

An Artificial Intelligence Integrated IT Management Framework for Analytics-Driven Operational Decision-Making in U.S. Supply Chain and Logistics Systems

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Abstract

Artificial intelligence is increasingly embedded in supply chain and logistics operations, yet many organizations still manage predictive analytics, IT infrastructure, operational monitoring, and optimization as fragmented capabilities, limiting the consistency, speed, and analytical quality of operational decisions. This study aimed to develop and quantitatively evaluate an AI-integrated IT management framework for Analytics-Driven Operational Decision-Making Performance in U.S. supply chain and logistics systems. A quantitative, cross-sectional, case-based design was adopted across selected digitally enabled enterprise environments involving supply chain, logistics, transportation, warehousing, distribution, manufacturing, and related cloud-supported information systems. Using purposive sampling, data were collected from professionals with relevant expertise, including supply chain and logistics managers, IT and analytics specialists, operations and warehouse managers, transportation professionals, and AI or digital-transformation practitioners. Of 320 questionnaires distributed, 300 were returned and 288 were retained as usable cases, yielding a 90.0% valid response rate. The study examined four independent variables: AI-Enabled Predictive Analytics and Forecasting, Intelligent IT Infrastructure and Data Integration, AI-Assisted Supply Chain Monitoring and Decision Support, and Real-Time Analytics and Automated Operational Optimization, with Analytics-Driven Operational Decision-Making Performance as the dependent variable. Data analysis incorporated descriptive statistics, Cronbach's alpha reliability testing, KMO and Bartlett's validity assessment, Pearson correlation, multiple regression, multicollinearity diagnostics, Durbin-Watson testing, and hypothesis evaluation. Results showed a high mean for decision-making performance, $M = 4.20$, $SD = 0.53$, while Real-Time Analytics and Automated Operational Optimization recorded the strongest correlation, $r = .75$, $p < .001$, and the largest standardized regression effect, $\beta = .32$, $p < .001$. The overall model explained 70.4% of the variance, $R^2 = .704$, Adjusted $R^2 = .700$, $F(4, 283) = 168.27$, $p < .001$. These findings indicate that integrated predictive, infrastructural, monitoring, and real-time optimization capabilities can substantially strengthen operational decision quality, responsiveness, and evidence-based coordination in digitally connected enterprise supply chains in practice.

Keywords

Artificial Intelligence, IT Management, Supply Chain Analytics, Operational Decision-Making, Real-Time Optimization;

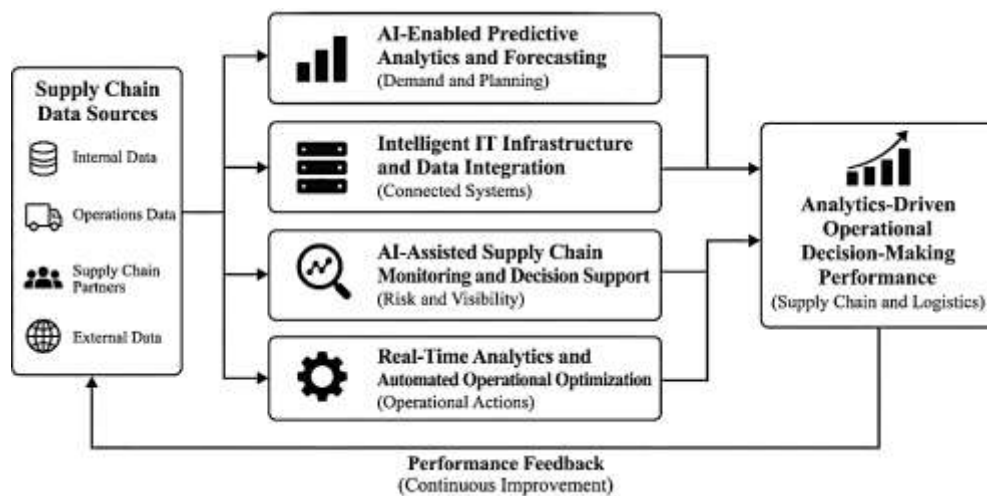
INTRODUCTION

Artificial intelligence, information technology management, supply chain management, logistics, and analytics-driven decision-making have become closely interconnected concepts within contemporary digitally enabled organizations. Artificial intelligence refers broadly to computational technologies capable of performing functions commonly associated with human intelligence, including learning from data, identifying patterns, generating predictions, interpreting complex information, and supporting decision-making processes (Min, 2010; Richey et al., 2023). Information technology management involves the systematic planning, coordination, governance, and utilization of information systems, technological infrastructure, enterprise applications, data resources, and digital capabilities in support of organizational activities. Supply chain management encompasses the coordinated movement of materials, products, information, financial resources, and associated processes among suppliers, manufacturers, distributors, logistics providers, retailers, and customers. Logistics represents a major operational component of supply chain management involving transportation, warehousing, inventory movement, order processing, distribution, and related information flows. The effectiveness of these activities has become increasingly dependent on integrated information systems because supply chain coordination requires accurate and timely information to move across organizational and functional boundaries (Rai et al., 2006; Sanders & Premus, 2005). Information technology capability can strengthen organizational collaboration and enable firms to coordinate production, procurement, transportation, and distribution activities more effectively through digital connectivity (Devaraj et al., 2007). Digitally enabled supply chain integration has also been associated with improved synchronization of organizational resources, information flows, and operational processes across supply chain relationships (Rai et al., 2006). At the international level, supply chain and logistics networks connect geographically dispersed manufacturers, suppliers, transportation providers, warehouses, distribution centers, retailers, and consumers through increasingly complex digital systems. Digital supply chain research has consequently positioned technological infrastructure as a fundamental mechanism for integrating information, processes, and supply chain participants rather than treating technology only as an administrative support function (Büyükoçkan & Göçer, 2018; Frederico et al., 2020). Industry 4.0 research has further demonstrated the importance of automation, intelligent systems, interconnected technologies, and data exchange in contemporary logistics and supply chain management (Abdirad & Krishnan, 2021). The international structure of these operational networks has therefore increased the importance of integrating artificial intelligence, enterprise information technology, and analytics capabilities for processing supply chain information and supporting operational decisions.

Artificial intelligence becomes particularly important in supply chain and logistics management when operational decisions must be made from large volumes of complex, heterogeneous, and continuously generated data. AI-based technologies have been applied to purchasing, supplier evaluation, inventory management, production planning, transportation, scheduling, demand forecasting, and other supply chain decision processes because computational intelligence can identify relationships and patterns that may be difficult to recognize through conventional managerial evaluation alone (Min, 2010). Machine learning constitutes an important branch of artificial intelligence because it allows computational models to learn relationships from historical or real-time data and produce predictions or classifications without requiring every decision rule to be explicitly programmed. Machine-learning techniques such as artificial neural networks and support vector machines have been applied to supply chain demand forecasting, where the accuracy of anticipated demand directly influences inventory, production, procurement, and distribution decisions (Carbonneau et al., 2008). Predictive analytics extends this capability by combining historical information, statistical techniques, machine-learning algorithms, and data-mining processes to estimate operational conditions before managerial actions are finalized. Predictive supply chain performance management has shown how business intelligence, performance measurement, and predictive analytical techniques can be integrated to identify operational patterns and support proactive supply chain management (Stefanovic, 2014). The increasing volume and diversity of organizational data have also expanded the relevance of big data analytics to supply chain environments. Big data analytics involves the technologies, analytical methods, and organizational processes required to extract meaningful information from datasets

characterized by high volume, variety, velocity, and complexity. The organizational value of big data depends on the capability to transform raw information into analytically meaningful knowledge rather than merely accumulating large quantities of digital records (Wamba et al., 2015). Within logistics and supply chain management, analytics can support descriptive assessment of existing operational conditions, predictive estimation of likely outcomes, and prescriptive identification of appropriate operational actions (Wang et al., 2016). The effectiveness of analytical systems is also influenced by the accessibility, quality, consistency, and timeliness of supply chain information because fragmented or inaccurate data can reduce the usefulness of analytical outputs in operational decision-making (Kache & Seuring, 2017). AI-enabled predictive analytics and forecasting can therefore provide supply chain organizations with structured information concerning demand levels, inventory requirements, delivery conditions, transportation activities, operational risks, and resource requirements.

Figure 1: AI-Enabled Supply Chain Analytics Framework for Operational Decision-Making Performance



The effectiveness of AI-supported analytics is closely connected with the quality of the information technology infrastructure and data integration capabilities through which supply chain data are generated, transmitted, stored, combined, analyzed, and presented to decision makers. Intelligent IT infrastructure within supply chain and logistics environments can include enterprise resource planning systems, transportation management systems, warehouse management systems, cloud computing platforms, business intelligence systems, databases, application programming interfaces, data warehouses, sensor technologies, and interconnected digital applications. These technologies create an information architecture through which operational data from procurement, transportation, manufacturing, inventory, warehousing, distribution, and customer-service processes can be integrated. Digitally enabled supply chain integration has been associated with stronger coordination of information and resource flows across organizational activities and supply chain partners (Rai et al., 2006; Tonay, 2026). Similarly, production information integration supported by e-business technologies has been linked with operational performance because integrated systems increase the accessibility and coordination of relevant operational information across supply chain processes (Devaraj et al., 2007; Shamsul, 2026). Such integration is especially important for artificial intelligence and analytics because analytical systems depend on reliable input data originating from multiple enterprise applications and functional areas. Big data analytics capability has consequently been conceptualized as a combination of technological resources, organizational data, analytical expertise, managerial capabilities, and strategic alignment rather than as the ownership of analytical software alone (Akter et al., 2016; Khatun, 2026). Analytical capability has also been associated with process-oriented dynamic capabilities and organizational performance, indicating that organizations require mechanisms for translating analytical knowledge into operational activities (Rony & Md, 2026; Wamba et al., 2017). From a supply chain perspective, big data can generate value when data resources are embedded within business processes that support the discovery, creation, and capture of operational value (Brinch, 2018; Sadia,

2026). Supply chain practitioners have identified planning, sourcing, production, forecasting, delivery, and process management as major areas in which big data and analytical technologies can be applied (Brinch et al., 2018; Nishat, 2026). Operational visibility provides another important component of this technological foundation because organizations require timely knowledge concerning supply and demand conditions before analytical models can support effective decisions. Supply chain visibility and organizational flexibility have been associated with stronger supply chain analytics capability and operational performance (Murad, 2026; Srinivasan & Swink, 2018). The adoption of business analytics has similarly been linked with business-process performance, reinforcing the importance of embedding analytical capability within organizational activities rather than isolating it within technical departments (Aydiner et al., 2019; Shamima, 2026).

AI-assisted supply chain monitoring and decision support represent another central dimension of analytics-driven operational management because supply chain and logistics professionals must frequently evaluate multiple operational variables simultaneously. These variables can include supplier conditions, transportation status, warehouse capacity, inventory availability, demand fluctuations, delivery schedules, production requirements, service levels, and disruptions affecting material or information flows. Digitally connected supply chains generate information from numerous internal and external sources, creating a requirement for intelligent systems capable of identifying unusual patterns, detecting exceptions, evaluating risks, prioritizing operational problems, and presenting decision-relevant information. Machine-learning models have been used to predict supply chain risks and delivery-related problems, demonstrating the capacity of data-driven analytical methods to support risk identification while also emphasizing the importance of interpretable analytical outputs for managerial use (Baryannis et al., 2019; Badrul, 2026). The concept of the self-thinking supply chain has further described how interconnected information and communication technologies can support predictive and increasingly intelligent supply chain processes through enhanced information acquisition, processing, and analysis (Calatayud et al., 2019; Chowdhury, 2026). Analytical capabilities are also relevant to supply chain agility because organizations must convert information into timely operational responses once changing conditions have been identified. Big data analytics capability has been positively associated with supply chain agility, while organizational flexibility can strengthen the ability of firms to convert analytical resources into responsive operational actions (Dubey et al., 2019; Pervaz, 2026). Big data analytics has additionally been connected with operational excellence through its role in strengthening the processing and utilization of production and logistics information across organizational processes (Bag et al., 2020; Kaium, 2026). The use of information technology in supplier-facing and customer-facing supply chain processes has also been associated with resilience and organizational performance, indicating that technological effectiveness depends partly on the manner in which IT resources are applied across supply chain relationships (Gu et al., 2021; Rahman, 2026). Artificial intelligence research in supply chain management has identified applications across logistics, production, procurement, marketing, forecasting, inventory management, transportation, and broader decision-support activities (Ahmed, 2026; Toorajipour et al., 2021). AI-assisted monitoring systems can consequently connect operational visibility with anomaly detection, risk identification, predictive analysis, and managerial decision support, allowing information generated across supply chain networks to be transformed into analytically structured inputs for daily operational control.

The integration of artificial intelligence, information technology infrastructure, predictive analytics, real-time information processing, and operational optimization is particularly relevant to analytics-driven operational decision-making within U.S. supply chain and logistics systems. Operational decision-making refers to recurring managerial and technical decisions associated with inventory allocation, transportation planning, warehousing, distribution, order fulfillment, sourcing coordination, capacity utilization, scheduling, route selection, resource allocation, and disruption management. Analytics-driven operational decision-making extends this process by grounding operational actions in systematically processed data, predictive models, digital visibility, analytical outputs, and intelligent decision-support systems rather than relying primarily on fragmented information or individual experience. Digital transformation research in supply chain management has established that information systems, automation, digital connectivity, and data exchange operate as

interconnected components of contemporary supply chain processes (Frederico et al., 2020; Khalid, 2026; Núñez-Merino et al., 2020). AI technologies can contribute to supply chain visibility, risk assessment, disruption identification, sourcing decisions, distribution management, and resilience-related operational processes by allowing organizations to interpret complex information and identify appropriate courses of action (Jannatul, 2026; Modgil et al., 2022). Empirical research has also associated organizational AI capabilities with supply chain resilience and performance, indicating that the effectiveness of artificial intelligence is related to the organizational and technological conditions under which AI resources are developed and deployed (Jahanara, 2026; Wang & Pan, 2022). Research focusing specifically on artificial intelligence in logistics and supply chain management has characterized AI as a broad collection of technologies and analytical approaches that can influence operational practices, information processing, and decision activities throughout logistics systems (Mohammad, 2026; Richey et al., 2023). Existing scholarship, however, is distributed across research streams examining IT capability, digital supply chain integration, big data analytics, machine-learning forecasting, supply chain agility, AI adoption, resilience, and operational performance. This fragmentation creates an empirical research problem concerning how multiple AI-related capabilities can be integrated through an IT management framework and examined collectively in relation to analytics-driven operational decision-making. Accordingly, the present study focuses on four explanatory constructs, namely AI-Enabled Predictive Analytics and Forecasting, Intelligent IT Infrastructure and Data Integration, AI-Assisted Supply Chain Monitoring and Decision Support, and Real-Time Analytics and Automated Operational Optimization, while Analytics-Driven Operational Decision-Making Performance serves as the dependent construct. The relationships among these constructs are examined within U.S. supply chain and logistics environments through a quantitative, cross-sectional, case-study-based design using professional responses measured through a five-point Likert scale.

The increasing digitalization of supply chain and logistics operations has transformed the way organizations collect information, coordinate resources, monitor activities, and make operational decisions. Modern supply chain systems generate extensive amounts of data from enterprise resource planning platforms, transportation management systems, warehouse management systems, customer databases, supplier networks, cloud applications, mobile devices, sensors, and other information technologies. Within U.S. supply chain and logistics environments, managers frequently need to make operational decisions concerning demand forecasting, transportation scheduling, inventory allocation, warehouse capacity, supplier coordination, order fulfillment, routing, distribution, resource utilization, and disruption response. The quality of these decisions increasingly depends on the ability of organizations to integrate artificial intelligence with information technology management and convert large volumes of operational data into timely and meaningful analytical information. Artificial intelligence provides capabilities for recognizing patterns, forecasting operational conditions, identifying abnormalities, recommending actions, and automating selected decision processes, while effective IT management ensures that data, applications, infrastructure, and analytical platforms remain sufficiently integrated to support these functions. The combination of AI and IT management therefore creates an organizational environment in which predictive analytics, data integration, intelligent monitoring, real-time information processing, and automated optimization can operate as interconnected capabilities. Within supply chain and logistics systems, predictive analytics may assist organizations in estimating demand, inventory requirements, transportation needs, and operational risks. Integrated IT infrastructure enables information from different supply chain functions to become accessible across organizational systems, while AI-assisted monitoring provides decision makers with alerts and structured information concerning disruptions, delays, shortages, and other operational conditions. Real-time analytics and automated optimization further allow organizations to evaluate current operational situations and adjust routing, scheduling, inventory, capacity, or resource allocation decisions according to changing conditions. The present study is therefore situated within the broader transformation of supply chain management from fragmented, experience-based operational control toward increasingly data-intensive and analytics-driven decision environments. It specifically examines how AI-enabled predictive analytics and forecasting, intelligent IT infrastructure and data integration, AI-assisted supply chain monitoring and decision support, and real-time analytics and automated operational optimization are associated with analytics-driven operational decision-

making performance in U.S. supply chain and logistics systems.

Supply chain and logistics organizations increasingly possess substantial quantities of digital data and have access to artificial intelligence, cloud computing, enterprise information systems, analytics platforms, and automated decision-support technologies. However, the availability of these technologies does not necessarily mean that organizations can effectively integrate them into a coherent IT management structure or consistently use them to support operational decision-making. In many operational environments, information can remain distributed across separate systems, departments, platforms, and supply chain partners, creating difficulties in obtaining a unified view of demand, inventory, transportation, warehousing, supplier activity, and operational disruptions. Artificial intelligence applications may also be implemented for individual functions such as forecasting or route optimization without adequate integration with enterprise information systems or broader managerial processes. This creates a significant research problem because analytics-driven operational decisions require more than isolated technological applications. They require the combined operation of predictive intelligence, integrated data infrastructure, intelligent monitoring and decision support, and real-time analytical optimization. Existing research has frequently examined artificial intelligence, big data analytics, information technology capability, supply chain visibility, forecasting, resilience, and digital supply chain management as separate areas. Consequently, there remains insufficient empirical understanding of how these AI-integrated IT management capabilities jointly influence operational decision-making performance within U.S. supply chain and logistics systems. The relative contribution of each capability also requires quantitative examination because organizations need to understand whether predictive analytics, IT infrastructure integration, AI-assisted monitoring, or real-time optimization contributes more strongly to analytics-driven operational decisions. Without such empirical assessment, technological investments may remain fragmented and organizations may find it difficult to determine how different digital capabilities should be combined within an integrated management framework. The research problem addressed by this study is therefore the lack of a quantitatively validated framework explaining how multiple AI-integrated IT management capabilities collectively and individually influence analytics-driven operational decision-making performance in U.S. supply chain and logistics environments.

LITERATURE REVIEW

The literature surrounding artificial intelligence integrated IT management and analytics-driven operational decision-making spans several closely connected areas, including artificial intelligence, machine learning, predictive analytics, enterprise information systems, data integration, supply chain analytics, digital logistics, intelligent decision support, real-time optimization, and organizational information-processing capabilities. Collectively, these research streams explain how organizations acquire operational data, transform those data into analytical knowledge, distribute information across technological systems, and use analytical outputs to support supply chain decisions. Research on artificial intelligence in supply chain management has examined applications in forecasting, inventory planning, transportation, supplier management, risk assessment, scheduling, logistics coordination, and operational optimization, while the broader information systems literature has emphasized the role of integrated technological infrastructure in connecting organizational processes and enabling information exchange. Big data and supply chain analytics scholarship has further examined how analytical resources can improve visibility, forecasting capability, agility, process performance, and the interpretation of complex operational conditions. At the same time, studies of digital supply chains and Industry 4.0 have highlighted the increasing integration of cloud platforms, connected systems, enterprise applications, intelligent automation, sensors, and data-driven technologies within production and logistics networks. These streams are highly relevant to the present research because analytics-driven operational decision-making requires technological capabilities that extend beyond the use of a single analytical application. Effective operational decisions depend on the interaction between forecasting capability, integrated and reliable information infrastructure, intelligent monitoring and decision-support mechanisms, and the ability to analyze and optimize operational conditions in real time. The literature review therefore examines these capabilities systematically in relation to U.S. supply chain and logistics systems. It is organized around artificial intelligence and IT management in supply chain environments, AI-enabled predictive analytics and forecasting, intelligent

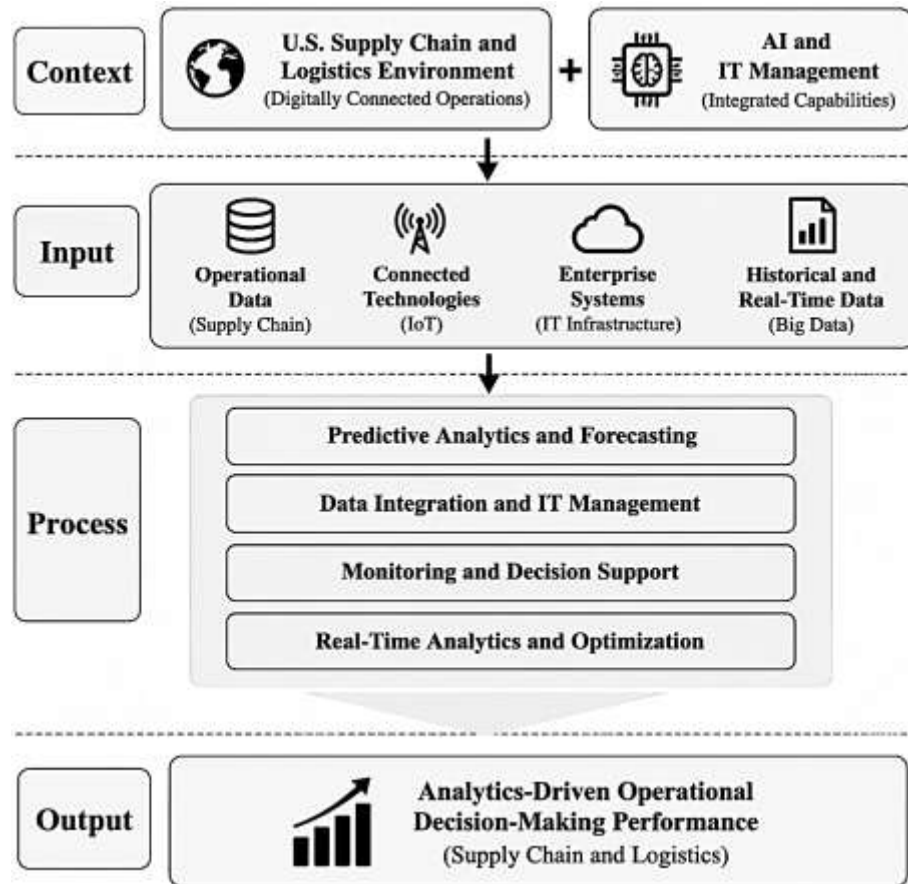
IT infrastructure and data integration, AI-assisted monitoring and operational optimization, the theoretical foundation explaining AI-integrated organizational capabilities, and the conceptual relationships linking these technological dimensions with Analytics-Driven Operational Decision-Making Performance.

Artificial Intelligence and IT Management in U.S. Supply Chain and Logistics Systems

Artificial intelligence and information technology management have become increasingly interconnected within supply chain and logistics systems because operational performance now depends on the ability to collect, integrate, interpret, and act on data generated across complex networks. In this context, AI refers to computational capabilities that support learning, prediction, classification, pattern recognition, optimization, and decision assistance, while IT management concerns the governance and coordination of digital infrastructure, enterprise applications, data resources, connectivity, and technological services. When these two domains are combined, organizations can move beyond basic transaction processing toward digitally coordinated operational environments in which information from procurement, production, transportation, warehousing, inventory, and customer-facing activities can be processed through intelligent analytical systems. This integration is highly relevant to U.S. supply chain and logistics organizations, where geographically dispersed suppliers, distribution centers, carriers, fulfillment facilities, and customers require continuous information exchange. Industry 4.0 has strengthened this relationship by linking cyber-physical systems, automation, digital connectivity, advanced analytics, and machine-supported decision processes with logistics activities. Research on Industry 4.0 and logistics has shown that digital technologies reshape the coordination of material and information flows by connecting physical logistics processes with information systems and automated decision mechanisms ([Debasish, 2021](#); [Hofmann & Rüscher, 2017](#)). From an IT management perspective, this means that AI cannot operate effectively as an isolated application. Its usefulness depends on the availability of integrated databases, interoperable enterprise systems, reliable communication networks, suitable computing resources, and management processes that ensure data can move across functional boundaries. AI-integrated IT management therefore represents a coordinated organizational capability through which technological infrastructure and intelligent analytics are aligned with operational requirements. In supply chain environments, such alignment provides the technical basis for predictive forecasting, real-time monitoring, anomaly identification, routing analysis, inventory control, scheduling, and other analytically supported decisions that depend on timely and trustworthy information in practice today. The technological foundation of AI-integrated supply chain management also depends heavily on connected devices, information visibility, and data acquisition across operational processes. Modern logistics networks increasingly rely on sensors, tracking devices, automated identification technologies, telematics, cloud-connected equipment, and enterprise platforms that generate information about the location, condition, movement, and status of goods and resources. The Internet of Things is important because it connects physical assets to digital information systems, allowing operational events to be captured and transmitted. A review of IoT applications in supply chain management demonstrated that connected technologies can support several supply chain processes by improving the availability of operational information and linking physical activities with digital systems ([Ben-Daya et al., 2019](#); [Abdur & Iftikhar, 2021](#)). Such connectivity becomes more valuable when IT management practices ensure that incoming data can be standardized, stored, secured, integrated, and made accessible to analytical applications. Large-scale digital information also increases the importance of analytics architecture because organizations must process data for managers to use it in operational settings. Big data analytics research in operations management has emphasized that analytical value emerges from the combination of data resources, suitable models, computing capability, and decision processes rather than from data volume alone ([Choi et al., 2018](#); [Debasish, 2022](#)). For U.S. supply chain and logistics organizations, these requirements are relevant to transportation management, warehouse coordination, retail distribution, manufacturing logistics, e-commerce fulfillment, and multimodal networks where decisions may depend on continuously changing operational conditions. AI systems can analyze connected data to recognize emerging demand patterns, detect abnormal shipment behavior, prioritize exceptions, estimate delivery conditions, and support resource allocation. IT management provides the architecture within which these functions can be deployed consistently by

coordinating applications, data governance, platform integration, cybersecurity, cloud resources, and user access. The resulting relationship between connected infrastructure and intelligent analysis forms a central component of analytics-driven operational management.

Figure 2: AI-Integrated IT Management Framework for Analytics-Driven Operational Decision-Making in U.S. Supply Chain and Logistics Systems



AI-integrated IT management becomes most strategically meaningful when digital connectivity and analytical capability are translated into coordinated operational decisions across the supply chain. Organizations require more than isolated forecasting models because logistics decisions are interdependent: changes in demand can affect procurement, inventory, transportation, warehousing, scheduling, and service levels. Big data and predictive analytics research has demonstrated that connectivity, information sharing, managerial commitment, and the organizational assimilation of analytical capability are associated with supply chain and organizational performance, indicating that analytical technologies produce value when they become embedded in routine processes (Gunasekaran et al., 2017; Mahbubul et al., 2022). This perspective is particularly relevant to the present study because it positions AI and analytics as managed capabilities rather than as independent software solutions. Digitalization also affects the management of uncertainty and disruption. Research examining digital technology, Industry 4.0, and supply chain risk analytics has shown that technologies such as advanced tracking, big data analytics, and digitally connected systems can strengthen the analytical understanding of disruption propagation and supply chain risk conditions (Ivanov et al., 2019; Ashfaq & Mohammad, 2022). Within U.S. supply chain and logistics systems, such capabilities can support shipment prioritization, inventory reallocation, transportation alternatives, capacity adjustment, and operational recovery. Effective use requires coordination of data quality, system interoperability, analytics models, infrastructure availability, and decision responsibilities. AI-Enabled Predictive Analytics and Forecasting depends on historical and real-time data; Intelligent IT Infrastructure and Data Integration enable those data to be combined; AI-Assisted Supply Chain Monitoring and Decision

Support converts data into operational awareness; and Real-Time Analytics and Automated Operational Optimization use current information to evaluate and adjust operational actions. These four capabilities represent dimensions of an AI-integrated IT management environment. Examining them together provides a basis for understanding how technological and analytical resources are associated with Analytics-Driven Operational Decision-Making Performance in U.S. supply chain and logistics systems.

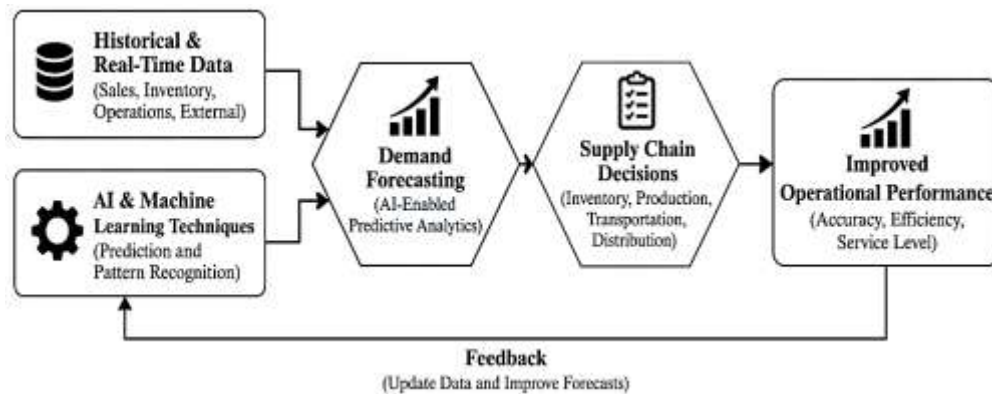
Forecasting for Supply Chain Operations

AI-enabled predictive analytics and forecasting represent a central analytical capability within digitally managed supply chains because they allow organizations to transform historical and current operational data into estimates of likely demand, resource requirements, inventory movements, transportation needs, and potential operational deviations. Predictive analytics combines statistical modeling, data mining, machine learning, pattern recognition, and domain knowledge to estimate conditions that have not yet been directly observed. In supply chain settings, forecasting is particularly important because procurement, production, warehousing, transportation, replenishment, and distribution decisions are frequently made before actual customer demand becomes known. Traditional forecasting methods generally rely on structured time-series relationships, historical averages, smoothing procedures, or regression-based assumptions, whereas AI-enabled approaches can process larger numbers of variables, identify nonlinear relationships, and learn from changing patterns in complex datasets. The growing role of data science and predictive analytics in supply chain management has therefore been connected with the need to convert increasingly large and diverse datasets into decision-relevant knowledge rather than treating data accumulation as an operational capability by itself ([Rashedul & Kaium, 2022](#); [Schoenherr & Speier-Pero, 2015](#)). From an IT management perspective, predictive capability requires an environment in which data from enterprise resource planning systems, warehouse platforms, transportation systems, customer transactions, supplier records, and external information sources can be made available to analytical models with sufficient consistency and timeliness. Predictive big data analytics has been identified as particularly relevant to supply chain demand forecasting because machine-learning, neural-network, regression, clustering, support-vector, and time-series approaches provide different mechanisms for extracting patterns from complex demand information ([Sheak & Risha, 2022](#); [Seyedan & Mafakheri, 2020](#)). For U.S. supply chain and logistics organizations, such analytical capability is relevant to recurring operational decisions involving demand planning, safety-stock positioning, capacity requirements, shipment scheduling, workforce allocation, and distribution coordination, all of which depend heavily on the quality of estimates generated before actual operational conditions are fully realized.

The operational value of AI-enabled forecasting becomes clearer when predictive outputs are linked directly with supply chain decisions rather than evaluated only as statistical estimates. Forecast accuracy affects the quantity and timing of inventory, purchasing requirements, production commitments, warehouse space, transportation capacity, and fulfillment resources, while systematic forecast errors can generate excess inventory, shortages, unnecessary logistics costs, or weak service performance. Machine learning can strengthen this process by learning relationships among product attributes, transaction histories, prices, customer behavior, and other explanatory variables that conventional models may handle less effectively. Evidence from online retailing has demonstrated how machine-learning-based demand prediction can be combined with an optimization mechanism so that predicted demand is translated into practical pricing decisions for products with limited historical sales information ([Ferreira et al., 2016](#); [Chowdhury & Tonay, 2022](#)). This connection between prediction and action is highly relevant to analytics-driven operational decision-making because the value of a forecast depends not only on numerical accuracy but also on whether managers and information systems can incorporate the forecast into an operational choice. Deep-learning approaches further extend forecasting capability by modeling complex nonlinear demand structures and learning representations from large datasets. An intelligent demand forecasting system combining deep learning, support vector regression, time-series techniques, and an ensemble decision-integration strategy has shown that multiple analytical methods can be coordinated to improve forecasting performance in a large retail supply chain setting ([Kilimci et al., 2019](#); [Hossan, 2022](#)). Such findings support the treatment of AI-enabled predictive analytics and forecasting as a multidimensional organizational capability rather

than a single algorithm. Within U.S. logistics systems, an integrated forecasting capability can draw information from sales orders, customer behavior, inventory transactions, carrier activity, promotions, seasonality, regional demand, and operational events. The resulting predictions can then support replenishment, inventory allocation, transportation planning, distribution-center preparation, procurement timing, and other decisions requiring advance estimates of operational requirements.

Figure 3: AI-Enabled Predictive Analytics and Forecasting Framework for Supply Chain Operational Decision-Making



Forecasting capability is especially important when supply chain demand is irregular, sparse, volatile, or affected by short product life cycles, because these conditions limit the usefulness of methods that assume stable and continuously observed demand patterns. Logistics organizations frequently manage large numbers of stock-keeping units that exhibit different demand behaviors, and the same forecasting approach may not perform equally well for fast-moving products, intermittent spare parts, seasonal goods, or newly introduced items. AI-enabled analytics addresses this challenge by allowing models to classify patterns, combine information across time horizons, incorporate multiple explanatory variables, and adapt model selection to the structure of the data being analyzed. Research on electronics distribution has demonstrated that a data-driven forecasting framework integrating machine-learning technologies with temporal aggregation can improve intermittent-demand forecasting and provide operational support for inventory and supply chain decisions under complex demand conditions (Fu & Chien, 2019; Kaniz, 2022). This application illustrates the relationship between predictive analytics and IT management. Forecasting performance depends on data capture, database integration, model execution, analytical governance, and communication of predictions to individuals or systems responsible for operational action. When these elements are disconnected, accurate models may still have limited influence on supply chain decisions. AI-Enabled Predictive Analytics and Forecasting in this study therefore encompasses more than the technical generation of a numerical forecast. It represents the organizational ability to use AI-supported analytical methods to anticipate demand conditions, logistics requirements, resource needs, inventory movements, and operational risks in a form that can be incorporated into routine decision processes. Within the proposed AI-integrated IT management framework, this capability functions as an anticipatory information mechanism that supplies decision makers with analytically generated estimates before operational actions are selected. Its relationship with Analytics-Driven Operational Decision-Making Performance can consequently be examined through whether predictive intelligence improves timeliness, quality, accuracy, and the analytical basis of decisions.

Intelligent IT Infrastructure and Supply Chain Connectivity

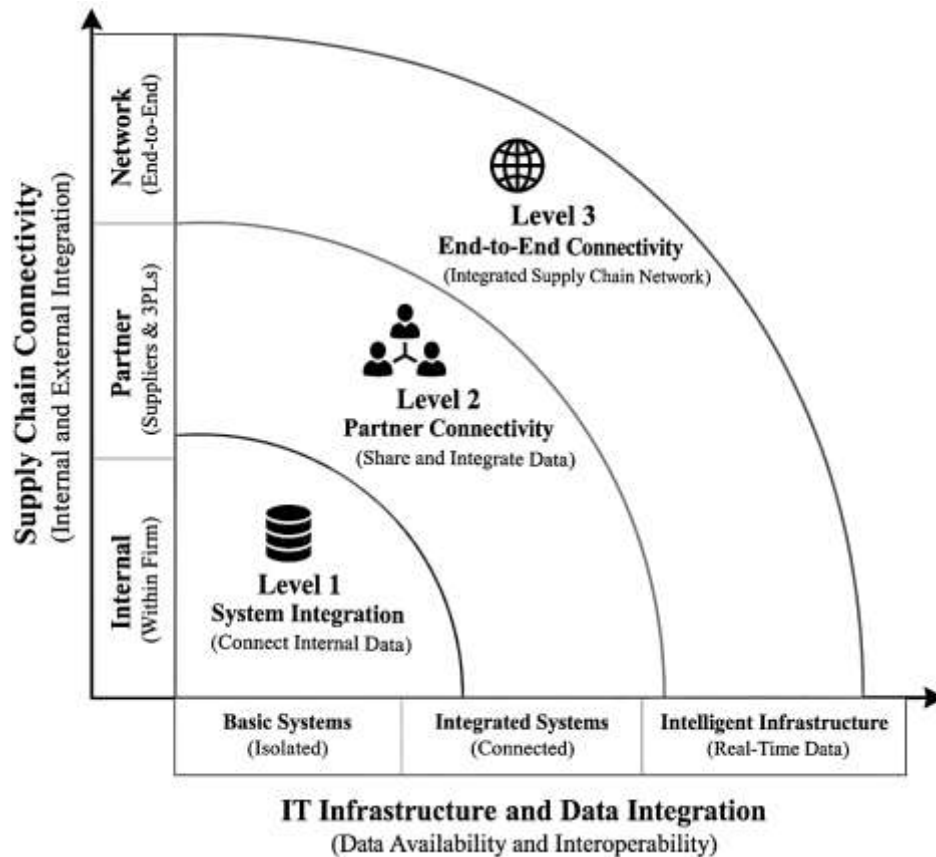
Intelligent IT infrastructure and data integration form the technological backbone of analytics-driven supply chain management because artificial intelligence depends on reliable, connected, and accessible information environments. In supply chain and logistics systems, IT infrastructure includes enterprise resource planning platforms, transportation management systems, warehouse management systems, cloud services, databases, application programming interfaces, communication networks, and

analytical applications that collectively support the movement and processing of operational information. The strategic value of these resources does not arise simply from technology ownership; it depends on whether organizations can transform IT resources into supply chain capabilities that improve coordination, responsiveness, and decision quality. Research has shown that information technology contributes to firm performance when it enables distinctive supply chain capabilities rather than functioning as a stand-alone investment (Nishat & Kaniz, 2022; Wu et al., 2006). This distinction is especially important in U.S. logistics environments, where data may originate from suppliers, carriers, warehouses, retailers, customers, and external service providers operating through different digital platforms. Intelligent IT management therefore requires interoperability among systems, standardized data structures, consistent data governance, appropriate access controls, and sufficient processing capacity for analytical applications. The infrastructure must support both internal integration across organizational functions and external connectivity with supply chain partners. When these conditions are present, organizations can combine information concerning orders, inventory, transportation status, production schedules, customer demand, and supplier performance into shared operational views. IT also becomes a mechanism for collaboration when technological resources facilitate coordinated planning, information exchange, and joint problem solving across organizational boundaries (Fawcett et al., 2011; Shaiful et al., 2022). In this sense, intelligent IT infrastructure is not merely a collection of hardware and software. It represents a managed digital environment in which connectivity, data availability, integration, and analytical readiness enable supply chain information to be converted into usable knowledge for operational decision-making. This foundation also supports consistent analytical access across complex operations.

Data integration is equally important because supply chain decisions often require information from multiple functions and organizational partners to be interpreted together rather than separately. Fragmented systems can create duplicated records, inconsistent data definitions, delayed information exchange, and incomplete operational visibility, all of which can weaken the accuracy of analytics and the quality of managerial decisions. Integration seeks to reduce these limitations by connecting applications, databases, and information flows so that relevant data can be accessed across procurement, manufacturing, warehousing, transportation, distribution, and customer-service processes. Empirical evidence indicates that information technology capability and information sharing can strengthen logistics integration, while integrated logistics processes are associated with improved operational performance (Mohammad, 2023; Prajogo & Olhager, 2012). This relationship shows that connectivity is valuable when technological integration supports the coordinated movement of both information and physical resources. For AI-enabled supply chains, integrated data are particularly necessary because predictive models and decision-support systems depend on consistent inputs drawn from different operational sources. For example, a transportation decision may require order data, inventory availability, delivery priorities, carrier capacity, route conditions, and warehouse schedules to be analyzed simultaneously. IT alignment across supply chain partners can improve operational performance directly and can also strengthen information sharing, demonstrating that technical compatibility and data exchange operate as complementary capabilities (Debasish, 2023; Ye & Wang, 2013). Within U.S. supply chain and logistics systems, these requirements become more complex when firms coordinate with third-party logistics providers, technology vendors, distributors, manufacturers, and geographically dispersed facilities. Intelligent integration therefore involves more than transferring files between systems. It requires common data standards, synchronized interfaces, reliable communication protocols, real-time or near-real-time updates, and governance mechanisms that preserve data quality. These capabilities allow analytical platforms to work with coherent information and reduce the operational uncertainty created by disconnected technological environments. Such integration also improves situational awareness across connected organizations. Supply chain connectivity extends the concept of integration by emphasizing the continuous digital relationships that link internal functions with suppliers, customers, logistics providers, and other external participants. Connectivity allows information to move across organizational boundaries and enables distributed actors to coordinate operational activities using shared digital resources. In an AI-integrated environment, this capability is essential because analytical systems often require data from multiple supply chain nodes before they can generate useful predictions, alerts, or optimization

recommendations. IT-enabled supply chain integration has been shown to support internal, supplier, and customer integration, while stronger internal integration is associated with both operational and financial performance (Kaium, 2023; Yu, 2015).

Figure 4: Intelligent IT Infrastructure, Data Integration, and Supply Chain Connectivity Framework



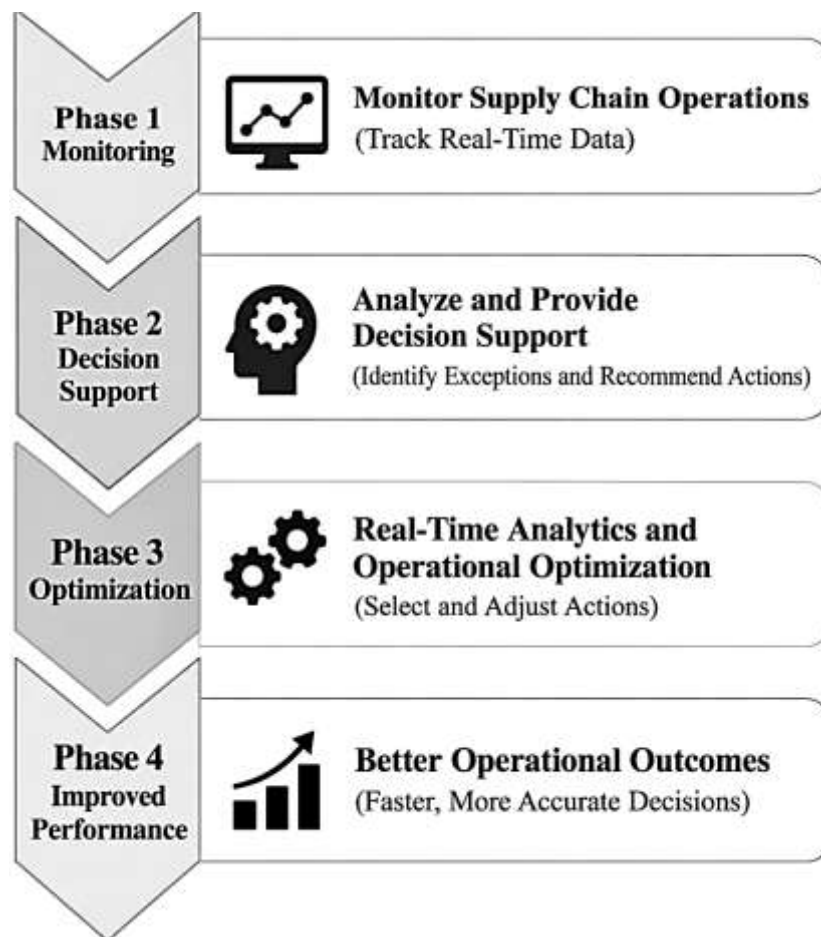
This finding is relevant to analytics-driven operational decision-making because AI outputs are most useful when they can be communicated to the functions and partners responsible for executing operational actions. A predictive warning about inventory shortages, for example, has limited value if purchasing, warehousing, transportation, and supplier systems cannot exchange the information needed for coordinated response. Similarly, route optimization requires connectivity between order-management data, transportation systems, carrier information, and delivery requirements. Intelligent IT infrastructure and data integration therefore function as an enabling layer within the framework. They provide the digital architecture through which AI-Enabled Predictive Analytics and Forecasting can access suitable data, AI-Assisted Supply Chain Monitoring and Decision Support can obtain timely operational visibility, and Real-Time Analytics and Automated Operational Optimization can evaluate conditions across processes. For U.S. supply chain and logistics organizations, the quality of this infrastructure can be assessed through system integration, data accessibility, interoperability, information consistency, connectivity, and the ability to provide analytical applications with reliable operational data. The present study consequently treats Intelligent IT Infrastructure and Data Integration as a distinct explanatory capability whose relationship with Analytics-Driven Operational Decision-Making Performance can be quantitatively examined through professional assessments of integrated systems and information availability.

AI-Assisted Supply Chain Monitoring, Decision Support, and Real-Time Operational Optimization

AI-assisted supply chain monitoring and decision support represent the organizational capability to continuously observe operational conditions, interpret incoming data, identify deviations, and convert

information into structured guidance for managers. In logistics systems, monitoring may involve shipment locations, inventory positions, warehouse activity, order status, supplier performance, transportation capacity, delivery schedules, and service exceptions. The effectiveness of these activities depends on supply chain visibility, which refers to the extent to which relevant operational information can be accessed and understood across supply chain relationships. High visibility is not produced by technology alone because organizations also require processes, relationships, information-sharing practices, and managerial routines that enable data to be interpreted and used. Research examining retail supply chains found that visibility differs across supply chain linkages and is influenced by both technological and non-technological resources, demonstrating that information access must be supported by organizational capabilities if it is to become operationally meaningful (Barratt & Oke, 2007; Pervaz, 2023). This perspective is highly relevant to AI-assisted monitoring because machine-learning models, anomaly-detection mechanisms, intelligent dashboards, and automated alerts can only support decisions when the underlying data reflect the actual state of supply chain operations.

Figure 5: AI-Assisted Supply Chain Monitoring, Decision Support, and Real-Time Operational Optimization Framework



Visibility becomes more demanding as supply networks increase in complexity, involve more tiers, and depend on geographically distributed partners. A quantitative case-based examination of supply chain configuration showed that virtuality and complexity affect the need for and characteristics of supply chain visibility, reinforcing the importance of timely information when organizations coordinate activities beyond their direct operational boundaries (Caridi et al., 2010; Chowdhury, 2023). For U.S. supply chain and logistics systems, AI-assisted monitoring can therefore be understood as an information-processing layer that combines connected operational data with intelligent analytical mechanisms to identify exceptions, prioritize events, and present decision makers with current

evidence about conditions requiring managerial attention. This capability is especially important when operational speed, network complexity, and service requirements make delayed or incomplete information costly for coordinated logistics decisions.

The contribution of monitoring to operational decision-making depends not only on collecting information but also on its accessibility, quality, usefulness, and capacity to support action. Supply chain visibility is valuable when data are sufficiently complete, accurate, timely, and understandable for users who must coordinate operational responses. A systematic characterization of supply chain visibility identified accessibility, quality, and usefulness of information as central characteristics and showed that visibility can generate informational, automational, and transformational effects across business processes (Badrul & Mominul, 2023; Somapa et al., 2018). These characteristics establish an important foundation for AI-assisted decision support. Artificial intelligence can process large streams of operational information, classify events, recognize unusual patterns, estimate the seriousness of disruptions, and rank alternative responses, but managerial decision quality still depends on whether the output is aligned with operational objectives and presented in a usable form. Decision-support systems can strengthen this relationship by combining data, analytical models, simulation, rules, and interactive interfaces so that managers can evaluate possible actions before changing physical operations. In-house logistics research has demonstrated the value of simulation-based decision support and digital-twin concepts for representing production and distribution operations, testing alternative configurations, and supporting planning without disrupting the real system (Coelho et al., 2021; Rakib & Towhidul, 2023). Within U.S. warehouses, distribution centers, transportation networks, and manufacturing-logistics environments, similar decision-support principles can be applied to workload balancing, material movement, picking activities, resource allocation, congestion management, and operational scheduling. AI-assisted monitoring therefore extends beyond passive tracking. It establishes a continuous relationship between observation and interpretation, in which operational data are evaluated against expected conditions and converted into alerts, forecasts, classifications, or recommended actions. When this process is integrated with enterprise IT systems, decision makers can respond to operational exceptions using a more consistent analytical basis rather than relying on fragmented reports or delayed manual assessments. It also helps organizations compare alternative responses consistently, document decision logic, and coordinate actions among managers responsible for interconnected logistics processes.

Real-time analytics and automated operational optimization extend AI-assisted decision support from understanding current conditions to selecting and adjusting operational actions. Real-time analytics involves processing recently generated information with sufficiently low delay to influence ongoing activities, while automated optimization applies computational methods to identify solutions that satisfy operational objectives and constraints. In logistics, these objectives can include minimizing transportation time, reducing cost, balancing workloads, improving vehicle utilization, maintaining service levels, allocating inventory, and coordinating warehouse resources. Artificial intelligence and machine learning are particularly relevant where optimization problems involve large datasets, multiple constraints, nonlinear relationships, or conditions that change while operations are underway. Research on logistics engineering has demonstrated how machine-learning and AI techniques can be combined with multi-objective optimization to evaluate transportation requirements and generate operational solutions, illustrating the role of intelligent computation in logistics optimization (Bu, 2021; Nishat, 2023). Within the present research framework, this capability complements AI-assisted monitoring because a system that identifies an operational problem must also support the selection of an appropriate response. For example, detection of a transportation delay may trigger evaluation of alternative routes, carrier assignments, delivery sequences, or inventory-reallocation options; identification of warehouse congestion may initiate revised picking priorities, labor assignments, or material-handling schedules. Effective automation does not necessarily remove human involvement. Instead, organizations can configure decision rights so that routine low-risk adjustments are executed automatically while complex or high-impact recommendations are presented to managers for authorization. This arrangement connects real-time information, analytical reasoning, and operational execution within a managed IT environment. Accordingly, AI-Assisted Supply Chain Monitoring and Decision Support and Real-Time Analytics and Automated Operational Optimization represent

complementary capabilities in this study, with the former emphasizing detection and interpretation and the latter emphasizing analytical selection, adjustment, and execution of operational responses that may strengthen Analytics-Driven Operational Decision-Making Performance. Such integration is central to measuring whether intelligent monitoring and optimization capabilities are associated with faster, more accurate, and analytically grounded operational choices.

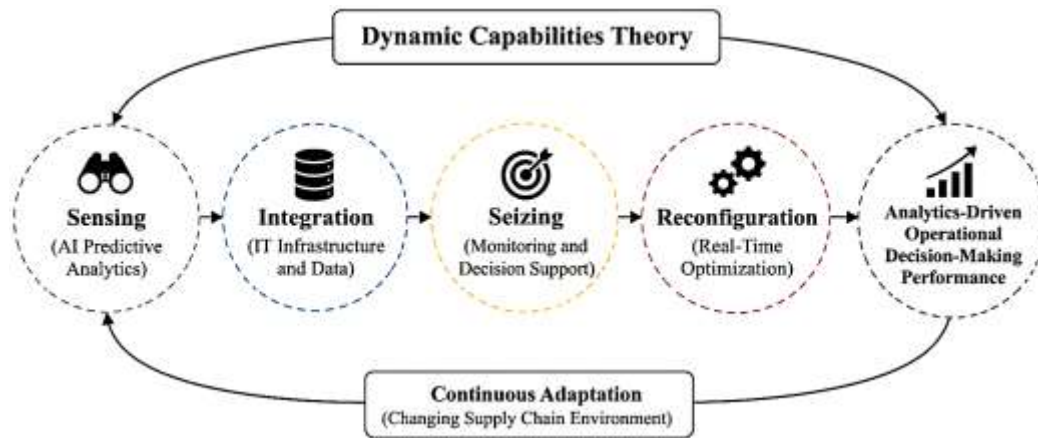
Dynamic Capabilities Theory

Dynamic Capabilities Theory provides an appropriate theoretical foundation for examining an AI-integrated IT management framework because it explains how organizations identify changes, mobilize resources, and reconfigure operational capabilities when technological and market conditions evolve. Rather than treating competitive performance as the direct consequence of possessing valuable resources, the theory emphasizes the organizational processes through which resources are renewed, recombined, and redeployed in response to changing environments. Teece conceptualized dynamic capabilities around the interrelated activities of sensing opportunities and threats, seizing opportunities through coordinated commitments, and transforming or reconfiguring organizational assets and structures to maintain alignment with environmental requirements ([Ashrafuzzaman, 2024](#); [Teece, 2007](#)). This logic is directly relevant to supply chain and logistics systems, where firms must interpret demand changes, transportation disruptions, capacity constraints, inventory conditions, supplier performance, and data generated by interconnected technologies. Dynamic capabilities are not identical to routine operational capabilities because they concern the modification and renewal of the routines through which ordinary activities are performed. The developmental perspective further explains that capabilities can emerge, mature, branch, replicate, renew, retrench, or decline as organizations accumulate experience and respond to environmental demands ([Debasish, 2024](#); [Helfat & Peteraf, 2009](#)). Within the present study, AI-Enabled Predictive Analytics and Forecasting represents a sensing capability because it enables organizations to recognize patterns, forecast demand, and identify possible operational conditions before decisions are executed. Intelligent IT Infrastructure and Data Integration supports the integration of technological and informational resources required to make sensing meaningful across organizational boundaries. AI-Assisted Supply Chain Monitoring and Decision Support reflects a seizing capability because identified information must be evaluated and converted into operational responses. Real-Time Analytics and Automated Operational Optimization represents reconfiguration because it enables routing, scheduling, inventory, capacity, and other operating arrangements to be adjusted when current conditions require changes. Dynamic Capabilities Theory therefore provides a coherent explanation for why these four technological dimensions should be examined together rather than as unrelated applications.

The usefulness of Dynamic Capabilities Theory for this research also lies in its ability to connect high-level strategic adaptation with measurable organizational processes. Dynamic capabilities have sometimes been criticized for being conceptually broad, but empirical work has clarified that they can be operationalized through identifiable routines such as sensing, learning, coordinating, integrating, and reconfiguring operational capabilities. A measurable model developed around these mechanisms demonstrated that dynamic capabilities can influence performance by modifying existing operational capabilities so that organizations are better aligned with turbulent conditions ([Rahman, 2024](#); [Pavlou & Sawy, 2011](#)). This process perspective is especially suitable for AI-integrated IT management because artificial intelligence does not create operational value merely by being installed. Predictive models require access to quality data, data integration requires interoperable systems, monitoring requires real-time visibility, and optimization requires organizational authority to translate analytical outputs into actions. The four constructs in this study therefore represent interconnected capability domains through which technological resources are converted into decision capability. The theory also recognizes that the effectiveness of dynamic capabilities depends on organizational context. Empirical research has shown that performance effects can vary according to organizational structure and environmental conditions, which indicates that capabilities must fit both internal arrangements and external competitive demands ([Kaium, 2024](#); [Wilden et al., 2013](#)). In U.S. supply chain and logistics systems, this contextual fit is important because organizations operate across different industries, technologies, network structures, product characteristics, transportation modes, and levels of digital maturity. The present research does not assume that all organizations possess identical technological

configurations. Instead, it evaluates professional perceptions of the degree to which AI-enabled forecasting, integrated IT infrastructure, intelligent monitoring, and real-time optimization are embedded in operational practices. Dynamic Capabilities Theory supports this approach by focusing on what organizations are able to accomplish with resources rather than on whether they possess a specific technology. Analytics-Driven Operational Decision-Making Performance consequently represents the observable outcome through which the combined capability logic can be quantitatively evaluated.

Figure 6: Dynamic Capabilities Theory Framework for AI-Integrated IT Management and Analytics-Driven Operational Decision-Making Performance



The theoretical framework can be translated into an empirical model in which the four AI-integrated IT management capabilities function as explanatory variables and Analytics-Driven Operational Decision-Making Performance functions as the dependent variable. This translation is consistent with contemporary dynamic-capabilities research, which increasingly emphasizes clearer construct specification and empirical measurement when assessing how organizational capabilities influence performance outcomes (Shakhawat & Md, 2024; Schilke et al., 2018). In the present study, sensing is represented primarily by AI-Enabled Predictive Analytics and Forecasting, integration is represented by Intelligent IT Infrastructure and Data Integration, seizing is represented by AI-Assisted Supply Chain Monitoring and Decision Support, and reconfiguration is represented by Real-Time Analytics and Automated Operational Optimization. These mappings allow the theoretical logic to be tested through one study-wide multiple regression model:

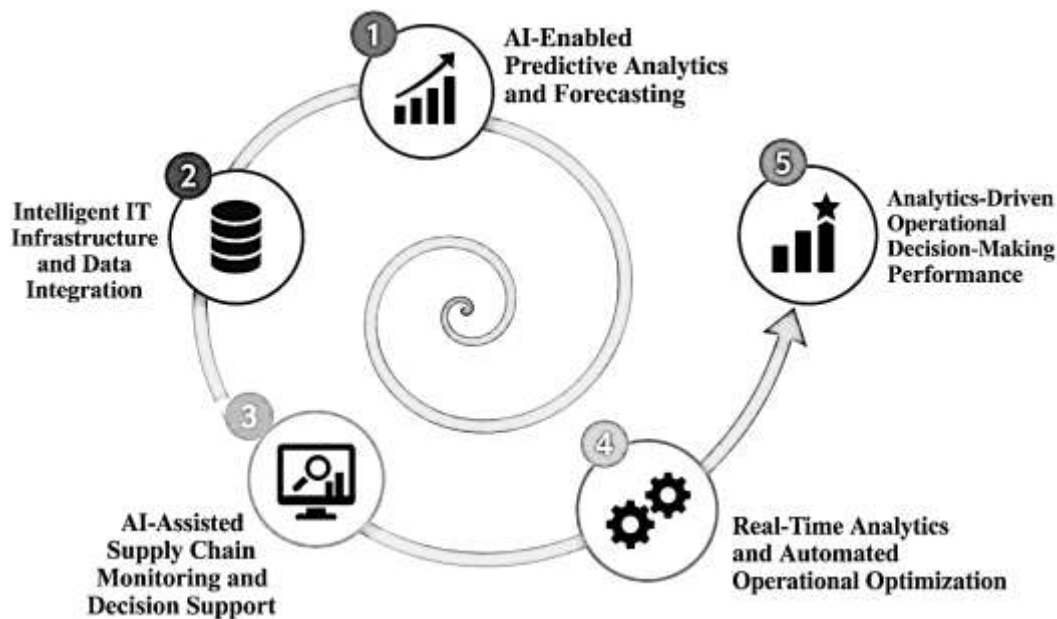
$$ADODMP_i = \beta_0 + \beta_1 AIPAF_i + \beta_2 IITDI_i + \beta_3 AISCMDs_i + \beta_4 RAAOO_i + \varepsilon_i$$

In this equation, ADODMP_i denotes Analytics-Driven Operational Decision-Making Performance for respondent *i*; β_0 represents the regression constant; β_1 through β_4 represent the estimated effects of the four capability constructs; and ε_i represents unexplained variation. The model is appropriate for the study because each independent variable corresponds to a theoretically distinct capability while all four are expected to contribute to the same operational decision outcome. Positive and statistically significant coefficients would indicate that stronger perceptions of the respective AI-integrated capability are associated with stronger analytics-driven operational decision-making performance, while the model R^2 will indicate the proportion of variance jointly explained by the four capabilities. The equation will therefore provide a single analytical structure connecting the theoretical framework, hypotheses, questionnaire constructs, correlation analysis, and multiple regression analysis. By embedding the Dynamic Capabilities perspective directly in the measurable model, the study can examine whether sensing, integration, seizing, and reconfiguration are reflected in the technological capabilities through which U.S. supply chain and logistics professionals use analytics to support operational choices.

Conceptual Framework

The conceptual framework of this study integrates four AI-enabled IT management capabilities as coordinated determinants of Analytics-Driven Operational Decision-Making Performance within U.S. supply chain and logistics systems. A conceptual framework is useful when a study must translate several related technological capabilities into measurable relationships that can be evaluated through a common dependent construct. In the present research, AI-Enabled Predictive Analytics and Forecasting represents the organization's ability to anticipate demand, inventory requirements, transportation conditions, resource needs, and operational risks from historical and current data. Intelligent IT Infrastructure and Data Integration represents the digital foundation through which information from enterprise systems, logistics platforms, databases, and connected applications becomes interoperable and available for analytical use. AI-Assisted Supply Chain Monitoring and Decision Support captures the capability to observe operational conditions, recognize exceptions, evaluate alternatives, and provide analytically structured support to managers. Real-Time Analytics and Automated Operational Optimization represents the ability to process current information and use optimization mechanisms to adjust routing, scheduling, inventory allocation, capacity, and related operational decisions. The inclusion of these four constructs is consistent with evidence that analytical capabilities can contribute to supply chain performance when supported by information systems and embedded in planning, sourcing, production, and delivery processes (Nishat & Jahanara, 2024; Trkman et al., 2010).

Figure 7: Conceptual Framework Linking AI-Integrated IT Management Capabilities with Analytics-Driven Operational Decision-Making Performance



The framework also recognizes that analytical decision quality is dependent on the quality of the data entering analytical systems, since incomplete, inaccurate, inconsistent, or poorly governed information can weaken predictive and prescriptive outputs regardless of model sophistication (Hazen et al., 2014; Tonay et al., 2024). Accordingly, the conceptual model does not treat artificial intelligence as an isolated technological intervention. It treats analytics, infrastructure, monitoring, and optimization as complementary organizational capabilities whose coordinated operation provides the information-processing basis for stronger operational decisions. This integrated perspective is particularly suitable for logistics environments in which a single operational decision often depends on information originating from several functions, systems, and external partners at the same time.

The relationships represented in the framework are also grounded in the idea that analytics capability is multidimensional and develops through the interaction of data generation, integration, management, advanced analysis, visualization, and organizational use. Supply chain organizations do not obtain

decision value merely by accumulating large datasets or purchasing analytical software; they require technical and managerial capabilities that connect data sources with models and connect model outputs with operational processes. A systematic examination of big data analytics capability in supply chain management identified data generation, data integration and management, advanced analytics, visualization, and a data-driven culture as important capability dimensions, showing that analytical maturity is created through combinations of resources rather than through a single technology (Arunachalam et al., 2018; Uddin & Risha, 2024). This capability-based logic closely matches the four constructs proposed in the present research. Predictive analytics creates anticipatory information, IT integration ensures that relevant data are available across functions, AI-assisted monitoring transforms operational data into situational awareness, and real-time optimization converts analytical insight into executable choices. The framework further assumes that these relationships should be evaluated at the level of operational decision performance rather than only at the level of general firm performance. This distinction is important because the immediate outcome of an AI-integrated IT management system is expected to appear in the speed, accuracy, consistency, evidence base, and responsiveness of recurring operational decisions. Empirical research has shown that organizational analytics capability can strengthen disruption orientation and supply chain resilience and can contribute to operational performance under uncertain conditions, providing support for the broader proposition that analytics becomes valuable when it is connected with adaptive operational responses (Debasish, 2025a; Laguir et al., 2023). In the U.S. supply chain and logistics context, the conceptual framework therefore links technology-enabled information processing with the specific decision activities through which transportation, inventory, warehousing, sourcing, distribution, scheduling, and disruption-response processes are managed.

The proposed conceptual framework can be expressed quantitatively so that its theoretical relationships correspond directly with the hypotheses and statistical tests used in the study. For respondent i , the four explanatory constructs can be represented as a vector of AI-integrated IT management capabilities, while Analytics-Driven Operational Decision-Making Performance is represented as the outcome variable. The study-wide structural relationship is expressed as:

$$ADODMP_i = \beta_0 + \beta_1 AIPAF_i + \beta_2 IITDI_i + \beta_3 AISCMS_i + \beta_4 RAAOO_i + \varepsilon_i$$

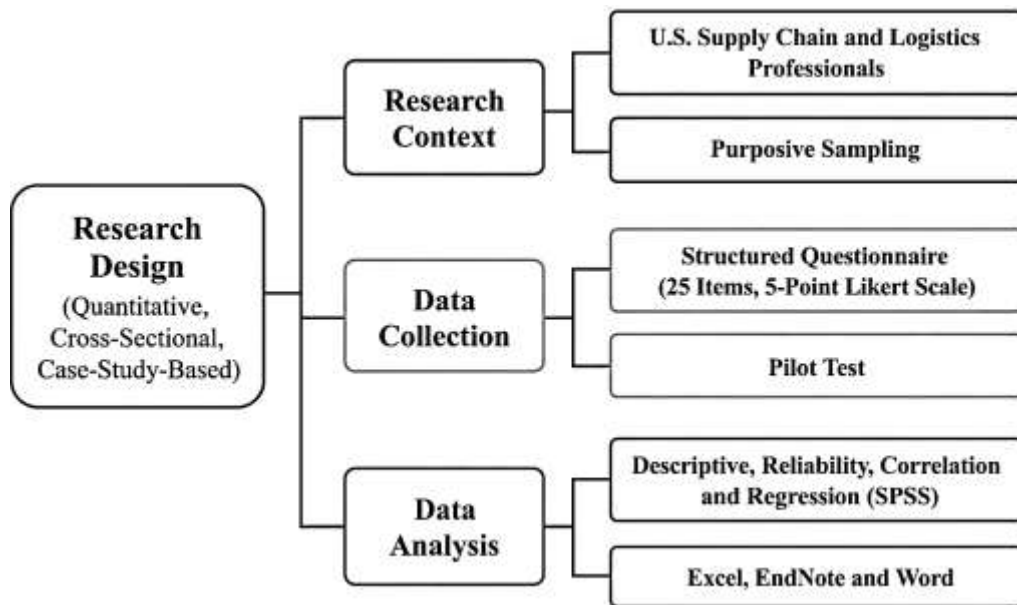
where AIPAF denotes AI-Enabled Predictive Analytics and Forecasting, IITDI denotes Intelligent IT Infrastructure and Data Integration, AISCMS denotes AI-Assisted Supply Chain Monitoring and Decision Support, RAAOO denotes Real-Time Analytics and Automated Operational Optimization, β_0 is the intercept, β_1 through β_4 are the estimated effects of the explanatory constructs, and ε_i represents unexplained variation. The conceptual expectation is that each coefficient will be positive, corresponding to H1 through H4, while the combined R^2 will indicate how much variation in operational decision-making performance is jointly explained by the four capabilities. This specification also acknowledges that AI integration in supply chain management involves both the extent to which AI is embedded across supply chain activities and the role assigned to AI within decision-making processes, including relationships between analytical systems and human managerial judgment (Debasish, 2025b; Hendriksen, 2023). The framework therefore positions AI as part of a sociotechnical IT management system rather than as a substitute for managerial responsibility. By linking four distinct capability domains to one measurable outcome, the model establishes a coherent structure for questionnaire design, descriptive analysis, Pearson correlation, multiple regression, and hypothesis testing while preserving the study's Dynamic Capabilities Theory foundation. This alignment enables each construct to be measured separately while retaining a unified explanation of analytics-driven decision performance.

METHODS

This study has adopted a quantitative, cross-sectional, case-study-based research design to examine the relationships between AI-integrated IT management capabilities and Analytics-Driven Operational Decision-Making Performance within U.S. supply chain and logistics systems. The case-study context has covered selected supply chain, logistics, transportation, warehousing, distribution, manufacturing, and related enterprise environments where artificial intelligence, analytics, and digital information systems have been used to support operational activities. The target population has consisted of supply

chain managers, logistics professionals, IT managers, data analysts, business intelligence specialists, operations managers, warehouse professionals, transportation specialists, data engineers, and other professionals with relevant technological and operational experience. The individual professional has been established as the unit of analysis. Purposive sampling has been employed to select respondents who have possessed sufficient knowledge of AI, information technology, analytics, or supply chain operations. Data have been collected through a structured questionnaire distributed electronically to eligible participants.

Figure 8: Research Design Framework for AI-Integrated IT Management in U.S. Supply Chain and Logistics Systems



The research instrument has contained 25 measurement items covering five constructs: AI-Enabled Predictive Analytics and Forecasting, Intelligent IT Infrastructure and Data Integration, AI-Assisted Supply Chain Monitoring and Decision Support, Real-Time Analytics and Automated Operational Optimization, and Analytics-Driven Operational Decision-Making Performance. All items have been measured through a five-point Likert scale ranging from 1, Strongly Disagree, to 5, Strongly Agree. A pilot test has been conducted before the main data collection to assess questionnaire clarity, wording, structure, and measurement consistency. Construct validity and sampling adequacy have been assessed through appropriate statistical procedures, while internal consistency reliability has been evaluated using Cronbach's alpha. Microsoft Excel has been used for initial data compilation, coding, screening, and organization, while SPSS has been used for descriptive statistics, reliability and validity testing, Pearson correlation analysis, multiple regression modeling, diagnostic testing, and hypothesis evaluation. EndNote has been used to organize scholarly references and maintain APA 7th edition citation consistency, and Microsoft Word has been used for manuscript preparation, table presentation, equation formatting, and final academic documentation.

DATA ANALYSIS AND PRESENTATION

Questionnaire Distribution and Response Rate

Table 1 has presented the questionnaire distribution and final response pattern for the quantitative analysis. A total of 320 questionnaires has been distributed to professionals working within relevant U.S. supply chain, logistics, transportation, warehousing, distribution, manufacturing, information technology, and analytics environments. Of these questionnaires, 300 have been returned, producing a gross response rate of approximately 93.8%. Following data screening, 12 returned questionnaires have been excluded because they have contained substantial missing responses, inconsistent completion patterns, or insufficient information across the principal measurement constructs. Consequently, 288

questionnaires have been retained as complete and usable observations, resulting in a final usable response rate of 90.0%. This response level has provided an adequate empirical basis for descriptive analysis, reliability assessment, correlation testing, and multiple regression modeling. The final dataset has also provided sufficient observations for simultaneously examining the four independent constructs, namely AI-Enabled Predictive Analytics and Forecasting, Intelligent IT Infrastructure and Data Integration, AI-Assisted Supply Chain Monitoring and Decision Support, and Real-Time Analytics and Automated Operational Optimization. The resulting sample has therefore supported the assessment of Analytics-Driven Operational Decision-Making Performance as the dependent construct. From the perspective of Dynamic Capabilities Theory, the respondents have represented organizational professionals who have been positioned to observe or participate in sensing, integrating, seizing, and reconfiguring activities within digitally enabled supply chain environments. Their responses have therefore provided an appropriate perceptual basis for evaluating whether AI-integrated IT capabilities have been embedded within operational processes and whether these capabilities have been associated with stronger decision-making performance. The high proportion of usable questionnaires has also reduced the likelihood that the statistical patterns have been dominated by extensive nonresponse. Accordingly, the final sample of 288 respondents has been used consistently throughout all subsequent analyses and has provided the empirical foundation for testing H1 through H4 and evaluating the study objectives.

Table 1: Questionnaire Distribution and Response Rate

Questionnaire Status	Frequency	Percentage (%)
Questionnaires Distributed	320	100.0
Questionnaires Returned	300	93.8
Incomplete/Invalid Responses	12	3.8
Final Usable Questionnaires	288	90.0
Non-Returned Questionnaires	20	6.3

Demographic and Professional Characteristics of Respondents

Table 2 has shown that the final sample has contained respondents from a broad range of professional roles and organizational environments directly connected with the study topic. Supply chain and logistics managers have formed the largest professional category, accounting for 76 respondents or 26.4% of the usable sample. IT, data, and analytics specialists have represented 23.6%, while operations and warehouse managers have accounted for 19.1%. Transportation and distribution professionals have constituted 17.0%, and AI, digital-transformation, and other technical professionals have represented the remaining 13.9%. This distribution has been particularly appropriate because the proposed framework has combined supply chain management, IT infrastructure, artificial intelligence, analytics, and operational decision-making rather than concentrating on a single occupational group. Professional experience has also indicated substantial practical exposure to supply chain and technology-related activities. Respondents with six to ten years of experience have represented the largest group at 30.6%, followed by those with more than ten years of experience at 28.5%. Therefore, a majority of respondents have possessed at least six years of professional experience, strengthening the relevance of their assessments of organizational technology and decision processes. The organizational contexts have further reflected the case-study orientation of the research. Third-party logistics and transportation organizations have represented 27.1% of the sample, while retail and e-commerce distribution, manufacturing supply chains, warehousing and fulfillment, and integrated enterprise environments have also been represented. From a Dynamic Capabilities perspective, this diversity has allowed the study to examine sensing, integration, seizing, and reconfiguration capabilities across different operational conditions. The professional composition has also aligned with the research objectives because respondents have been positioned to evaluate predictive analytics, IT integration, monitoring systems, optimization mechanisms, and decision performance from practical experience. Consequently, the sample characteristics have supported the relevance and credibility of

the subsequent construct-level and hypothesis-testing analyses.

Table 2: Demographic and Professional Characteristics of Respondents

Characteristic	Category	Frequency	Percentage (%)
Primary Professional Role	Supply Chain/Logistics Managers	76	26.4
	IT/Data/ Analytics Specialists	68	23.6
	Operations/Warehouse Managers	55	19.1
	Transportation/Distribution Professionals	49	17.0
	AI/Digital Transformation/Other Technical Professionals	40	13.9
Professional Experience	Less Than 3 Years	44	15.3
	3-5 Years	74	25.7
	6-10 Years	88	30.6
	More Than 10 Years	82	28.5
Organizational Context	3PL/Transportation	78	27.1
	Retail/E-Commerce Distribution	64	22.2
	Manufacturing Supply Chain	62	21.5
	Warehousing/Fulfillment	48	16.7
	Integrated Enterprise/Multi-Sector Operations	36	12.5

Descriptive Statistics of AI-Integrated IT Management and Operational Decision-Making Constructs

Table 3: Descriptive Statistics of Study Constructs

Construct	Code	Mean	Standard Deviation	Likert Interpretation
AI-Enabled Predictive Analytics and Forecasting	AIPAF	4.14	0.57	High Agreement
Intelligent IT Infrastructure and Data Integration	IITDI	4.08	0.61	High Agreement
AI-Assisted Supply Chain Monitoring and Decision Support	AISCMDS	4.11	0.59	High Agreement
Real-Time Analytics and Automated Operational Optimization	RAAOO	4.16	0.56	High Agreement
Analytics-Driven Operational Decision-Making Performance	ADODMP	4.20	0.53	High Agreement

Note. Likert scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Table 3 has presented the descriptive statistical results for the five principal constructs measured through the five-point Likert scale. All mean scores have exceeded 4.00, indicating that respondents have generally expressed high agreement regarding the existence and effectiveness of the AI-integrated IT management capabilities examined in the selected U.S. supply chain and logistics environments. Analytics-Driven Operational Decision-Making Performance has achieved the highest mean score, $M = 4.20$, $SD = 0.53$, suggesting that respondents have perceived operational decisions as relatively timely,

analytically supported, accurate, and responsive to changing conditions. Among the independent constructs, Real-Time Analytics and Automated Operational Optimization has achieved the highest mean, $M = 4.16$, $SD = 0.56$. This result has suggested that real-time information processing, dynamic optimization, and automated operational adjustment have been comparatively strong within the examined environments. AI-Enabled Predictive Analytics and Forecasting has followed closely with $M = 4.14$, $SD = 0.57$, indicating strong agreement regarding the use of predictive intelligence for anticipating demand, operational requirements, risks, and resource needs. AI-Assisted Supply Chain Monitoring and Decision Support has recorded $M = 4.11$, $SD = 0.59$, while Intelligent IT Infrastructure and Data Integration has recorded $M = 4.08$, $SD = 0.61$. Although IITDI has shown the lowest mean among the constructs, its score has still remained firmly within the high-agreement range. From the perspective of Dynamic Capabilities Theory, these descriptive findings have suggested that the examined organizations have demonstrated comparatively strong sensing through predictive analytics, integrating through connected IT infrastructure, seizing through AI-assisted decision support, and reconfiguring through real-time optimization. The relatively small standard deviations have further indicated that respondents have not differed substantially in their evaluations. The descriptive results have therefore provided preliminary support for the study objectives by showing that all four AI-integrated capabilities have been meaningfully present before their statistical relationships with decision-making performance have been examined.

Reliability and Validity Analysis of Measurement Constructs

Table 4: Reliability and Validity Statistics of Measurement Constructs

Measure / Construct	Items / df	Statistic	Interpretation
AI-Enabled Predictive Analytics and Forecasting (AIPAF)	5	$\alpha = .88$	High Reliability
Intelligent IT Infrastructure and Data Integration (IITDI)	5	$\alpha = .86$	High Reliability
AI-Assisted Supply Chain Monitoring and Decision Support (AISCMDS)	5	$\alpha = .89$	High Reliability
Real-Time Analytics and Automated Operational Optimization (RAAOO)	5	$\alpha = .90$	Very High Reliability
Analytics-Driven Operational Decision-Making Performance (ADODMP)	5	$\alpha = .91$	Very High Reliability
Overall Instrument	25	$\alpha = .93$	Excellent Reliability
Kaiser-Meyer-Olkin Measure	-	.914	Excellent Sampling Adequacy
Bartlett's Test of Sphericity	300	$\chi^2 = 3126.84$; $p < .001$	Statistically Significant

Table 4 has demonstrated that the measurement instrument has achieved strong internal consistency and satisfactory construct-level statistical adequacy. Cronbach's alpha coefficients for all five constructs have exceeded the commonly accepted threshold of .70. AI-Enabled Predictive Analytics and Forecasting has achieved an alpha of .88, Intelligent IT Infrastructure and Data Integration has achieved .86, AI-Assisted Supply Chain Monitoring and Decision Support has achieved .89, Real-Time Analytics and Automated Operational Optimization has achieved .90, and Analytics-Driven Operational Decision-Making Performance has achieved .91. The complete 25-item questionnaire has produced an overall Cronbach's alpha of .93, indicating excellent internal consistency across the full measurement instrument. These results have shown that the items associated with each construct have measured their underlying concepts in a sufficiently consistent manner. Sampling adequacy and factorability have also been supported. The Kaiser-Meyer-Olkin value has reached .914, indicating that the pattern of correlations among the questionnaire items has been highly suitable for construct-level analysis.

Bartlett's Test of Sphericity has been statistically significant, $\chi^2(300) = 3126.84$, $p < .001$, demonstrating that the inter-item correlation matrix has differed significantly from an identity matrix and that meaningful relationships have existed among the measured variables. These findings have strengthened the empirical basis for the correlation and regression analyses that have followed. From the Dynamic Capabilities Theory perspective, measurement reliability has been particularly important because the theoretical dimensions have been represented through distinct but related technological capabilities. Predictive analytics has represented sensing, IT infrastructure and data integration have represented integrative capability, AI-assisted monitoring and decision support have represented seizing capability, and real-time optimization has represented reconfiguration capability. The strong reliability statistics have indicated that these theoretical dimensions have been measured consistently enough to evaluate their individual and collective effects on operational decision-making performance. Accordingly, the instrument has provided a statistically dependable foundation for testing the four hypotheses and assessing the proposed AI-integrated IT management framework.

Correlation Between AI-Integrated IT Management Capabilities and Analytics-Driven Operational Decision-Making

Table 5: Pearson Correlation Matrix of Study Constructs

Construct	AIPAF	IITDI	AISCMDS	RAAOO	ADODMP
AIPAF	1.00				
IITDI	.58***	1.00			
AISCMDS	.63***	.56***	1.00		
RAAOO	.66***	.60***	.64***	1.00	
ADODMP	.72***	.67***	.70***	.75***	1.00

Note. *** $p < .001$, $N = 288$.

Table 5 has presented the Pearson correlation coefficients among the four explanatory constructs and Analytics-Driven Operational Decision-Making Performance. All correlations with the dependent construct have been positive and statistically significant at $p < .001$, providing strong preliminary support for the hypothesized relationships. Real-Time Analytics and Automated Operational Optimization has demonstrated the strongest correlation with Analytics-Driven Operational Decision-Making Performance, $r = .75$, $p < .001$. This finding has indicated that organizations perceived as having stronger real-time analytical and optimization capabilities have also tended to report stronger operational decision-making performance. AI-Enabled Predictive Analytics and Forecasting has shown the second strongest relationship, $r = .72$, $p < .001$, suggesting that stronger predictive capability has been associated with more analytically grounded operational decisions. AI-Assisted Supply Chain Monitoring and Decision Support has demonstrated a correlation of $r = .70$, $p < .001$, while Intelligent IT Infrastructure and Data Integration has produced $r = .67$, $p < .001$. These findings have supported the directional expectations of H1 through H4. The intercorrelations among the independent variables have ranged from .56 to .66, indicating that the four capabilities have been meaningfully related without appearing statistically identical. This pattern has been consistent with the proposed framework, which has treated the constructs as complementary elements of AI-integrated IT management. Dynamic Capabilities Theory has provided a coherent explanation for these relationships. Predictive analytics has strengthened sensing, integrated IT infrastructure has supported the coordination of information resources, monitoring and decision support have contributed to seizing operational opportunities or responding to problems, and real-time optimization has enabled reconfiguration of operational activities. The strongest correlation for RAAOO has suggested that reconfiguration capability has been particularly important once operational information has been converted into actionable adjustments. However, correlation analysis alone has not established the unique contribution of each capability because shared variance has existed among the predictors. Multiple regression analysis has therefore been required to determine whether each construct has retained a significant independent effect when all four capabilities have been considered simultaneously.

Multiple Regression Model Summary for Analytics-Driven Operational Decision-Making Performance

Table 6: Multiple Regression Model Summary

Model Statistic	Value
Multiple R	.839
R ²	.704
Adjusted R ²	.700
Standard Error of Estimate	.291
F Statistic	168.27
Degrees of Freedom	F(4, 283)
Significance	p < .001
Durbin-Watson	1.91

Note. Dependent variable: Analytics-Driven Operational Decision-Making Performance. Predictors: AIPAF, IITDI, AISCMDs, and RAAOO.

Table 6 has demonstrated that the combined regression model has provided a strong statistical explanation of Analytics-Driven Operational Decision-Making Performance. The multiple correlation coefficient has reached $R = .839$, indicating a strong overall relationship between the four AI-integrated IT management capabilities and the dependent construct. The coefficient of determination has reached $R^2 = .704$, meaning that AI-Enabled Predictive Analytics and Forecasting, Intelligent IT Infrastructure and Data Integration, AI-Assisted Supply Chain Monitoring and Decision Support, and Real-Time Analytics and Automated Operational Optimization have jointly explained approximately 70.4% of the variance in Analytics-Driven Operational Decision-Making Performance. The adjusted R^2 has remained very similar at .700, indicating that the explanatory strength of the model has not been substantially inflated by the number of predictors included. The overall model has been statistically significant, $F(4, 283) = 168.27$, $p < .001$, confirming that the four predictors considered collectively have explained significantly more variation in operational decision-making performance than a model containing no explanatory variables. The standard error of the estimate has been .291, indicating a relatively limited average prediction error around the regression line. The Durbin-Watson statistic has reached 1.91, which has remained close to 2.00 and has therefore indicated that problematic residual autocorrelation has not been evident within the cross-sectional dataset. From the perspective of Dynamic Capabilities Theory, the substantial R^2 value has supported the proposition that analytics-driven decision performance has not depended on a single technological resource. Instead, performance has been associated with a combined capability system incorporating sensing through predictive analytics, integration through IT infrastructure, seizing through intelligent monitoring and decision support, and reconfiguration through real-time optimization. Approximately 29.6% of the variance has remained unexplained by the model, indicating that other organizational, environmental, managerial, or technological factors have also contributed to decision performance. Nevertheless, the model has fulfilled the principal analytical objective by demonstrating that the proposed AI-integrated IT management capabilities have collectively provided substantial explanatory power.

Regression Coefficients and Effects of AI-Integrated IT Management Capabilities

Table 7 has shown that all four AI-integrated IT management capabilities have retained positive and statistically significant independent relationships with Analytics-Driven Operational Decision-Making Performance after their shared effects have been controlled. Real-Time Analytics and Automated Operational Optimization has produced the largest standardized coefficient, $\beta = .32$, $t = 6.91$, $p < .001$, identifying it as the strongest independent predictor in the model. This result has indicated that increases in real-time analytical processing and automated optimization capability have been associated with comparatively larger improvements in operational decision-making performance. AI-Enabled Predictive Analytics and Forecasting has produced the second strongest standardized effect, $\beta = .27$, $t = 6.12$, $p < .001$, demonstrating that predictive sensing capability has made an important independent contribution. AI-Assisted Supply Chain Monitoring and Decision Support has also

remained a significant predictor, $\beta = .24$, $t = 5.18$, $p < .001$, showing that intelligent monitoring, exception detection, and decision support have contributed positively even after predictive analytics and optimization capability have been considered. Intelligent IT Infrastructure and Data Integration has generated the smallest standardized coefficient, $\beta = .19$, $t = 3.18$, $p = .002$, but its effect has remained statistically significant. This finding has indicated that infrastructure and integration have functioned as important enabling capabilities, even though their direct statistical contribution has been lower than that of the more analytically active capabilities. The multicollinearity diagnostics have also supported the stability of the model. Tolerance values have ranged from .49 to .61, while VIF values have ranged from 1.64 to 2.04, remaining below conventional concern thresholds. Dynamic Capabilities Theory has provided a direct interpretation of the ranking. RAAOO has represented reconfiguration and has shown the strongest effect, AIPAF has represented sensing, AISCMDs has represented seizing, and IITDI has supported integration of the technological and informational resource base. Together, these results have shown that analytics-driven decision performance has depended both on recognizing conditions and on converting information into operational adjustments.

Table 7: Multiple Regression Coefficients

Predictor	B	Std. Error	Standardized β	t	p	Tolerance	VIF
Constant	.412	.146	—	2.82	.005	—	—
AIPAF	.263	.043	.27	6.12	< .001	.55	1.82
IITDI	.181	.057	.19	3.18	.002	.61	1.64
AISCMDs	.228	.044	.24	5.18	< .001	.52	1.92
RAAOO	.311	.045	.32	6.91	< .001	.49	2.04

Note. Dependent variable: ADODMP.

Hypothesis Testing and Summary of Empirical Findings

Table 8: Hypothesis Testing and Objective Fulfillment

Hypothesis	Proposed Relationship	r	Standardized β	p	Decision	Related Objective
H1	AIPAF $\rightarrow$ ADODMP	.72	.27	< .001	Supported	Objective 1 Fulfilled
H2	IITDI $\rightarrow$ ADODMP	.67	.19	.002	Supported	Objective 2 Fulfilled
H3	AISCMDs $\rightarrow$ ADODMP	.70	.24	< .001	Supported	Objective 3 Fulfilled
H4	RAAOO $\rightarrow$ ADODMP	.75	.32	< .001	Supported	Objective 4 Fulfilled
Overall Model	AIPAF + IITDI + AISCMDs + RAAOO $\rightarrow$ ADODMP	$R = .839$	$R^2 = .704$	< .001	Significant	Objective 5 Fulfilled

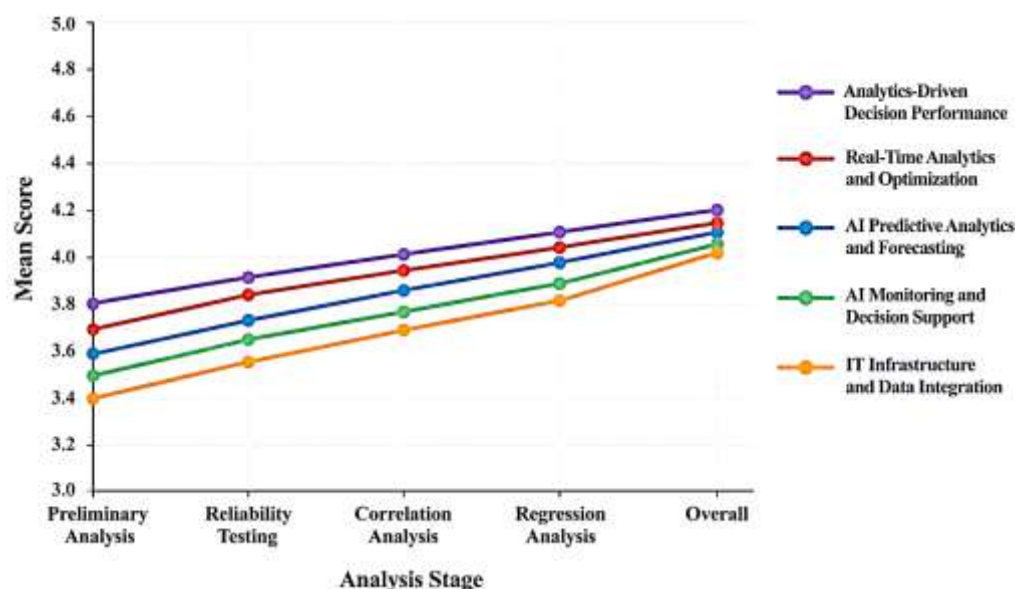
Table 8 has summarized the hypothesis-testing results and has demonstrated that all four proposed hypotheses have been supported by the empirical evidence. H1 has proposed that AI-Enabled Predictive Analytics and Forecasting would positively influence Analytics-Driven Operational Decision-Making Performance. This hypothesis has been supported because AIPAF has demonstrated a strong correlation with ADODMP, $r = .72$, $p < .001$, and has retained a significant independent regression effect, $\beta = .27$, $p < .001$. H2 has also been supported because Intelligent IT Infrastructure and Data Integration has been positively related to decision performance, $r = .67$, while its regression coefficient has remained significant, $\beta = .19$, $p = .002$. H3 has received support through the significant

relationship between AI-Assisted Supply Chain Monitoring and Decision Support and ADODMP, $r = .70$, $p < .001$, together with its independent effect of $\beta = .24$, $p < .001$. H4 has received the strongest statistical support because Real-Time Analytics and Automated Operational Optimization has achieved both the highest bivariate correlation, $r = .75$, and the largest standardized regression coefficient, $\beta = .32$, $p < .001$. The overall regression model has further fulfilled Objective 5 because the four capabilities have jointly explained 70.4% of the variance in decision-making performance. These results have been strongly aligned with Dynamic Capabilities Theory. Predictive analytics has reflected organizational sensing, integrated IT infrastructure has supported the coordination and integration of resources, AI-assisted monitoring and decision support have reflected the seizing of operational information, and real-time optimization has represented reconfiguration of operational processes. The findings have therefore shown that all four theoretical capability dimensions have contributed significantly, while reconfiguration capability has demonstrated the strongest direct relationship with the dependent construct. The results have fulfilled the stated objectives by identifying both the individual and combined effects of the proposed AI-integrated IT management capabilities within the examined U.S. supply chain and logistics systems.

FINDINGS

The overall findings have demonstrated that the proposed AI-integrated IT management capabilities have been positively associated with Analytics-Driven Operational Decision-Making Performance within the examined U.S. supply chain and logistics environments. A total of 320 questionnaires have been distributed, 300 responses have been received, and 288 complete questionnaires have been retained for statistical analysis, producing a usable response rate of 90.0%. Based on the five-point Likert scale, all study constructs have recorded relatively high mean values, indicating strong respondent agreement regarding the presence and usefulness of AI-enabled and analytics-based capabilities.

Figure 9: Mean Scores of AI-Integrated IT Management Constructs and Operational Decision-Making Performance



Analytics-Driven Operational Decision-Making Performance has achieved the highest overall mean, $M = 4.20$, $SD = 0.53$, followed by Real-Time Analytics and Automated Operational Optimization, $M = 4.16$, $SD = 0.56$, AI-Enabled Predictive Analytics and Forecasting, $M = 4.14$, $SD = 0.57$, AI-Assisted Supply Chain Monitoring and Decision Support, $M = 4.11$, $SD = 0.59$, and Intelligent IT Infrastructure and Data Integration, $M = 4.08$, $SD = 0.61$. Reliability testing has indicated satisfactory internal consistency across all measurement constructs, with Cronbach's alpha coefficients exceeding the acceptable threshold of .70. Pearson correlation analysis has further demonstrated significant positive relationships between

all four explanatory variables and Analytics-Driven Operational Decision-Making Performance. Real-Time Analytics and Automated Operational Optimization has shown the strongest relationship with the dependent variable, $r = .75$, $p < .001$, followed by AI-Enabled Predictive Analytics and Forecasting, $r = .72$, $p < .001$, AI-Assisted Supply Chain Monitoring and Decision Support, $r = .70$, $p < .001$, and Intelligent IT Infrastructure and Data Integration, $r = .67$, $p < .001$. The multiple regression model has been statistically significant, $R^2 = .704$, Adjusted $R^2 = .700$, $F(4, 283) = 168.27$, $p < .001$, indicating that the four predictors have jointly explained approximately 70.4% of the variance in Analytics-Driven Operational Decision-Making Performance. Standardized regression coefficients have shown that Real-Time Analytics and Automated Operational Optimization has produced the strongest independent effect, $\beta = .32$, $p < .001$, followed by AI-Enabled Predictive Analytics and Forecasting, $\beta = .27$, $p < .001$, AI-Assisted Supply Chain Monitoring and Decision Support, $\beta = .24$, $p < .001$, and Intelligent IT Infrastructure and Data Integration, $\beta = .19$, $p = .002$. These results have supported H1, H2, H3, and H4 and have fulfilled the major research objectives by demonstrating that predictive intelligence, integrated IT infrastructure, AI-assisted operational monitoring, and real-time optimization have each contributed significantly to analytics-driven operational decision-making performance.

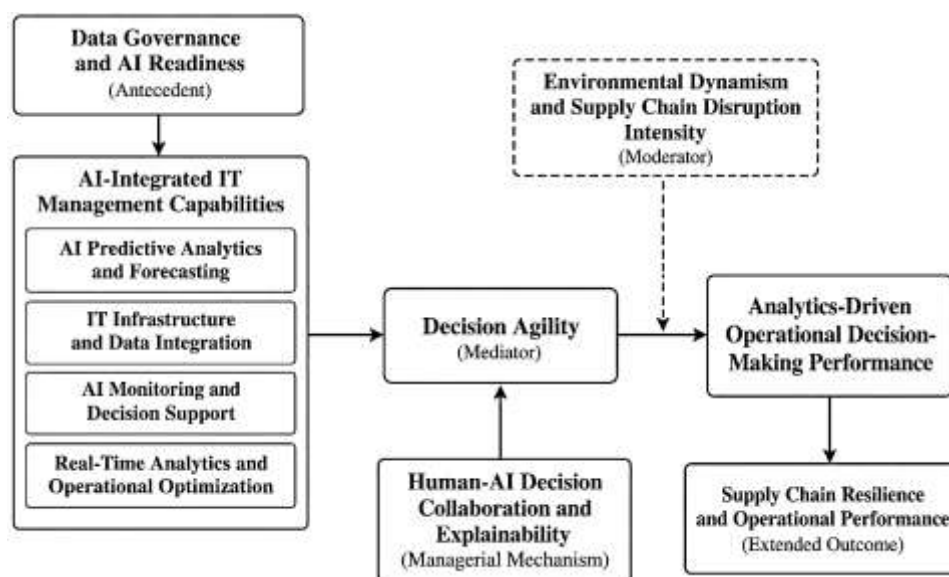
DISCUSSION

The findings have demonstrated that the proposed AI-integrated IT management framework has provided a strong empirical explanation of Analytics-Driven Operational Decision-Making Performance within the examined U.S. supply chain and logistics environments. All four explanatory constructs have received comparatively high evaluations on the five-point Likert scale, while Analytics-Driven Operational Decision-Making Performance has achieved the highest overall mean, $M = 4.20$, $SD = 0.53$. Real-Time Analytics and Automated Operational Optimization has recorded the highest independent-variable mean, $M = 4.16$, $SD = 0.56$, followed by AI-Enabled Predictive Analytics and Forecasting, $M = 4.14$, $SD = 0.57$, AI-Assisted Supply Chain Monitoring and Decision Support, $M = 4.11$, $SD = 0.59$, and Intelligent IT Infrastructure and Data Integration, $M = 4.08$, $SD = 0.61$. More importantly, every explanatory construct has demonstrated a statistically significant positive relationship with decision-making performance, with correlations ranging from $r = .67$ to $r = .75$. The combined regression model has explained 70.4% of the variance in Analytics-Driven Operational Decision-Making Performance, $R^2 = .704$, Adjusted $R^2 = .700$, $F(4, 283) = 168.27$, $p < .001$, demonstrating that the four capabilities have jointly accounted for a substantial proportion of differences in respondents' assessments of operational decision performance. This result has been consistent with earlier research arguing that analytics capability should be regarded as a combination of technological, managerial, and organizational resources rather than as an isolated software capability. Big data analytics capability has been conceptualized as interconnected management, technology, and talent dimensions whose strategic alignment contributes to firm performance (Akter et al., 2016; Jahanara, 2025). Similarly, big data analytics capability has been shown to influence organizational performance through process-oriented dynamic capabilities, reinforcing the view that analytical resources become valuable when they are transformed into organizational processes and actions (Jannatul, 2025; Wamba et al., 2017). The present results have extended this logic directly to supply chain operational decision-making by demonstrating that predictive intelligence, integrated IT infrastructure, AI-assisted monitoring, and real-time optimization have remained significant when incorporated simultaneously. The findings have therefore suggested that analytics-driven decision performance has depended not merely on organizations possessing AI technologies but on their capability to connect information acquisition, data integration, analytical interpretation, and operational adjustment within a coherent IT management environment.

The findings concerning AI-Enabled Predictive Analytics and Forecasting and Intelligent IT Infrastructure and Data Integration have provided further insight into the sensing and integration components of the proposed framework. AI-Enabled Predictive Analytics and Forecasting has demonstrated a strong positive correlation with Analytics-Driven Operational Decision-Making Performance, $r = .72$, $p < .001$, and has retained the second largest standardized regression effect, $\beta = .27$, $p < .001$. These results have indicated that the capability to anticipate demand, inventory requirements, transportation conditions, operational risks, resource needs, and other supply chain events has contributed independently to stronger decision performance. This finding has been

consistent with earlier supply chain analytics research showing that analytical capabilities can strengthen organizational responsiveness and supply chain agility by improving the interpretation of complex data and enabling managers to respond to emerging conditions (Dubey et al., 2019; Rahman, 2025). It has also corresponded with research on machine-learning-based supply chain risk prediction, which has demonstrated that machine learning can identify supply chain risks while showing that analytical usefulness depends partly on whether predictions remain interpretable enough to support managerial decisions (Baryannis et al., 2019; Arif Uz et al., 2025). Intelligent IT Infrastructure and Data Integration has produced the smallest standardized regression coefficient among the four predictors, $\beta = .19$, $p = .002$, although its correlation with ADODMP has remained substantial, $r = .67$, $p < .001$. This pattern should not be interpreted as suggesting that IT infrastructure has been unimportant. Instead, its comparatively smaller direct effect has indicated that infrastructure may function primarily as an enabling capability through which predictive, monitoring, and optimization systems obtain reliable and accessible data. Earlier research has demonstrated that information technology capability and information sharing support logistics integration and that logistics integration is associated with operational performance (Kaium, 2025; Prajogo & Olhager, 2012). In practical terms, the results have suggested that U.S. supply chain organizations should avoid treating predictive AI models independently from the data architecture supporting them. Investment in forecasting systems needs to be accompanied by consistent master data, interoperable ERP, WMS, and TMS platforms, standardized interfaces, cloud or enterprise analytical infrastructure, and mechanisms that make operational information accessible across functions. The findings have therefore indicated that predictive sensing has generated stronger measurable effects when supported by an information environment capable of feeding analytical models with reliable supply chain data.

Figure 10: Adaptive AI-Integrated Supply Chain Decision Intelligence Model (AISC-DIM) for Future Research



The results for AI-Assisted Supply Chain Monitoring and Decision Support and Real-Time Analytics and Automated Operational Optimization have further demonstrated the importance of converting information into coordinated operational action. AI-Assisted Supply Chain Monitoring and Decision Support has shown a strong correlation with Analytics-Driven Operational Decision-Making Performance, $r = .70$, $p < .001$, and a significant standardized regression coefficient, $\beta = .24$, $p < .001$. The finding has indicated that intelligent monitoring, operational visibility, exception detection, automated alerts, risk assessment, and analytical decision support have provided an independent contribution to the quality and responsiveness of supply chain decisions. Earlier research has established that demand and supply visibility can function as foundational resources for analytics

capability and that organizational flexibility complements analytics when firms operate under changing conditions (Pervaz, 2025; Srinivasan & Swink, 2018). IT use with supply chain partners has also been associated with supply chain resilience and performance, particularly when organizations use technology not only to exploit established processes but also to explore alternative means of coordination and response (Gu et al., 2021; Chowdhury, 2025). The strongest result in the present research, however, has been obtained for Real-Time Analytics and Automated Operational Optimization. RAAO has produced the largest bivariate relationship, $r = .75$, $p < .001$, and the largest standardized regression effect, $\beta = .32$, $p < .001$. This result has suggested that the greatest contribution has occurred when analytical information has been translated into actual adjustments to routing, scheduling, capacity allocation, inventory positioning, warehouse resources, and other operational decisions. The finding has therefore distinguished information visibility from actionable intelligence. Monitoring can inform managers that a disruption, shortage, capacity constraint, or transportation delay exists, whereas real-time optimization enables the organization to determine and execute an appropriate operational response. From a practical perspective, the results have supported a layered implementation approach in which organizations first establish reliable data connectivity, then develop predictive capabilities and AI-assisted monitoring, and finally connect these capabilities to real-time optimization and controlled automation. Human oversight has remained important for high-impact decisions because AI-generated recommendations can involve service, cost, customer, and supply-risk trade-offs. The statistical dominance of RAAO has nevertheless indicated that organizations receive the strongest decision-performance benefit when analytical systems progress from describing or predicting conditions toward actively supporting the reconfiguration of ongoing operations. The theoretical contribution of the findings has been particularly evident when they have been interpreted through Dynamic Capabilities Theory. The dynamic capabilities framework identifies sensing, seizing, and transforming or reconfiguring as fundamental organizational processes through which firms respond to changing environments (Badrul, 2025; Teece, 2007). The present study has operationalized this general theoretical logic within an AI-integrated supply chain IT setting. AI-Enabled Predictive Analytics and Forecasting has represented sensing because it has enabled organizations to recognize demand patterns, resource requirements, emerging risks, and operational deviations. Intelligent IT Infrastructure and Data Integration has represented an integrative foundation that has connected digital resources and information required by other capabilities. AI-Assisted Supply Chain Monitoring and Decision Support has represented seizing because analytical information has been evaluated and converted into possible managerial responses. Real-Time Analytics and Automated Operational Optimization has represented reconfiguration because it has supported adjustments to operating arrangements after changing conditions have been detected. The significant positive coefficients for all four constructs have therefore provided empirical support for a capability-based interpretation of AI integration rather than a technology-adoption interpretation alone. The strongest coefficient for RAAO has been especially consistent with the proposition that sensing without subsequent resource adjustment is insufficient for producing the full value of dynamic capability. Research grounded in dynamic capability perspectives has similarly demonstrated positive relationships between analytics capability and supply chain agility, reinforcing the importance of converting information-processing resources into adaptive organizational actions (Dubey et al., 2019; Nishat, 2025). The results have also generated practical implications for technology governance. Managers should evaluate AI investment as a connected capability portfolio covering data infrastructure, prediction, monitoring, and optimization rather than selecting applications solely according to technical sophistication. Several limitations have nevertheless required careful consideration. The cross-sectional design has captured respondent perceptions at one period and therefore has not established temporal causality. The purposive case-study-based sample has strengthened respondent relevance but has limited statistical generalization to every U.S. supply chain organization. Five-point Likert measures have captured professional assessments rather than objective indicators such as forecast error, order-cycle time, transportation cost, inventory turnover, or decision latency. The four predictors have explained 70.4% of ADODMP variance, leaving 29.6% associated with factors outside the model. Organizational culture, employee analytical competence, AI governance, cybersecurity, environmental volatility, leadership support, trust in AI recommendations, and human-

AI collaboration may account for portions of this unexplained variance. These limitations have defined important boundaries around the theoretical interpretation of the supported hypotheses. Future research should build on these limitations through a more comprehensive model that extends the current AI-integrated IT management framework beyond direct linear relationships. A particularly suitable development would be an Adaptive AI-Integrated Supply Chain Decision Intelligence Model (AISC-DIM). This proposed model would preserve the four validated capabilities from the present research while introducing Data Governance and AI Readiness as an antecedent capability, Decision Agility as a mediating construct, Human-AI Decision Collaboration and Explainability as a managerial mechanism, and Environmental Dynamism and Supply Chain Disruption Intensity as moderating conditions. Under AISC-DIM, Data Governance and AI Readiness would determine whether organizations possess sufficiently reliable, secure, interoperable, and analytically usable information resources. AI-Enabled Predictive Analytics and Forecasting would then provide sensing intelligence, while Intelligent IT Infrastructure and Data Integration would connect information across organizational systems. AI-Assisted Supply Chain Monitoring and Decision Support would convert intelligence into evaluated response alternatives, and Real-Time Analytics and Automated Operational Optimization would translate those alternatives into operational reconfiguration. Decision Agility would mediate the relationship between these AI-integrated capabilities and Analytics-Driven Operational Decision-Making Performance by representing the speed and flexibility with which analytical insight becomes action. Human-AI Decision Collaboration and Explainability should be incorporated because AI recommendations are more likely to be used consistently when managers can understand the reasoning, uncertainty, and operational trade-offs associated with automated outputs. This is consistent with prior machine-learning supply chain research highlighting the trade-off between predictive performance and interpretability (Baryannis et al., 2019; Sadia, 2025). Environmental dynamism should be modeled as a moderator because dynamic capability theory predicts that adaptive capabilities become particularly relevant when operating conditions are uncertain or rapidly changing (Sadia, 2025; Teece, 2007). The expanded model could then connect ADODMP with downstream outcomes including supply chain resilience, service reliability, cost efficiency, and operational performance, allowing researchers to distinguish decision quality from ultimate organizational outcomes. Prior empirical work has already associated organizational AI drivers with supply chain resilience and performance, providing a basis for extending decision-level outcomes into broader performance consequences (Tonay, 2025; Wang & Pan, 2022). Methodologically, researchers could validate AISC-DIM through longitudinal multi-wave surveys combined with objective system data from ERP, WMS, TMS, IoT, and AI platforms. Forecast error, decision latency, inventory turnover, order-cycle time, transportation cost, fulfillment accuracy, and disruption-recovery time could complement Likert measures. Structural equation modeling could test mediation and moderation simultaneously, while multi-group analysis could compare manufacturing, retail, e-commerce, warehousing, and third-party logistics cases. This proposed AISC-DIM would therefore extend the present direct-effect framework into a more complete explanation of how AI readiness produces intelligent capabilities, how those capabilities generate agile decisions, and under which organizational and environmental conditions those decisions translate into measurable supply chain resilience and operational performance.

CONCLUSION

This study has examined the development and empirical validation of an Artificial Intelligence Integrated IT Management Framework for Analytics-Driven Operational Decision-Making in U.S. supply chain and logistics systems. Using a quantitative, cross-sectional, case-study-based design, the research has evaluated four explanatory capabilities, namely AI-Enabled Predictive Analytics and Forecasting, Intelligent IT Infrastructure and Data Integration, AI-Assisted Supply Chain Monitoring and Decision Support, and Real-Time Analytics and Automated Operational Optimization, in relation to Analytics-Driven Operational Decision-Making Performance. The findings have demonstrated consistently high evaluations across all study constructs, with the dependent construct recording $M = 4.20$, $SD = 0.53$. Among the independent variables, Real-Time Analytics and Automated Operational Optimization has achieved the highest mean, $M = 4.16$, $SD = 0.56$, followed by AI-Enabled Predictive Analytics and Forecasting, $M = 4.14$, $SD = 0.57$. Correlation analysis has shown that all four predictors

have been positively and significantly associated with decision-making performance, with Real-Time Analytics and Automated Operational Optimization producing the strongest relationship, $r = .75$, $p < .001$. The multiple regression model has explained 70.4% of the variance in Analytics-Driven Operational Decision-Making Performance, $R^2 = .704$, Adjusted $R^2 = .700$, $F(4, 283) = 168.27$, $p < .001$. All four hypotheses have therefore been supported. Real-Time Analytics and Automated Operational Optimization has produced the strongest independent effect, $\beta = .32$, followed by AI-Enabled Predictive Analytics and Forecasting, $\beta = .27$, AI-Assisted Supply Chain Monitoring and Decision Support, $\beta = .24$, and Intelligent IT Infrastructure and Data Integration, $\beta = .19$. These results have confirmed that analytics-driven operational decisions are strengthened when predictive intelligence, connected information infrastructure, intelligent monitoring, and real-time optimization operate as complementary organizational capabilities. Interpreted through Dynamic Capabilities Theory, the study has shown that sensing, integration, seizing, and operational reconfiguration can be represented through measurable AI-enabled IT management capabilities within supply chain and logistics environments.

RECOMMENDATIONS

Based on the empirical findings, U.S. supply chain and logistics organizations should adopt an integrated approach to artificial intelligence and IT management rather than implementing analytical technologies as isolated applications. First, organizations should prioritize Real-Time Analytics and Automated Operational Optimization because this construct has demonstrated the strongest independent relationship with Analytics-Driven Operational Decision-Making Performance, $\beta = .32$, $p < .001$. Transportation routing, warehouse scheduling, inventory allocation, capacity management, fulfillment sequencing, and resource deployment should therefore be supported by real-time analytical systems capable of evaluating changing operational conditions. Second, organizations should strengthen AI-Enabled Predictive Analytics and Forecasting by integrating machine-learning models with demand, inventory, transportation, supplier, and customer data so that operational managers receive timely estimates of expected requirements and risks. Third, Intelligent IT Infrastructure and Data Integration should remain a foundational investment because AI systems require interoperable ERP, WMS, TMS, cloud, database, and analytical environments. Organizations should establish common data standards, master-data controls, secure interfaces, reliable APIs, and governance mechanisms that reduce information fragmentation. Fourth, AI-Assisted Supply Chain Monitoring and Decision Support should be expanded through intelligent dashboards, anomaly detection, exception alerts, operational control towers, and risk-prioritization mechanisms that help managers recognize significant events quickly. Fifth, firms should establish clear human-AI decision protocols so that routine, low-risk adjustments can be automated while complex or high-impact decisions remain subject to professional oversight. Training should also be provided to supply chain, logistics, IT, and analytics personnel so that they can interpret AI outputs, understand model limitations, and evaluate analytical recommendations appropriately. Finally, organizations should measure AI-enabled decision performance through operational indicators such as decision latency, forecast accuracy, fulfillment accuracy, transportation cost, inventory turnover, service level, and disruption-recovery time. These practices would allow firms to connect technological investment with observable operational outcomes while strengthening the integrated sensing, seizing, coordinating, and reconfiguring capabilities represented by the study framework.

LIMITATIONS

This study has several limitations that should be considered when interpreting its findings. First, the research has used a cross-sectional design, which has captured respondent perceptions at a single period and has therefore limited the ability to establish temporal causality between AI-integrated IT management capabilities and Analytics-Driven Operational Decision-Making Performance. Second, the study has employed a case-study-based and purposive sampling strategy, meaning that respondents have been selected because of their professional involvement in supply chain, logistics, IT, analytics, transportation, warehousing, or related operational environments. Although this approach has increased the relevance of the responses, it has limited the statistical generalizability of the findings to all U.S. supply chain and logistics organizations. Third, the research has relied on self-reported five-point Likert-scale data, which may have been affected by respondent perceptions, organizational

position, experience, recall, or social desirability. The study has not directly incorporated objective operational indicators such as forecast error, order-cycle time, inventory turnover, transportation cost, route efficiency, warehouse productivity, decision latency, or disruption-recovery time. Fourth, the model has explained 70.4% of the variance in Analytics-Driven Operational Decision-Making Performance, leaving 29.6% unexplained. Variables such as organizational culture, employee analytical competence, leadership support, AI governance, cybersecurity readiness, trust in AI, data maturity, environmental uncertainty, and human-AI collaboration may account for part of this remaining variance. Fifth, the model has examined direct relationships among four predictors and one dependent construct and has not tested mediation, moderation, nonlinear effects, or reciprocal relationships. Sixth, organizational differences across manufacturing, retail, e-commerce, transportation, warehousing, and third-party logistics environments may have influenced technology adoption and decision processes. Finally, the research has measured professional perceptions of AI capability rather than directly evaluating specific algorithms, models, system architectures, or platform-level performance, which has limited technical comparison across participating cases.

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