demirkesen, 2022). This opacity creates a trust deficit, making managers hesitant to rely on AI recommendations for high-stakes decisions. Consequently, the success of AI adoption is shown to be highly dependent on "soft" organizational factors. These include strong leadership, the development of a technological culture (Barney & Hesterley, 2023), and, crucially, investing in the digital skills and literacy of the workforce (Qu & Kim, 2024).

This leads to a critical finding: the value of AI in SCM is not in replacing human decision-makers but in augmenting them. The "black box" trust deficit (Sadikoglu & Demirkesen, 2022) illustrates that the entire AI-agility value chain can be broken at the final step if the human-in-the-loop rejects the AI's recommendation. Therefore, the literature strongly implies that organizational investment in human-AI collaboration, digital literacy, and a supportive technological culture (Kim et al., 2022; Qu & Kim, 2024; Barney & Hesterley, 2023) is as important, if not more important, than the investment in the technology itself.

4. CONCLUSION

4.1. Principal Findings

This systematic literature review synthesized 41 recent academic articles (2020-2024) to understand the impact of Artificial Intelligence on supply chain decision-making and operational agility. The findings provide clear answers to the three research questions.

In response to RQ1, this review found that AI in SCM is best understood as a convergent ecosystem of technologies, where AI and machine learning (ML) for predictive analytics, risk management, and forecasting (Kim et al., 2022; Müller et al., 2022; Park et al., 2021) are enabled by a sensory layer of IoT and Big Data (Tiwari et al., 2024; Tsao et al., 2024) and an action layer of intelligent automation and robotics (Sayudin, 2023).

In response to RQ2, the primary impact of this ecosystem is the transformation of decision-making. It facilitates a fundamental paradigm shift away from reactive, experience-based judgments and toward a proactive, anticipatory, and data-driven model (Liu et al., 2021; Müller et al., 2022; Sodhi et al., 2023). This change in cognitive capability and decision temporality is the central mechanism enabling agility.

In response to RQ3, this transformed decision-making capability directly enhances operational agility, which functions as a critical mediator for firm performance (Habibi, 2024; He et al., 2023). The impact of this agility is twofold: it provides defensive agility (resilience) to mitigate disruptions (Blome & Schoenherr, 2021) and offensive agility (competitiveness) to drive innovation and secure market position (Habibi, 2024; Tavana et al., 2023).

Overall, this review concludes that AI is a transformative force that redefines operational agility, elevating it from a simple response mechanism to a predictive, offensive capability. However, the realization of this potential is not guaranteed by technology alone; it is gated by significant socio-technical barriers, most notably the need for organizational culture (Barney & Hesterley, 2023), digital skills (Qu & Kim, 2024), and human-AI trust (Sadikoglu & Demirkesen, 2022) to evolve in parallel with the technology.

4.2. Limitations and Future Research Directions

This SLR is subject to limitations inherent in its methodology. The search was restricted to two major databases (Scopus and Web of Science) and English-language articles, which may have omitted relevant studies from other sources or in other languages. The 2020-2024 timeframe, while ensuring timeliness, necessarily excludes foundational work on this topic. Furthermore, the rapid pace of AI development (Wulandari & Hadi, 2023; Acar & Uzun, 2022) means that new applications are emerging faster than the peer-review process can fully validate their long-term impact.

Based on the synthesis and discussion, particularly the identification of the socio-technical gap, this review proposes a clear agenda for future research:

Addressing the "Black Box": Research is urgently needed on the application of Explainable AI (XAI) frameworks within SCM. Studies should investigate whether XAI (Sadikoglu & Demirkesen, 2022) can demonstrably improve managerial trust and adoption rates of AI-driven recommendations.

Quantifying the Socio-Technical Link: While the literature identifies "culture" (Barney & Hesterley, 2023) and "skills" (Qu & Kim, 2024) as critical, more empirical, quantitative work is needed. Future studies should aim to quantify the moderating effect of these organizational variables on the AI-agility-performance relationship.

Metrics and Measurement: As firms pursue "hyperagility" (Cohen & Kouvelis, 2021), new performance measurement frameworks are required. Research should focus on developing and validating metrics that can capture this dynamic capability and its direct causal link to performance outcomes like innovation (Habibi, 2024).

Investigating Emerging AI: The impact of next-generation AI is still largely conceptual. Empirical studies and new systematic reviews will be necessary to assess the tangible impact of Generative AI (Acar & Uzun, 2022) and Quantum AI (Wulandari & Hadi, 2023) on supply chain optimization, decision-making, and strategic advantage.

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