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Artificial Intelligence, Decision Quality, and Supply Chain Performance: A Dynamic Capabilities Perspective

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ABSTRACT

This study examines how artificial intelligence (AI)-enabled capability influences supply chain adaptability and operational performance through analytics capability and decision quality. Drawing on the dynamic capabilities view and decision-support systems theory, the study develops a decision-centric framework in which analytics capability supports sensing, decision quality represents the seizing mechanism, and supply chain adaptability reflects reconfiguring processes. Using survey data from 300 supply chain professionals across manufacturing, logistics, and retail sectors, the model is tested using partial least squares structural equation modeling (PLS-SEM). The results show that AI-enabled capability significantly enhances analytics capability, which in turn improves decision quality. Decision quality has a strong positive effect on supply chain adaptability, which subsequently improves operational performance. In addition, environmental uncertainty strengthens the relationship between decision quality and supply chain adaptability. The findings highlight decision quality as a critical micro-foundational capability that translates analytical insights into adaptive operational actions. By shifting the focus from data availability to decision effectiveness, this study provides a process-oriented explanation of how AI-enabled analytics create operational value in complex supply chain environments. From a practical perspective, the results suggest that organizations should integrate AI-driven analytics with structured decision-making processes to enhance adaptability and improve operational performance.
Keywords: Artificial intelligence; Supply chain analytics; Decision quality; Supply chain adaptability; Operational performance; AI-enabled decision-making

INTRODUCTION

The rapid adoption of artificial intelligence (AI) and advanced analytics has significantly transformed supply chain management by enabling organizations to process large volumes of data,

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automate operational decisions, and enhance system-wide visibility (Tavana & Dessouky, 2025). Prior research has shown that AI-driven systems improve forecasting accuracy, coordination, and operational efficiency across supply chain networks (Taha Kandil, 2025; Zhu, Yang, & Feng, 2025). Despite these advancements, many organizations continue to experience inconsistent performance gains from AI investments, particularly in dynamic and uncertain environments (Wankhede et al., 2024). This paradox suggests that the availability of advanced analytical capabilities alone does not guarantee improved operational outcomes.

AI-enabled capability and analytics capability represent related but distinct organizational resources. AI-enabled capability refers to the technological infrastructure and intelligent systems that support data acquisition, processing, prediction, and automation. In contrast, analytics capability reflects the organization's ability to transform data into meaningful insights through analytical processes, models, and interpretation. While AI-enabled capability provides the technological foundation, analytics capability represents the organizational competence required to extract value from available data. This distinction is important because the present study proposes that AI-enabled capability contributes to operational outcomes primarily through its influence on analytics capability and subsequent decision-making processes.

A critical but underexplored issue is how analytical insights generated by AI systems are translated into effective operational decisions and adaptive system behavior (Samiei, Jafarpanah, & Mohammadi, 2025). While prior research has extensively examined AI and analytics as drivers of performance, limited attention has been given to the decision-making processes that convert data-driven insights into actionable outcomes (Soltanifar & Lotfi, 2011). This gap is particularly important in supply chain systems, where the effectiveness of decisions directly determines responsiveness, efficiency, and overall system performance (Abourokbah, Mashat, & Salam, 2023; Taha Kandil, 2025; Zhu et al., 2025).

To address this limitation, this study introduces decision quality as a central operational mechanism that explains how analytical insights are translated into effective actions within supply chain systems (Abourokbah et al., 2023). Decision quality is defined as the extent to which decisions are data-consistent, analytically justified, timely, and aligned with operational constraints and objectives. While prior research in decision-support systems and analytics has emphasized the role of information and analytical tools in supporting decision-making, it has paid limited attention to the effectiveness of decisions as an outcome of these processes (Scholl, LaRussa, Hahlweg, Kobrin, & Elwyn, 2018; Shrestha, Ben-Menahem, & Von Krogh, 2019).

Decision quality is distinguished from related concepts such as decision effectiveness, decision-making capability, and decision-support effectiveness. Decision effectiveness usually refers to the outcomes or success of a decision after implementation, whereas decision quality focuses on the properties of the decision at the point of choice, including whether it is timely, analytically justified, data-consistent, and aligned with operational constraints. Similarly, decision-making capability refers to a broader organizational capacity involving routines, skills, and governance structures, while decision-support effectiveness emphasizes the usefulness of information systems and analytical tools. In contrast, decision quality captures the operational mechanism through which AI-enabled analytics are converted into implementable supply chain actions. This

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distinction allows the study to explain not only whether AI and analytics improve performance, but how analytical insights become operationally valuable through better decisions.

By explicitly incorporating decision quality into the analytical framework, this study shifts the focus from data availability to decision effectiveness as the key mechanism through which AI-enabled analytics create operational value. From an industrial engineering perspective, decision quality represents a critical link between analytical intelligence and the execution of operational processes such as inventory control, production planning, and logistics coordination. This perspective provides a more realistic and process-oriented explanation of how data-driven insights are converted into adaptive and high-performing supply chain systems.

This study draws on the dynamic capabilities view (DCV) and decision-support systems (DSS) theory to develop a structured, decision-centric framework. The DCV posits that organizations achieve superior performance through their ability to sense opportunities, seize them through effective decisions, and reconfigure resources accordingly (Teece, 2007). Complementing this perspective, DSS theory emphasizes the role of data, analytical models, and information systems in improving the effectiveness of decision-making processes (Scholl et al., 2018).

Integrating these perspectives, this study explicitly maps AI-enabled capability to the sensing function, analytics capability to the development of analytical insights, decision quality to the seizing mechanism, and supply chain adaptability to the reconfiguration of operational processes. This structured mapping provides a process-oriented explanation of how technological and analytical capabilities are transformed into performance outcomes. By positioning decision quality as the central mechanism linking sensing and reconfiguring activities, the study advances a more precise and operationally relevant interpretation of dynamic capabilities in AI-enabled supply chain systems.

Decision quality is particularly aligned with the seizing dimension of dynamic capabilities because seizing involves selecting and committing to courses of action based on identified opportunities and threats. While sensing focuses on recognizing and interpreting environmental signals, seizing reflects the organization's ability to transform those insights into concrete decisions regarding resource allocation, operational priorities, and strategic responses. In supply chain environments, analytical insights alone do not generate value unless decision-makers are able to evaluate alternatives, assess trade-offs, and implement appropriate responses. Decision quality therefore represents the effectiveness of this decision commitment process. High-quality decisions ensure that sensed information is translated into timely and analytically justified actions, making decision quality a direct manifestation of the seizing capability proposed by Teece (2007). This interpretation extends the dynamic capabilities literature by operationalizing seizing through a measurable decision-oriented mechanism within AI-enabled supply chain systems.

From an industrial engineering perspective, decision quality represents a critical link between analytical insights and the execution of operational processes such as inventory control, production planning, and logistics coordination (Hu, Jin, & Qin, 2025). High-quality decisions enable organizations to improve resource utilization, reduce inefficiencies, and enhance system responsiveness. By explicitly modeling this transformation process, the study contributes to a

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deeper understanding of how AI-enabled analytics improve system-level performance and operational efficiency in complex supply chain environments.

Accordingly, this study develops and empirically tests a structured analytical model that examines the relationships among AI-enabled capability, analytics capability, decision quality, supply chain adaptability, and operational performance. The model captures both direct and indirect effects, enabling a comprehensive assessment of the pathways through which AI influences organizational outcomes. The model is tested using survey data collected from supply chain professionals across multiple industries and analyzed using partial least squares structural equation modeling (PLS-SEM), which is widely used for examining complex causal relationships in operations and industrial engineering research (Hair & Alamer, 2022).

This study contributes to the industrial engineering and operations management literature by introducing decision quality as a central operational mechanism that explains how AI-enabled analytics are transformed into adaptive and high-performing supply chain systems. Unlike prior research that primarily focuses on technological and analytical capabilities as direct drivers of performance (Korir & Tenai, 2020; Ludwikowska & Tworek, 2022), this study explicitly conceptualizes decision quality as a micro-foundational capability that links data-driven insights to operational execution.

By integrating decision quality within the dynamic capabilities' framework, the study provides a structured explanation of how sensing, seizing, and reconfiguring processes jointly drive performance outcomes (Teece, 2007). In addition, the study demonstrates that AI-enabled and analytics capabilities influence performance through both indirect decision-centric pathways and direct system-level mechanisms, offering a more comprehensive understanding of how AI-driven systems create operational value. This process-oriented perspective advances existing research by shifting the focus from data availability to decision effectiveness, providing a more precise and industrial engineering–relevant explanation of performance improvement in complex supply chain environments.

Although prior studies have established positive relationships between AI adoption, analytics capability, and supply chain performance, most research has focused primarily on technological capabilities and information-processing benefits. Existing studies commonly examine AI and analytics as direct antecedents of operational efficiency, forecasting accuracy, responsiveness, and organizational performance. However, relatively limited attention has been devoted to the intermediate decision-making mechanisms through which analytical insights are translated into operational actions. Furthermore, prior research often treats decision-making as an implicit process rather than an explicitly modeled construct. This study extends the literature by introducing decision quality as a distinct operational capability and positioning it as the central mechanism linking analytical insights to adaptive supply chain responses. By integrating AI-enabled capability, analytics capability, decision quality, supply chain adaptability, and operational performance within a unified dynamic capabilities framework, the study provides a more comprehensive explanation of how AI-generated insights are transformed into tangible operational outcomes.

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The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 describes the research methodology and data analysis procedures. Section 4 presents the empirical results. Section 5 discusses the findings and their theoretical and managerial implications, and Section 6 concludes the study with limitations and directions for future research.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Theoretical Foundation and Analytical Perspective

This study is grounded in the dynamic capabilities view (DCV) and decision-support systems (DSS) theory to explain how AI-enabled technologies are transformed into operational performance outcomes within complex supply chain environments (Raj, Kumar, Narayanan, Kirca, & Jeyaraj, 2025; Zheng, Alzaman, & Diabat, 2023). The DCV posits that firms achieve sustained competitive advantage through their ability to sense opportunities and threats, seize them through appropriate decisions, and reconfigure resources accordingly (Teece, 2007). These capabilities are particularly relevant in supply chains characterized by volatility and uncertainty, where rapid adaptation is essential (Hossain, Ahmed, Chowdhury, Govindan, & Jaradat, 2024). Complementing this perspective, DSS theory emphasizes the role of data, analytical models, and information systems in enhancing the effectiveness and efficiency of managerial decision-making processes (Scholl et al., 2018; Soltanifar & Lotfi, 2011). While prior research has extensively examined AI and analytics as technological and informational resources (Afriyie, Du, & Ibn Musah, 2019; Alegre & Chiva, 2013), limited attention has been given to how these resources are translated into high-quality decisions and adaptive operational outcomes.

Building on these theoretical foundations, this study adopts a decision-centric analytical framework that explicitly models the sequential transformation of capabilities. Within this framework, AI-enabled capability provides the technological infrastructure for data acquisition and processing, analytics capability supports the sensing of environmental signals, decision quality represents the seizing mechanism that converts analytical insights into effective decisions, and supply chain adaptability reflects the reconfiguration of operational processes in response to environmental changes. This structured approach addresses a key limitation in existing literature by shifting the focus from isolated technological effects to an integrated process perspective. By incorporating decision quality as a central mechanism, the study advances a more nuanced understanding of how AI-driven insights are operationalized within organizations to generate performance outcomes.

AI-Enabled Capability and Analytics Capability

AI-enabled capability refers to the deployment of advanced computational models, including machine learning algorithms, predictive forecasting models, and optimization-based decision systems, to support supply chain operations (Misuraca & Viscusi, 2020). These technologies enable organizations to perform demand forecasting, inventory optimization, anomaly detection, and real-time decision support. Unlike traditional information systems, AI-enabled systems incorporate adaptive learning and predictive capabilities, allowing organizations to anticipate disruptions and optimize operational decisions dynamically. Prior studies demonstrate that such AI-driven capabilities significantly enhance analytical depth, accuracy, and responsiveness within supply chain systems (Taha Kandil, 2025; Zhu et al., 2025).

Furthermore, AI-driven systems facilitate the integration of heterogeneous data sources, enabling organizations to develop more comprehensive and accurate analytical models. This integration enhances the ability of firms to identify patterns, detect anomalies, and anticipate disruptions across supply chain networks (Wankhede et al., 2024). However, the development of analytics capability is not automatic and depends on the effective alignment between technological infrastructure, data governance, and analytical expertise. Without such alignment, investments in AI may not translate into meaningful analytical improvements (Ganuthula, 2025). From the DCV perspective, AI-enabled capability strengthens the sensing function of organizations by improving their ability to collect and interpret data. Therefore, it is hypothesized that:

H1: AI-enabled capability positively influences analytics capability.

Analytics Capability and Decision Quality

Analytics capability plays a central role in enabling organizations to process complex data and generate actionable insights that support operational decision-making. It encompasses the ability to collect, integrate, analyze, and visualize data in ways that enhance situational awareness and reduce uncertainty. Prior research suggests that organizations with strong analytics capabilities are better equipped to interpret dynamic conditions, identify patterns, and anticipate future scenarios, thereby supporting more informed and structured decision processes (Taha Kandil, 2025; Wankhede et al., 2024). These capabilities are particularly critical in supply chain environments, where timely and accurate insights are essential for coordinating operations and responding to disruptions.

However, the availability of analytical insights does not inherently guarantee effective decision-making. The value of analytics is realized only when insights are translated into decisions that are analytically justified, data-consistent, and aligned with operational constraints. In this study, decision quality is defined as the extent to which decisions are grounded in reliable data, supported by analytical reasoning, and appropriately aligned with operational objectives and system conditions (Hu et al., 2025). From a decision-support systems perspective, analytics capability serves as a key informational input that enhances the quality of decisions by improving the accuracy, relevance, and interpretability of insights (Shrestha et al., 2019).

From an industrial engineering perspective, analytics capability enables the development of structured decision models that support operational processes such as inventory planning, production scheduling, and logistics coordination. These models reduce uncertainty and provide decision-makers with analytically grounded alternatives, improving the consistency and reliability of decisions. As a result, organizations with higher levels of analytics capability are more likely to produce high-quality decisions that can be effectively implemented within operational systems. In supply chain contexts, analytics capability supports decisions related to inventory replenishment, supplier selection, production scheduling, and transportation planning. By providing decision-

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makers with timely and accurate insights, analytics capability reduces uncertainty and improves the consistency and effectiveness of operational decisions.Therefore, it is hypothesized that:
H2: Analytics capability positively influences decision quality.

Decision Quality and Supply Chain Adaptability
Decision quality is a critical determinant of an organization's ability to respond effectively to dynamic and uncertain supply chain environments (Hossain et al., 2024; Zheng et al., 2023). High-quality decisions enable firms to implement appropriate operational adjustments, allocate resources efficiently, and respond rapidly to disruptions. In supply chains, where delays or inaccuracies in decision-making can lead to significant inefficiencies, the quality of decisions directly influences the organization's responsiveness and flexibility. Prior studies emphasize that effective decision-making is closely linked to supply chain adaptability, as it enables organizations to adjust operations in response to changing demand patterns and supply conditions (Abourokbah et al., 2023).

From the dynamic capabilities' perspective, decision quality represents the seizing capability, where organizations act upon sensed information to capture opportunities or mitigate risks (Teece, 2007). Even when analytics capability provides accurate and timely insights, poor decision quality can prevent organizations from translating these insights into effective actions. This highlights the importance of decision quality as a bridge between information processing and operational execution. By enabling organizations to make timely and effective decisions, decision quality enhances their ability to reconfigure processes and respond to environmental changes. For instance, high-quality decisions enable organizations to rapidly adjust inventory levels, modify production schedules, identify alternative suppliers, and reroute logistics operations when disruptions occur. These actions enhance the organization's ability to adapt to changing market conditions and unexpected supply chain disturbances. Thus, it is hypothesized that:
H3: Decision quality positively influences supply chain adaptability.

Supply Chain Adaptability and Operational Performance
Supply chain adaptability reflects the ability of organizations to adjust their operations in response to environmental changes, including demand fluctuations, supply disruptions, and market uncertainty (Manzoor et al., 2022; Raj et al., 2025). Adaptable supply chains are characterized by flexibility, responsiveness, and the ability to reconfigure resources effectively (Bag, Rahman, Srivastava, Shore, & Ram, 2023). These characteristics enable organizations to maintain operational efficiency while responding to dynamic conditions. Prior research demonstrates that adaptability is a key driver of operational performance, as it allows firms to minimize disruptions, optimize resource utilization, and improve service levels (Abourokbah et al., 2023; Le, Vo, & Venkatesh, 2022).

From a dynamic capabilities' perspective, adaptability represents the reconfiguring stage, where organizations implement changes based on insights and decisions. Firms that effectively reconfigure their supply chain processes are better positioned to achieve superior performance outcomes, including improved responsiveness, reduced operational costs, and enhanced decision

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effectiveness. This highlights the importance of aligning analytical insights and decision-making processes with operational capabilities. Therefore, it is hypothesized that:
H4: Supply chain adaptability positively influences operational performance.

Sequential Mediation Mechanisms
A key contribution of this study lies in examining the sequential transformation process through which AI-enabled capability influences performance outcomes (Mehmood, Nazir, Fan, & Nazir, 2025). While AI provides the technological infrastructure for data processing and analytics capability enables the interpretation of data, decision quality and adaptability serve as critical intermediate mechanisms that translate these capabilities into operational outcomes (Dahan & Levi-Bliech, 2024). This process reflects a structured pathway in which technological resources are transformed into performance outcomes through a series of interrelated capabilities.
Specifically, analytics capability is expected to improve decision quality by providing accurate and timely insights, which in turn enhances supply chain adaptability by enabling effective operational responses (Abourokbah et al., 2023). This sequential relationship highlights the importance of decision quality as a bridging mechanism that connects analytical insights with adaptive actions. Prior research suggests that the value of analytics is realized only when it leads to effective decisions and operational improvements (Wankhede et al., 2024). By explicitly modeling this sequential mediation, this study provides a more comprehensive understanding of how AI-driven insights are operationalized within organizations. Therefore, it is hypothesized that:
H5: Decision quality mediates the relationship between analytics capability and supply chain adaptability.
H6: Analytics capability and decision quality sequentially mediate the relationship between AI-enabled capability and supply chain adaptability.

Direct Effects of AI and Analytics Capabilities
While the proposed framework emphasizes a decision-centric transformation process in which analytics capability improves operational outcomes through decision quality and supply chain adaptability, AI-enabled and analytics capabilities may also exert direct effects on operational processes (Yu, Zeng, & Zhang, 2025). In modern supply chain systems, AI technologies are increasingly embedded within operational infrastructures, enabling real-time monitoring, automated decision execution, and algorithm-driven optimization (Wang & Zhang, 2025). These systems can perform tasks such as anomaly detection, demand forecasting, inventory optimization, and routing adjustments with minimal human intervention (Qalati, Jiang, Gyedu, & Manu, 2024). As a result, certain performance improvements may occur independently of human decision-making processes, reflecting the direct operational impact of AI-enabled systems.
Similarly, analytics capability can directly enhance operational performance by improving planning accuracy, coordination efficiency, and resource allocation (Raj et al., 2025). Advanced analytics tools enable organizations to process large volumes of data and generate actionable insights that can be directly integrated into operational systems. For example, predictive analytics can improve demand planning accuracy, while prescriptive analytics can optimize production

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scheduling and logistics operations. These improvements contribute directly to operational performance outcomes, including reduced costs, improved service levels, and enhanced process efficiency (Taha Kandil, 2025; Zhu et al., 2025).

From an industrial engineering perspective, these direct effects represent automation-driven efficiency gains and system-level optimization enabled by AI and analytics technologies. While decision quality remains a critical mechanism for translating analytical insights into adaptive operational actions, not all improvements are mediated through human decision processes (Hu et al., 2025). Instead, some effects arise from embedded analytical models and automated execution systems that operate continuously within supply chain infrastructures. This dual pathway (combining human decision-making and system automation) provides a more realistic representation of how AI-enabled capabilities influence operational outcomes in complex and dynamic environments.

The inclusion of these direct effects is theoretically consistent with both the dynamic capabilities view and contemporary AI-enabled operations literature. While the dynamic capabilities framework emphasizes capability transformation through sensing, seizing, and reconfiguring processes, advanced digital technologies may simultaneously generate operational benefits through automation, algorithmic optimization, and continuous system monitoring. Consequently, a dual-pathway perspective provides a more realistic representation of how AI-enabled systems create operational value in modern supply chains.

Accordingly, in addition to the indirect relationships specified in the decision-centric framework, this study proposes that AI-enabled capability and analytics capability also exert direct effects on supply chain adaptability and operational performance. These direct effects complement the mediated pathways and reflect the multifaceted role of AI and analytics in modern supply chain systems.

Beyond their indirect effects through decision quality and adaptability, AI-enabled and analytics capabilities may generate value through embedded operational mechanisms. Contemporary AI systems increasingly function as autonomous or semi-autonomous operational infrastructures that continuously monitor, analyze, and execute decisions in real time. For example, AI-enabled systems can automatically adjust inventory parameters, optimize transportation routes, and identify operational anomalies without requiring extensive managerial intervention. These automated capabilities directly improve operational responsiveness and increase the adaptability of supply chain processes. Similarly, analytics capability contributes to operational performance through enhanced forecasting accuracy, process synchronization, and resource optimization. By improving the quality of planning and coordination activities, analytics capability can reduce inefficiencies and enhance operational outcomes independently of the broader adaptation process. Therefore, both AI-enabled capability and analytics capability may influence operational outcomes through direct system-level effects in addition to the indirect decision-centric pathway proposed in this study. Therefore, it is hypothesized that:

H7: AI-enabled capability positively influences supply chain adaptability.

H8: Analytics capability positively influences operational performance.

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Environmental Uncertainty as a Boundary Condition

Environmental uncertainty refers to the degree of unpredictability in market demand, supply conditions, and external disruptions affecting supply chain operations (Zhao, Hong, & Lau, 2023). In highly uncertain environments, organizations face increased volatility, complexity, and information ambiguity, which place greater pressure on operational decision-making processes. Under such conditions, the ability to make timely and analytically justified decisions becomes critical for maintaining system responsiveness and operational stability (Tang, Yao, Boadu, & Xie, 2023).

Prior research suggests that environmental uncertainty amplifies the importance of data-driven decision-making, as organizations must rely more heavily on real-time information and predictive insights to respond effectively to disruptions (Abourokbah et al., 2023; Zhu et al., 2025). In such environments, inaccurate or delayed decisions can propagate quickly through supply chain systems, leading to inefficiencies such as inventory imbalances, service disruptions, and increased operational costs. From both the dynamic capabilities and industrial engineering perspectives, decision quality represents the mechanism through which organizations convert analytical insights into effective operational actions (Teece, 2007). As uncertainty increases, the effectiveness of this mechanism becomes more critical, as only high-quality decisions can support timely adaptation and prevent system-level inefficiencies.

A moderation effect is theoretically most relevant at the transition point between decision-making and operational action. While environmental uncertainty may influence information processing and analytical activities, these earlier stages primarily concern the generation and interpretation of insights. In contrast, the relationship between decision quality and supply chain adaptability reflects the implementation of decisions through operational adjustments and resource reconfiguration. Under stable conditions, organizations can often rely on established routines and standardized procedures. However, as uncertainty increases, the consequences of poor decisions become more severe and the value of high-quality decisions becomes more pronounced. In such contexts, timely, analytically justified, and operationally aligned decisions play a critical role in enabling organizations to adapt effectively to changing conditions. Therefore, environmental uncertainty is expected to strengthen the influence of decision quality on adaptability more directly than other relationships within the proposed framework.

This study focuses on the moderating role of environmental uncertainty specifically on the relationship between decision quality and supply chain adaptability, as this linkage represents the transition from decision-making to operational execution. While AI and analytics capabilities enhance information processing, it is the effectiveness of decisions that determines how organizations respond to uncertain conditions. Accordingly, it is hypothesized that:

H9: Environmental uncertainty positively moderates the relationship between decision quality and supply chain adaptability, such that the relationship is stronger under higher levels of uncertainty.

Research Framework

Based on the above theoretical arguments, this study proposes a decision-centric analytical framework that integrates AI-enabled capability, analytics capability, decision quality, supply

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chain adaptability, and performance within a unified structure. Unlike prior studies that focus on isolated relationships (Ferreira & Coelho, 2020; Zehir, Can, & Karaboga, 2015), this framework captures both direct and indirect effects, providing a comprehensive explanation of how AI-driven insights are transformed into operational outcomes. The framework highlights the sequential transformation of capabilities and emphasizes the critical role of decision quality as a missing mechanism in existing research. The proposed conceptual model is illustrated in Figure 1.

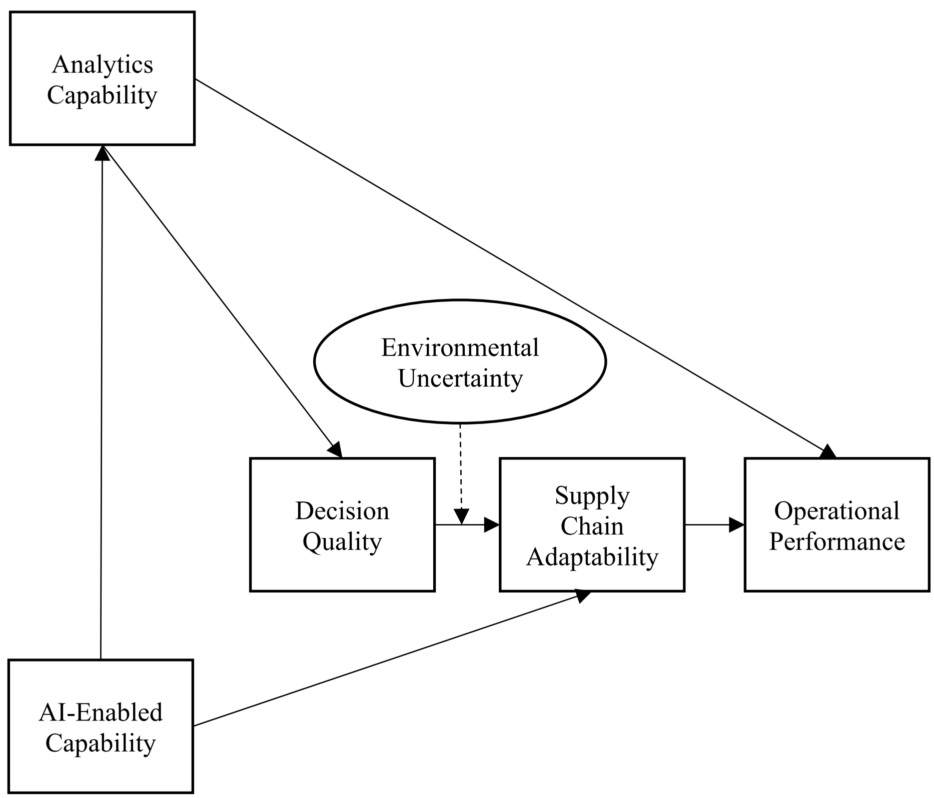

Figure 1. Conceptual Model

METHODOLOGY

Research Design, Sampling, and Data Collection

This study adopts a quantitative research design to examine the relationships among AI-enabled capability, analytics capability, decision quality, supply chain adaptability, and operational performance. A cross-sectional survey approach was employed, as it enables the collection of standardized data from many organizations and is widely used in operations and information systems research for theory testing (Hair & Alamer, 2022). The unit of analysis is the organization, with respondents providing firm-level assessments of capabilities and performance outcomes.

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A purposive sampling strategy was employed to target professionals with direct involvement in supply chain operations, analytics, and decision-making processes. The respondent group included supply chain managers, logistics managers, operations managers, procurement managers, analytics specialists, and senior executives involved in supply chain planning and decision-making activities. These individuals were selected because of their direct involvement in operational decision processes, AI-enabled systems, and analytics-supported supply chain activities. Their professional responsibilities provided them with the knowledge necessary to evaluate organizational capabilities, decision quality, adaptability, and operational performance. To ensure respondent suitability and data quality, participants were required to meet specific qualification criteria, including a minimum of three years of professional experience in supply chain, logistics, operations management, or data analytics roles. In addition, screening questions were used at the beginning of the survey to confirm respondents' familiarity with AI-enabled systems and their involvement in data-driven decision-making processes within their organizations. This approach ensured that responses were provided by knowledgeable informants with relevant domain expertise. Data were collected from manufacturing, logistics, and retail firms located in North America (primarily Canada and the United States) and Europe (including Germany, the United Kingdom, and France) between March and June 2025.

The selection of industries was guided by their high level of exposure to data-intensive operations and AI-enabled technologies, where real-time decision-making and adaptability are critical. Manufacturing, logistics, and retail sectors are widely recognized as leading adopters of AI-driven supply chain solutions, making them appropriate contexts for examining the proposed relationships. These regions were selected due to their advanced digital infrastructure and high levels of AI and analytics adoption in supply chain operations, making them appropriate contexts for examining data-driven decision-making processes. However, the findings should be interpreted within digitally mature environments, and caution should be exercised when generalizing the results to less digitally developed contexts. Respondents were recruited through professional networks, industry associations, and LinkedIn-based outreach across the selected regions to ensure adequate representation of firms engaged in AI-enabled supply chain practices. Although the sample includes respondents from multiple countries across North America and Europe, detailed country-level distribution was not recorded, and therefore the results should be interpreted as representative of digitally mature supply chain contexts rather than specific national settings.

A total of 520 questionnaires were distributed through professional networks and industry contacts, resulting in 327 responses. After excluding incomplete and inconsistent responses, 300 valid responses were retained for analysis, yielding an effective response rate of 57.7%. The sample size exceeds the recommended threshold based on the 10-times rule and power analysis guidelines for PLS-SEM (Hair & Alamer, 2022). The sample includes firms of varying sizes and levels of experience, providing a diverse and representative dataset for empirical analysis. Although objective performance data (e.g., cost reduction, lead time) would provide additional insights, perceptual measures are widely used in operations and information systems research and have been shown to be reliable proxies for firm performance, particularly when objective data are difficult to obtain across multiple organizations. The sample characteristics are presented in Table 1.

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Table 1. Sample Characteristics

Variable	Category	Frequency	Percentage (%)
Industry	Manufacturing	92	30.7
	Retail	6	21.3
	Logistics	78	26.0
	Other	66	22.0
Firm Size	Small (<50 employees)	88	29.3
	Medium (50–249)	121	40.3
	Large (≥250)	91	30.4
Experience	<5 years	72	24.0
	5–10 years	109	36.3
	>10 years	119	39.7

Measurement Development and Instrument Design

All constructs were measured using multi-item scales adapted from established and validated literature, ensuring content validity and theoretical consistency. The measurement items were carefully refined and contextualized to reflect AI-enabled supply chain operations while preserving the conceptual meaning of the original scales. AI-enabled capability was adapted from Zhu et al. (2025), analytics capability from Taha Kandil (2025), supply chain adaptability from Le et al. (2022), and operational performance from Raj et al. (2025). These scales have been widely validated, ensuring content validity and theoretical consistency. All constructs in this study were modeled as reflective constructs, as the measurement items are conceptualized as manifestations of the underlying latent variables rather than forming them. Changes in the latent construct are expected to be reflected in changes across all indicators, and the indicators are assumed to be interchangeable and highly correlated. This specification is consistent with prior research in supply chain management and information systems, where capabilities and performance-related constructs are typically operationalized reflectively (Hair & Alamer, 2022).

Particular attention was given to the operationalization of decision quality as a central construct in the proposed model. Unlike traditional perceptual or behavioral constructs, decision quality in this study is conceptualized as an operational capability reflecting the effectiveness of data-driven decision-making within supply chain processes. The measurement items capture key dimensions of decision effectiveness, including data accuracy, analytical justification, timeliness, and alignment with operational objectives. These dimensions are consistent with decision-support systems and operations management literature, where high-quality decisions are defined by their ability to translate analytical insights into effective and implementable actions. By operationalizing decision quality in this manner, the construct reflects a domain-specific capability relevant to industrial engineering contexts rather than a purely cognitive or psychological evaluation.

Decision quality is conceptualized as an operational capability reflecting the effectiveness of data-driven decision-making within supply chain processes. Although treated as a focal construct in this study, its measurement is grounded in prior decision-making and information systems literature

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(e.g., Shrestha et al., 2019; Wankhede et al., 2024). The construct captures key dimensions of decision effectiveness, including data accuracy, analytical justification, timeliness, and alignment with operational objectives. To ensure domain relevance, all items were carefully adapted and contextualized to reflect supply chain decision processes such as demand forecasting, inventory management, and disruption response (Shrestha et al., 2019; Wankhede et al., 2024). The construct captures the extent to which decisions are accurate, timely, and effective in achieving operational objectives. To enhance measurement precision, all items were contextualized to reflect specific supply chain decision processes, such as demand forecasting, inventory optimization, and disruption response.

A pre-test involving five academic experts and eight industry professionals was conducted to ensure clarity and relevance. Minor wording refinements were applied. All items were measured using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), which is widely used in operations and information systems research to ensure response consistency and comparability across constructs. Measurement items, loadings, and VIF values are presented in Table 2.

Table 2. Measurement Items, Loadings, and VIF

Construct	Code	Measurement Item	Loading	VIF
AI	AI1	AI-based systems support supply chain decision-making	0.89	2.11
	AI2	AI is used for demand forecasting and prediction	0.91	2.25
	AI3	AI technologies are integrated into operational processes	0.88	2.03
	AI4	AI improves supply chain visibility and monitoring	0.87	1.98
AC	AC1	Real-time analytics are used in decision processes	0.90	2.34
	AC2	Predictive analytics support operational planning	0.92	2.41
	AC3	Analytics improves the accuracy of insights used for decision-making	0.89	2.18
	AC4	Big data analytics capabilities are well developed	0.88	2.09
DQ	DQ1	Decisions are based on accurate and reliable data	0.91	2.21
	DQ2	Decisions are made in a timely manner	0.90	2.30
	DQ3	Decisions are analytically justified based on data insights	0.92	2.36
	DQ4	Decisions align with strategic objectives	0.89	2.18

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SA	SA1	The supply chain responds quickly to changes	0.87	2.02
	SA2	Operations can be reconfigured efficiently	0.88	2.15
	SA3	The organization is flexible under uncertainty	0.85	1.94
	SA4	The supply chain adapts to demand fluctuations	0.86	2.01
OP	OP1	Operational costs have decreased	0.91	2.36
	OP2	Order fulfillment speed has improved	0.93	2.48
	OP3	Service level (e.g., delivery reliability) has improved	0.90	2.27
	OP4	Inventory turnover efficiency has improved	0.92	2.39

Data Screening and Common Method Bias Assessment

Prior to analysis, the dataset was screened to ensure data quality and suitability for structural equation modeling. Cases with excessive missing values were removed, while remaining missing data were handled using mean substitution. Outlier detection based on standardized residuals indicated no extreme values, and the distributional properties of the data (skewness and kurtosis) suggested no severe deviations from normality.

Given the use of self-reported, single-informant survey data, several procedural and statistical remedies were employed to mitigate and assess common method bias (CMB). Procedurally, respondents were assured of anonymity and confidentiality to reduce evaluation apprehension and social desirability bias. In addition, the questionnaire was carefully designed to separate predictor and criterion variables and to minimize item ambiguity.

Statistically, multiple approaches were applied to assess the potential impact of CMB. First, Harman's single-factor test indicated that the first factor accounted for 34.2% of the total variance, which is below the critical threshold of 50%, suggesting that common method bias is unlikely to be a dominant concern. However, given the limitations of this test, additional and more robust procedures were employed.

Following the recommendations of Podsakoff, MacKenzie, Lee, and Podsakoff (2003) and Kock (2015), a full collinearity assessment was conducted by examining variance inflation factor (VIF) values for all latent constructs. All VIF values were below the conservative threshold of 3.3, indicating that common method bias is not a serious concern.

Furthermore, a marker variable approach was employed as a robustness check by introducing a theoretically unrelated construct to capture potential method variance. The results showed that controlling for the marker variable did not significantly alter the structural relationships, providing additional evidence that common method bias does not materially affect the findings.

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Analytical Technique

The proposed model was analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4. PLS-SEM was selected as the most appropriate analytical technique due to the study's prediction-oriented objective and the complexity of the proposed model, which includes multiple mediating and moderating relationships.

Unlike covariance-based SEM, which focuses on model fit and theory confirmation, PLS-SEM emphasizes variance explanation and predictive capability, making it particularly suitable for examining capability-driven mechanisms in operations and industrial engineering research by Hair and Alamer (2022) and Shmueli et al. (2019),. In addition, PLS-SEM is well suited for models involving sequential mediation and interaction effects, as it can efficiently estimate complex relationships without imposing strict distributional assumptions.

The analysis followed a two-stage approach. First, the measurement model was evaluated in terms of indicator reliability, internal consistency reliability (Cronbach's alpha and composite reliability), and convergent validity using average variance extracted (AVE). Discriminant validity was assessed using the heterotrait–monotrait (HTMT) ratio.

Second, the structural model was evaluated by examining path coefficients, t-values, and confidence intervals obtained through bootstrapping with 5,000 resamples, ensuring robust statistical inference. In addition, the model's explanatory and predictive capabilities were assessed using the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). Moderation analysis was conducted by creating an interaction term and assessing its significance within the PLS-SEM framework.

Ethical Considerations

Participation in this study was entirely voluntary, and informed consent was obtained from all respondents prior to data collection. Participants were clearly informed about the purpose of the research, the nature of the questions, and their right to withdraw from the study at any time without any consequences.

All responses were collected anonymously, and no personally identifiable information was recorded. The data were used solely for academic research purposes and were stored securely in accordance with standard data protection practices.

The study adhered to established ethical guidelines for research involving human participants, ensuring confidentiality, transparency, and responsible data handling throughout the research process. These procedures were implemented to minimize potential bias and to ensure the integrity and reliability of the collected data.

RESULTS

Measurement Model Assessment

The measurement model was evaluated to ensure reliability and validity of the constructs, following established PLS-SEM guidelines (Hair & Alamer, 2022). Indicator reliability was first assessed by examining outer loadings. As reported in Table 2, all indicator loadings exceed the

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recommended threshold of 0.70, confirming that the indicators adequately represent their respective constructs.

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR). All values exceed the recommended threshold of 0.70, indicating satisfactory reliability across all constructs. Convergent validity was evaluated using average variance extracted (AVE), with all constructs exceeding the threshold of 0.50, confirming that each construct explains a substantial portion of the variance of its indicators.

Discriminant validity was assessed using the heterotrait–monotrait (HTMT) ratio. As presented in Table 3, all HTMT values are below the conservative threshold of 0.85, indicating that the constructs are empirically distinct. In addition, cross-loadings were examined to ensure that each indicator loads highest on its intended construct, further supporting discriminant validity. Overall, the results confirm that the measurement model demonstrates adequate reliability and validity, providing a robust foundation for subsequent structural model analysis.

Table 3. Measurement Model Assessment (Reliability and Discriminant Validity)

Construct	Alpha	CR	AVE	AI	AC	DQ	SA	OP
AI	0.91	0.94	0.79	—				
AC	0.90	0.93	0.77	0.72	—			
DQ	0.91	0.94	0.78	0.69	0.74	—		
SA	0.88	0.92	0.74	0.68	0.70	0.73	—	
OP	0.92	0.95	0.81	0.65	0.69	0.72	0.74	—

Note: *HTMT values are reported below the diagonal.*

Structural Model and Hypothesis Testing

The structural model was evaluated using path coefficients, t-values, and confidence intervals obtained through bootstrapping with 5,000 resamples. The results are presented in Table 4.

AI-enabled capability has a strong positive effect on analytics capability ($\beta = 0.63$, $p < 0.001$), indicating that AI technologies serve as a foundational enabler of analytical infrastructure by enhancing data processing, integration, and real-time analytical capabilities. Analytics capability, in turn, significantly improves decision quality ($\beta = 0.61$, $p < 0.001$), suggesting that the ability to generate accurate and timely insights directly enhances the effectiveness of operational decision-making processes.

Decision quality exerts a substantial positive effect on supply chain adaptability ($\beta = 0.55$, $p < 0.001$), demonstrating that high-quality decisions enable organizations to translate analytical insights into adaptive operational actions. Furthermore, supply chain adaptability significantly improves operational performance ($\beta = 0.46$, $p < 0.001$), confirming its role as a key driver of efficiency and responsiveness in dynamic environments.

In addition to the indirect relationships, AI-enabled capability has a direct positive effect on supply chain adaptability ($\beta = 0.29$, $p < 0.001$), while analytics capability directly influences operational performance ($\beta = 0.34$, $p < 0.001$). These results indicate that AI and analytics capabilities

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contribute to operational outcomes through both decision-centric pathways and direct system-level mechanisms.

The moderating effect of environmental uncertainty was also examined. The interaction term between decision quality and environmental uncertainty (DQ × EU) is positive and significant ($\beta = 0.14$, $p < 0.01$), indicating that environmental uncertainty strengthens the relationship between decision quality and supply chain adaptability. This suggests that in more uncertain environments, the effectiveness of decision-making becomes increasingly critical for enabling adaptive responses. Overall, the results provide strong support for the proposed model and highlight the importance of both mediated and direct pathways through which AI-enabled and analytics capabilities influence operational performance.

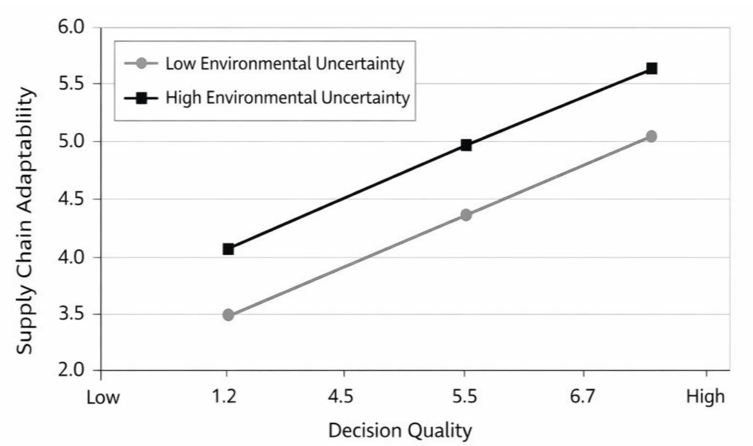

Figure 2. Moderating Effect of Environmental Uncertainty

Table 4. Structural Model Results

Path	β	t-value	p-value	Lower CI	Upper CI	Hypothesis
AI → AC	0.63	14.82	<0.001	0.55	0.71	H1 Supported
AC → DQ	0.61	13.40	<0.001	0.52	0.69	H2 Supported
DQ → SA	0.55	11.28	<0.001	0.46	0.63	H3 Supported
SA → OP	0.46	9.35	<0.001	0.37	0.54	H4 Supported
AI → SA	0.29	5.62	<0.001	0.19	0.38	H7 Supported

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AC → OP	0.34	6.91	<0.001	0.25	0.42	H8 Supported
DQ × EU → SA	0.14	3.21	<0.01	0.06	0.22	H9 Supported

***Note**: β = standardized path coefficient; CI = 95% confidence interval based on bootstrapping (5,000 resamples).*

In addition to statistical significance, the magnitude of the path coefficients indicates meaningful effect sizes across the proposed relationships. The strongest effect is observed between AI-enabled capability and analytics capability, followed by the impact of analytics capability on decision quality, highlighting the central role of analytical processes in the model. The effects of decision quality on adaptability and adaptability on performance are also substantial, confirming the importance of decision-centric mechanisms in driving operational outcomes.

Mediation Analysis

The mediation effects were assessed using bootstrapping procedures to examine both direct and indirect relationships. The results, presented in Table 5, provide strong evidence of both simple and sequential mediation mechanisms.

First, decision quality significantly mediates the relationship between analytics capability and supply chain adaptability ($\beta = 0.34$, $p < 0.001$), indicating that analytics capability enhances adaptability primarily through improving decision-making effectiveness. This finding highlight that the value of analytics is realized through its impact on decision quality rather than through direct effects alone.

Second, a significant sequential mediation effect is observed in the relationship between AI-enabled capability and supply chain adaptability through analytics capability and decision quality ($\beta = 0.21$, $p < 0.001$). This result supports the proposed capability transformation process, demonstrating that AI-enabled capability influences adaptability through a structured pathway involving intermediate analytical and decision-making mechanisms.

The presence of both significant indirect and direct effects indicates partial mediation, suggesting that AI and analytics capabilities influence supply chain adaptability through both decision-centric processes and direct system-level mechanisms. Overall, these findings confirm the central role of decision quality as a key mediating mechanism that translates analytical insights into adaptive operational actions within supply chain systems.

Table 5. Mediation Results

Path	Indirect Effect (β)	t-value	p-value	Result
AC → DQ → SA	0.34	8.72	<0.001	H5 Supported
AI → AC → DQ → SA	0.21	7.15	<0.001	H6 Supported

Model Evaluation and Predictive Power

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The proposed model demonstrates strong explanatory and predictive capability. As shown in Table 6, the coefficient of determination (R^2) values indicates moderate to substantial explanatory power across endogenous constructs. Specifically, analytics capability ($R^2 = 0.40$), decision quality ($R^2 = 0.47$), supply chain adaptability ($R^2 = 0.58$), and operational performance ($R^2 = 0.62$) are well explained by the model.
Predictive relevance was assessed using Q^2 values, all of which are greater than zero, indicating that the model has strong predictive capability. Effect size (f^2) values further confirm the substantive impact of key predictors, particularly the strong effects of AI-enabled capability on analytics capability and analytics capability on decision quality.
In addition to explanatory power, the model's out-of-sample predictive performance was evaluated using the PLSpredict procedure by Shmueli et al. (2019). The results indicate that the majority of PLS-SEM prediction errors (RMSE values) are lower than those of the linear regression benchmark, demonstrating superior predictive performance. Furthermore, all Q^2_predict values exceed zero, confirming the model's predictive relevance.
To assess potential multicollinearity, inner variance inflation factor (VIF) values were examined and found to be below the recommended threshold of 3.3, indicating that multicollinearity is not a concern. The standardized root mean square residual (SRMR) value of 0.056 indicates an acceptable model fit. Overall, these results confirm that the model is both explanatory and predictive, reinforcing its relevance for analyzing capability-driven performance mechanisms in AI-enabled supply chain systems.

Table 6. Model Quality and Predictive Power

Construct	R^2	Q^2	f^2
AC	0.40	0.29	—
DQ	0.47	0.33	0.24
SA	0.58	0.38	0.26
OP	0.62	0.41	0.29

Interpretation of Key Findings

The findings provide strong support for the proposed decision-centric analytical framework and offer important insights into how AI-enabled capabilities are transformed into operational outcomes. The results confirm that AI-enabled capability serves as a foundational driver of analytics capability, highlighting its role in enabling data processing, integration, and real-time analytical functions within supply chain systems. A key insight emerging from this study is the central role of decision quality as a mechanism linking analytics capability to supply chain adaptability. While analytics capability enables the generation of accurate and timely insights, its value is realized only when these insights are translated into effective decisions. This finding explains why organizations with similar analytical capabilities may experience different performance outcomes, emphasizing decision quality as a critical differentiating capability.
Furthermore, the strong relationship between decision quality and supply chain adaptability demonstrates that high-quality decisions enable organizations to translate analytical insights into

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adaptive operational actions. This suggests that adaptability is not solely driven by technological or analytical capabilities but is fundamentally dependent on decision-making effectiveness.

The results also reveal that supply chain adaptability significantly improves operational performance, reinforcing its role as a key driver of efficiency and responsiveness in dynamic environments. In addition, the presence of both direct and indirect effects indicates that AI-enabled and analytics capabilities influence performance through multiple pathways, including both decision-centric mechanisms and direct system-level processes. Overall, the findings support a structured capability transformation process in which AI-enabled capability enhances analytics capability, analytics capability improves decision quality, and decision quality drives adaptability and performance outcomes.

DISCUSSION

Interpretation of Key Findings

The findings of this study provide strong support for the proposed decision-centric framework and offer important theoretical insights into how AI-enabled capabilities are transformed into operational outcomes within supply chain systems. Consistent with the dynamic capabilities view, the results confirm that AI-enabled capability strengthens the organization's sensing function by enhancing analytics capability. This finding reinforces the role of AI as a foundational technological enabler that supports data processing, integration, and real-time analysis in complex operational environments.

A key contribution of this study lies in identifying decision quality as a central mechanism linking analytics capability to supply chain adaptability. While prior research has primarily focused on analytics capability as a direct driver of performance, the findings demonstrate that its impact is largely contingent upon the effectiveness of decision-making processes. This extends decision-support systems theory by emphasizing that the value of analytics is realized not through data processing alone, but through its ability to enhance decision effectiveness.

Furthermore, the results highlight that decision quality functions as the "seizing" capability within the dynamic capabilities framework. By enabling organizations to act upon analytical insights, decision quality plays a critical role in translating sensed information into adaptive operational responses. This provides a more explicit and operationalized interpretation of the seizing process, which has often remained abstract in prior research (Cantele, Russo, Kirchoff, & Valcozzena, 2023; Harsono, Hidayat, Iqbal, & Abdillah, 2025)

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The strong relationship between supply chain adaptability and operational performance further supports the "reconfiguring" dimension of dynamic capabilities. Organizations that effectively reconfigure their operational processes in response to environmental changes are better positioned to achieve superior performance outcomes. This finding reinforces the importance of adaptability as a system-level capability that connects decision-making processes with performance results.

Finally, the presence of both direct and indirect effects suggests that AI-enabled and analytics capabilities influence performance through multiple pathways. While decision quality represents

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a key mediating mechanism, certain performance improvements may also arise from direct system-level effects, such as automation and real-time optimization. This dual-path perspective provides a more comprehensive understanding of how AI-driven systems create value in modern supply chain environments.

Theoretical Contributions

This study makes several important contributions to the literature on AI-enabled supply chain management, dynamic capabilities, and decision-support systems.

First, the study introduces decision quality as a central mechanism that explains how analytics capability is translated into operational outcomes. While prior research has predominantly focused on AI and analytics as direct drivers of performance, the findings demonstrate that their impact is largely mediated through the effectiveness of decision-making processes. By explicitly modeling decision quality, this study addresses a critical gap in the literature and provides a more complete explanation of how data-driven insights are operationalized within organizations (Yang, Huang, Guan, & Xiao, 2025; Zehir et al., 2015).

Second, this study extends the dynamic capabilities view by offering a structured and empirically validated mapping of sensing, seizing, and reconfiguring processes within AI-enabled supply chain systems. Specifically, analytics capability represents the sensing function, decision quality captures the seizing mechanism, and supply chain adaptability reflects the reconfiguring capability. This explicit operationalization advances prior research by transforming abstract dynamic capability processes into measurable and testable constructs (Teece, 2007).

Third, the study contributes to decision-support systems literature by repositioning analytics capability as part of a broader decision-making process rather than as an isolated technological capability. The findings demonstrate that analytics capability creates value primarily through its impact on decision quality, thereby shifting the focus from data processing to decision effectiveness as the key source of performance improvement.

Finally, the study provides a process-oriented perspective on AI-enabled supply chain management by identifying a sequential capability transformation mechanism. The results show that AI-enabled capability influences operational outcomes through a structured pathway involving analytics capability, decision quality, and supply chain adaptability. This sequential perspective advances existing research by offering a more comprehensive understanding of how technological capabilities are transformed into performance outcomes in complex and dynamic environments.

Mechanism Explanation and Mediation Insights

The mediation analysis provides deeper insight into the mechanisms through which AI-enabled capability influences supply chain adaptability. The results confirm that decision quality plays a central mediating role, indicating that analytics capability contributes to adaptability primarily by improving the effectiveness of decision-making processes. This finding highlight that the value of analytics is not inherent in data processing itself, but in its ability to support high-quality decisions that can be effectively implemented within operational systems.

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Furthermore, the presence of a significant sequential mediation effect demonstrates that the impact of AI-enabled capability unfolds through a structured capability transformation process. Specifically, AI-enabled capability enhances analytics capability, which improves decision quality, ultimately leading to greater supply chain adaptability. This sequential pathway provides a process-based explanation of how technological and analytical resources are translated into operational outcomes.

The results also indicate partial mediation, suggesting that AI-enabled and analytics capabilities influence supply chain adaptability through both indirect and direct pathways. While decision quality represents a key mechanism linking analytics to adaptability, some effects arise from direct system-level processes such as automation, real-time monitoring, and algorithm-driven optimization. Overall, these findings reinforce the role of decision quality as a critical bridging mechanism that connects analytical insights with adaptive operational actions. By explicitly identifying this mechanism, the study advances a more nuanced and process-oriented understanding of how AI-enabled analytics create value within supply chain systems.

Managerial Implications

The findings of this study provide several actionable implications for managers seeking to improve supply chain performance through AI-enabled analytics. First, organizations should move beyond the mere adoption of AI technologies and focus on integrating analytics into structured decision-making processes. The results demonstrate that analytics capability alone does not guarantee improved performance unless it translates into high-quality decisions. Therefore, managers should invest in decision-support systems, real-time dashboards, and standardized analytical frameworks that ensure decisions are data-consistent, timely, and aligned with operational constraints.

Second, organizations should embed AI-driven analytics directly into core operational processes to enhance system-level efficiency. This includes integrating predictive analytics into demand forecasting and inventory management, incorporating optimization models into production scheduling, and leveraging real-time analytics for dynamic logistics coordination. By linking analytical insights directly to operational execution, firms can reduce inefficiencies and improve responsiveness across the supply chain.

Third, improving decision quality requires organizational capability development. Managers should invest in training programs that enhance data-driven decision-making skills, promote collaboration between analytics and operations teams, and establish clear decision-making protocols. For example, organizations can implement AI-supported demand planning systems, inventory optimization dashboards, exception-management alerts, and digital control towers that provide managers with real-time visibility into operational conditions. These tools can improve the speed, consistency, and analytical rigor of supply chain decision-making. Ensuring that analytical insights are interpretable and actionable is essential for translating data into effective operational decisions.

To operationalize decision-quality improvement, organizations should establish formal decision protocols requiring major operational decisions to be supported by analytical evidence and performance data. Managers should also implement integrated decision dashboards that combine

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real-time analytics, forecasting outputs, inventory information, and operational performance indicators within a unified decision-support environment. In addition, organizations should introduce post-decision review processes to evaluate decision outcomes, identify sources of error, and continuously improve decision-making practices. These initiatives can help ensure that AI-generated insights are consistently translated into effective operational actions.

Finally, managers should align decision-making processes with environmental conditions. The findings indicate that in highly uncertain environments, the effectiveness of decision-making becomes more critical. Accordingly, organizations should prioritize rapid, data-driven decision-making supported by real-time analytics and, where appropriate, automation. By strengthening decision quality and aligning it with environmental uncertainty, firms can enhance adaptability and achieve more resilient and efficient operational outcomes.

Relative Importance and Practical Insights

The analysis reveals differences in the relative strength of relationships within the model, providing additional practical insights. The strongest effect is observed between AI-enabled capability and analytics capability, indicating that AI serves as a foundational enabler of data-driven processes. This suggests that organizations must first establish strong AI capabilities before they can fully leverage analytics. In contrast, the relationships between analytics capability, decision quality, and adaptability are more balanced, indicating that these capabilities operate in a complementary manner. This highlights the importance of adopting a holistic approach that integrates technological, analytical, and decision-making capabilities. The presence of both direct and indirect effects further suggests that organizations should not rely solely on one pathway but should develop multiple capabilities simultaneously to achieve optimal performance outcomes.

Limitations and Future Research

Despite its contributions, this study has several limitations that should be acknowledged. First, the use of a cross-sectional research design limits the ability to establish definitive causal relationships. Although the proposed relationships are grounded in well-established theoretical frameworks and supported by empirical analysis, future research could employ longitudinal designs to capture the dynamic evolution of AI-enabled and analytics capabilities over time.

Second, the study relies on perceptual measures collected from single respondents within each organization. While such measures are widely used and validated in operations and information systems research, future studies could incorporate objective performance indicators (e.g., cost efficiency, lead time, and service level metrics) to further strengthen the robustness of the findings. In addition, the sample was drawn primarily from organizations operating in North America and Europe, where digital infrastructure, analytics capabilities, and AI adoption levels are relatively advanced. Consequently, the findings may not be directly generalizable to emerging economies characterized by lower levels of digital maturity, resource constraints, or different institutional conditions. Future research should examine the proposed framework in emerging market contexts to assess the robustness of the relationships across different economic and technological environments.

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Third, the sample is drawn from organizations operating in digitally mature regions, specifically North America and Europe. Although these contexts are appropriate for examining AI-enabled supply chain practices, the findings may not fully generalize to less digitally developed environments. Future research could extend the model to emerging economies to examine how varying levels of digital maturity influence the proposed relationships.

Finally, while this study focuses on key capability-based mechanisms, other organizational and contextual factors may also influence AI-enabled decision-making processes. Future research could incorporate variables such as organizational culture, leadership, and technological readiness to provide a more comprehensive understanding of AI-driven supply chain transformation. Future studies should also employ longitudinal research designs to examine how AI-enabled capability, analytics capability, decision quality, and adaptability evolve over time. Such designs would provide stronger evidence regarding capability development and causal ordering. In addition, future research could utilize multi-source data by combining survey responses with objective operational indicators such as inventory turnover, delivery performance, lead times, and cost efficiency metrics. These approaches would reduce potential common method bias and provide a more comprehensive assessment of the operational impact of AI-enabled decision-making capabilities.

CONCLUSION

This study develops and empirically validates a decision-centric analytical framework that explains how AI-enabled capability influences supply chain adaptability and operational performance through analytics capability and decision quality. Drawing on the dynamic capabilities view and decision-support systems theory, the study demonstrates that AI serves as a foundational enabler of analytics capability, which enhances decision quality and enables organizations to translate analytical insights into adaptive operational actions. The findings confirm that supply chain performance is not driven solely by technological adoption, but by the effective transformation of data-driven insights into high-quality decisions and responsive operational processes. From an industrial engineering perspective, the findings highlight the importance of integrating AI-driven analytics with operational decision processes to enhance system efficiency and responsiveness.

The study makes several important contributions to the literature. First, it introduces decision quality as a critical intermediate mechanism, addressing a key gap in existing research on AI-enabled supply chain management. By identifying decision quality as the link between analytics capability and adaptability, the study provides a more complete explanation of how analytical insights are operationalized within organizations. Second, it advances the dynamic capabilities perspective by explicitly integrating sensing (analytics capability), seizing (decision quality), and reconfiguring (adaptability) within a unified and empirically validated framework. Third, the study offers evidence of a sequential capability transformation process, demonstrating that the impact of AI on performance unfolds through a series of interrelated capabilities rather than through direct effects alone.

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From a practical perspective, the findings highlight the importance of focusing not only on the adoption of AI and analytics technologies but also on improving decision-making processes. Organizations should invest in systems and practices that enhance decision quality, such as real-time analytics platforms, decision-support tools, and data-driven management approaches. By strengthening decision quality, firms can better leverage analytical insights to improve adaptability and achieve superior performance outcomes in dynamic environments.

Despite its contributions, this study has several limitations. The use of cross-sectional data restricts the ability to establish causal relationships, suggesting that future research should employ longitudinal designs to examine capability development over time. Additionally, the findings may vary across industries and levels of digital maturity, indicating the need for further validation in different contexts. Future research could also extend the model by incorporating additional variables such as environmental uncertainty, organizational culture, and leadership to provide a more comprehensive understanding of AI-enabled decision-making processes.

Overall, this study provides a structured and decision-oriented perspective on AI-enabled supply chain management, emphasizing the central role of decision quality in transforming analytical insights into operational outcomes. By bridging the gap between analytics and action, the proposed framework contributes to a more nuanced understanding of how organizations can leverage AI to enhance adaptability and performance in increasingly complex and uncertain environments.

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