AI-Enabled Demand Forecasting, Technological Capability, and Supply Chain Performance: Empirical Evidence from the Global Logistics Sector

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***Abstract*—This study advances understanding of artificial intelligence (AI) integration within supply chain management, with a particular emphasis on AI-enabled demand forecasting. The research examines 1) the extent of adoption of AI-driven forecasting practices, 2) the role of technological and organizational readiness, captured through data infrastructure, workforce skills, and management support, as antecedents, and 3) the mediating effect of AI adoption on the relationship between readiness and supply chain performance. Grounded in the resource-based view and technology adoption theory, a conceptual model was developed and empirically validated using data from global logistics firms, with structural equation modeling applied as the primary analytical technique. The findings confirm that readiness factors significantly foster AI adoption, which in turn exerts both a direct effect on supply chain performance and a mediating effect linking readiness to performance. By focusing on the global logistics sector and empirically validating this mediating mechanism, the study provides novel insights into how firms can translate technological readiness into superior operational outcomes, offering theoretical contributions to AI assimilation literature and practical guidance for managers.**

Keywords*—*AI-enabled demand forecasting; technological capability; data infrastructure; workforce skills; management support; supply chain performance; artificial intelligence

I. Introduction

Over the past decade, the configuration of global supply chains has been subject to profound and unprecedented changes, reshaping their operational dynamics and strategic orientation. Driven by fluctuating market demands, geopolitical uncertainties, the rapid growth of e-commerce, and the increasing need for advanced data-driven insights, the economic environment remains in constant flux, prompting organizations to adapt swiftly and effectively to these evolving dynamics. In this context, forecasting based on AI-enabled intelligence has emerged as a critical determinant of success and a strategic lever for sustaining competitive advantage [1]. The central challenge is not to justify the benefits of AI in forecasting or to assess its limitations, but to define the prerequisites for its effective deployment and the crucial mechanisms that facilitate its adoption.

Scholars and industry practitioners have increasingly aligned around a growing momentum toward AI-based strategies, particularly with the advancement of machine learning and predictive analytics. As a robust application of contemporary technologies, AI-powered demand forecasting is gaining recognition as a leading method for managing supply chains with elevated efficiency and performance [2]. AI has thus evolved into a vital tool in the domain of supply chain management [3].

The interest in exploring this specific research area underscores the criticality of a core business function. Indeed, several academics [4] argue that despite AI's increasing relevance, the literature still lacks a comprehensive understanding of how companies can effectively shift from conventional techniques to AI-based forecasting models. While recent contributions have illuminated the drivers and consequences of AI integration on business outcomes [5], there remains an evident gap regarding how to successfully innovate under the paradigm of AI-driven forecasting. In addressing this challenge, the present study posits that understanding the value of AI in supply chain contexts requires not only an analysis of its precursors and its direct effects on firm performance but also an exploration of its mediating function in linking organizational preparedness to performance outcomes.

As part of corporate integration within an evolving knowledge-driven ecosystem, a firm's technological and organizational preparedness has frequently been acknowledged in scholarly works as a fundamental condition for successful digital transformation. Aligned with this view, the technology-organization-environment framework posits that in order to fully capitalize on emerging technologies, firms must cultivate internal competencies to enable the effective assimilation of such innovations [6]. Accordingly, examining supply chain effectiveness in the context of AI implementation through the lens of organizational readiness has become both a managerial imperative and a vibrant field of inquiry.

This article pursues three main objectives. First, it seeks to assess the extent of AI-enabled forecasting adoption based on technological and organizational preparedness. Second, it evaluates the direct influence of AI utilization on supply chain outcomes. Third, it investigates more intricate relationships by analyzing the mediating role of AI integration between organizational readiness and performance, as advocated in prior research [7]. Specifically, this study aims to capture the indirect effects of internal readiness on organizational outcomes via the intermediary of AI adoption. This emerging research stream, which integrates the resource-based view with

AI assimilation frameworks, is regarded as particularly relevant for conceptualizing and empirically verifying novel relationships that capture the multifaceted dimensions of the phenomenon. Accordingly, the contributions of this study are threefold: 1) it examines the global logistics sector, an important but under-investigated context for AI adoption; 2) it consolidates multiple readiness factors into a single integrative model; and 3) it empirically demonstrates the mediating role of AI adoption in translating readiness into superior supply chain performance.

To address these objectives, a conceptual model was developed and empirically assessed through the testing of multiple hypotheses. The remainder of the paper is structured as follows. Section II reviews the literature and formulates the research hypotheses. Section III describes the methodology, including data collection, measurement, and analytical strategy. Section IV presents the results, while Section V discusses theoretical and managerial implications. Section VI concludes with limitations and avenues for future research.

II. Literature Review and Research Hypotheses

During the last ten years, AI-enabled forecasting has become a focal point in supply chain management discourse. The model is founded on the assumption that firms can, and are encouraged to, employ sophisticated analytical techniques across both internal and external data sources to enhance the accuracy of their forecasts. From a data-centric organizational standpoint, the AI model encourages the integration of advanced technologies, including machine learning, predictive analytics, and generative adversarial networks (GANs) [8].

By AI-enabled demand forecasting, we aim the activities of leveraging advanced algorithms on large datasets, grouped according to three major technologies identified through an extensive literature review: predictive analytics using machine learning, deep learning models for time-series analysis, and advanced simulation tools such as generative AI. Consistent with prevailing research in the field, this study highlights these technologies by investigating a new research direction that has the potential to advance current knowledge [9]. Specifically, we examine the level of AI adoption by assessing its determinants, technological and organizational readiness, and their impact on firm performance. In doing so, two approaches have been advocated to better understand success in the modern supply chain: the technology adoption approach and the resource-based view. We specify three more specific objectives on which we rely to structure our discourse. First, we show the impact of readiness on the adoption of AI [10]. Then, we assess the effect of AI adoption on supply chain performance. Finally, we propose the articulation between readiness and performance through the mediation of AI practices.

A. The Impact of Technological and Organizational Capabilities on AI Adoption

According to existing research, there is a broad consensus that forecasting from an AI perspective would require the firm to possess certain resources and a state of readiness to ensure the better adoption of these complex practices and to take full advantage of them [11]. In resource-based theory, the primary object of research consists of building and regenerating competitive advantages. In this respect, a firm's internal resources and state of readiness dictate its ability to adapt to an ever-changing environment. For this research, we identify three readiness factors that are extensively supported in the literature as key drivers facilitating the adoption of new and complex technologies: quality, workforce skills and AI literacy, management support, strategic alignment and data infrastructure.

1) The impact of data infrastructure and quality on the degree of AI adoption: Academic discussions on AI implementation emphasize the necessity of a robust data infrastructure for organizations looking to leverage advanced analytics [12]. Data quality, accessibility, and integration constitute critical sources of competitive advantage and are essential for the effective application of AI principles. AI algorithms, particularly machine learning, are fundamentally dependent on large volumes of high-quality, structured data. Without a solid data foundation, the outputs of these models are unreliable, hindering adoption. Challenges such as data silos and poor data quality are consistently cited as major barriers to AI implementation [13]. Conversely, firms that have invested in data warehouses, data lakes, and robust ETL (Extract, Transform, Load) processes are better positioned to experiment with and deploy AI models successfully. Therefore, a mature data infrastructure would favor the strategic decision-making process and lead to the successful implementation of AI forecasting practices.

Accordingly, this study seeks to test the relationship between organizational data infrastructure and the extent of AI adoption, as stated in the following research hypothesis:

- H1a - A robust data infrastructure and high data quality foster the degree of adoption of AI-enabled demand forecasting practices.

2) The impact of workforce skills and AI literacy on the degree of AI adoption: A second key determinant of organizational readiness, consistently supported in the literature, is the firm’s human capital, particularly the AI literacy and competencies of its workforce. This concept is well established and closely relates to absorptive capacity [14], defined as the ability to identify, assimilate, and apply new knowledge. In AI research, considerable emphasis has been placed on the critical role of a skilled workforce for successful implementation [15]. Organizations aiming to adopt AI must not only acquire the technology but also have internal expertise to manage, interpret, and leverage its outputs. To date, most studies have identified the “skills gap” as a major barrier [16]. We therefore posit that a skilled workforce, comprising data scientists, analysts, and AI-savvy managers, empowers firms to effectively recognize and harness the value of AI applications. Furthermore, the ability to integrate the outputs of AI models into existing business processes is essential to take full advantage of their virtues. To empirically examine the linkage between this capability and AI adoption, we propose the second sub-hypothesis.

- H1b - Workforce skills and AI literacy foster the degree of adoption of AI-enabled demand forecasting practices.

3) The impact of management support and strategic alignment on the degree of AI adoption: Management support and strategic alignment refer to the firm's ability to provide resources for AI initiatives. In a context of technological change, this support is a central element for firms seeking to innovate. To better succeed in an AI adoption approach, companies must show commitment from leadership. The literature highlights that a key challenge for managers during AI implementation is securing sufficient budget and aligning the initiative with broader business objectives [15]. Strong executive sponsorship can significantly enhance the extent of AI adoption and ensure sustained investment by mitigating concerns over resource reallocation. Moreover, the presence of a clear strategic vision for AI can be marked by its integration into the company's long-term plan. This strategic alignment ensures that AI projects are not isolated experiments but are tied to core business objectives, such as cost reduction or market share growth. This vision seems to be an important factor in the performance of an AI strategy by enabling the company to properly value its investments and show stakeholders the importance of these new capabilities. Despite growing interest, empirical research on the direct relationship between management support and the extent of AI adoption remains limited. To address this gap, we propose to empirically examine this relationship through the formulation of the third sub-hypothesis:

- H1c - Management support and strategic alignment foster the degree of adoption of AI-enabled demand forecasting practices.

B. AI Adoption and Supply Chain Performance

In supply chain management, numerous studies highlight the critical role of AI, arguing that different AI techniques can markedly boost organizational performance. This relationship is supported by three main factors. The rationale underpinning this affirmative correlation is predicated upon three principal factors. Primarily, enterprises integrating AI in their forecasting processes benefit from a significant increase in accuracy due to the ability of algorithms to analyze vast and complex datasets [17]. This improved accuracy directly reduces inventory holding costs and the risk of stockouts. Secondly, the literature on AI in supply chains emphasizes automation and efficiency. Engaging AI for forecasting automates a complex and time-consuming task, freeing up human capital for more strategic activities [18]. Consequently, this leads to a reduction in costs associated with manual forecasting. As Sajja et al. (2025) argue, in today's highly competitive and rapidly evolving environment, companies are increasingly adopting AI-driven approaches to mitigate cost and risk challenges. Ultimately, by leveraging AI-enabled forecasting, firms can improve their service levels and overall operational performance. These practices enable the supply chain to be more responsive and consequently improve customer satisfaction with better product availability [19].

However, in reviewing the literature, we found that large-scale empirical studies remained limited until recently. Since the early 2020s, studies have begun to robustly examine the effect of AI on the performance of supply chains. Hasan et al. (2024) demonstrated that AI applications are positively associated with improvements in operational efficiency and innovation performance. Parida et al. (2012), in a parallel context, examined the impact of inbound openness on performance, reporting positive effects. More recently, studies by Singh (2025) and Boualam et al. (2025) concluded that AI adoption promotes internal efficiency and consequently gives the company a competitive advantage and superior performance. The results of their empirical examinations indicated that AI-driven intelligence has a strong effect on collaboration and firm performance [20-21].

Based on these theoretical and empirical findings, we aim to examine the positive relationship between the extent of AI practice adoption and supply chain performance. Consequently, we propose the following research hypothesis:

- H2: The degree of adoption of AI-enabled demand forecasting practices improves supply chain performance.

C. The Role of AI Adoption as a Mediator Between Readiness and Performance

Existing studies consistently emphasize the critical role of a company's preparedness in establishing a competitive edge. This preparedness is regarded as a pathway for businesses to develop and enhance new abilities, enabling them to make effective use of their resources. Numerous researchers have leveraged this idea to illustrate its influence on the pursuit of innovative initiatives and, ultimately, on overall business success.

Consequently, in environments marked by scarce resources and fluctuating markets, organizations depend on their technical and operational preparedness to prioritize the discovery and application of cutting-edge, AI-supported strategic technologies. Utilizing their data frameworks [6], staff expertise [11], and executive endorsement, leaders must promote the smooth integration of these advancements into internal planning systems through AI-driven demand prediction techniques, which are broadly acknowledged as crucial drivers of performance.

Building on the analysis presented, this study perceives supply chain effectiveness as the product of efforts to unify resources and expertise. As a result, companies may improve their outcomes more efficiently by capitalizing on their preparedness, which empowers them to adopt emerging technologies, recognize market possibilities, and harness new insights. Nevertheless, there remains a scarcity of hands-on research exploring the link between preparedness and performance within an AI framework. This gap makes it compelling to explore how AI adoption serves as a bridge between these preparedness components and organizational success. Therefore, the following hypotheses regarding mediating relationships are proposed:

- H3a: The degree of AI adoption mediates the relationship between data infrastructure and firm performance.
- H3b: The degree of AI adoption mediates the relationship between workforce skills and firm performance.
- H3c: The degree of AI adoption mediates the relationship between management support and firm performance.

III. Methodology

In light of the preceding developments, this research seeks to assess the level of adoption of AI-enabled demand forecasting practices as shaped by technological and organizational readiness factors. Additionally, it evaluates the subsequent impact of this adoption on supply chain performance. The conceptual model depicted in Fig. 1 articulates the underlying research problem and provides the basis for empirical validation.

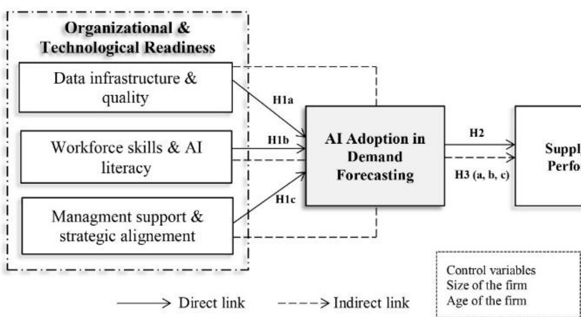

Fig. 1. Conceptual framework illustrating AI adoption's mediating role between readiness and supply chain performance.

A. Model Specification

To fulfill the research objectives, this study adopts a quantitative approach to empirically evaluate the proposed hypotheses. Data were gathered through a field survey administered to firms within the global logistics industry. The following sections elaborate on the sampling strategy, data collection process, and the measurement of key variables.

The following regression equations describe the direct effects model used to test hypotheses H1a to H2:

$$AI\_ADOPT = \beta_0 + \beta_1(DATA\_INFRA) + \beta_2(SKILLS) + \beta_3(SUPPORT) + \beta_4(SIZE) + \beta_5(AGE) + \varepsilon_1 \quad (1)$$

$$PERF = \gamma_0 + \gamma_1(AI\_ADOPT) + \gamma_2(SIZE) + \gamma_3(AGE) + \varepsilon_2 \quad (2)$$

Where:

- AI_ADOPT is the degree of AI Adoption.
- PERF is the Supply Chain Performance.
- DATA_INFRA, SKILLS, and SUPPORT are the organizational readiness factors.
- SIZE and AGE are control variables.
- β_0 and γ_0 are the intercepts.
- $\beta_1...\beta_5$ and $\gamma_1...\gamma_3$ are the regression coefficients to be calculated.
- ε_1 and ε_2 are the error terms.

B. Data Collection Procedure and Sample Design

In this empirical investigation, data were collected using a structured questionnaire, selected for its effectiveness in capturing standardized responses across a large sample. Particular attention was given to the clarity and precision of the questionnaire items to ensure unambiguous interpretation by respondents.

The sampling process was primarily based on a global directory of logistics and supply chain management firms, supplemented by purposive outreach to industry professionals through platforms such as LinkedIn. Following a non-probabilistic convenience sampling approach, and in alignment with practices commonly adopted in logistics research, a total of 235 valid responses were obtained. Data were collected through multiple channels, electronic distribution, postal mailings, telephone interviews, and in-person administration, to enhance participation. This multi-modal strategy resulted in a response rate of approximately 41%, which is consistent with empirical studies in the field.

C. Measures of the Variables

Ensuring construct validity and reliability, the variables were defined through a comprehensive literature review and measured using multi-item instruments on a 5-point Likert scale.

1) Technological and organizational readiness: This was operationalized through three distinct constructs:

a) Data Infrastructure and Quality (DATA_INFRA): We selected six items based on the literature concerning data readiness for AI. These items assessed: the accessibility of data across the organization, the quality and accuracy of historical data, the integration of data from various sources (sales, marketing, external factors), data security protocols, the scalability of data storage, and the availability of real-time data streams.

b) Workforce Skills and AI Literacy (SKILLS): We refer to the operationalization of absorptive capacity [19] adapted to an AI context. Four dimensions were chosen: the capacity to attract and retain talent with data science skills (acquisition); the ability of staff to understand and interpret AI model outputs (assimilation); the capacity to integrate AI insights into daily operational workflows (transformation); and the ability to leverage AI for commercial and strategic purposes (exploitation).

c) Management Support and Strategic Alignment (SUPPORT): We selected three items reflecting leadership commitment: the capacity of management to champion and fund AI projects; the existence of a clear, strategic roadmap for AI integration; and the alignment of AI initiatives with core business objectives (cost reduction, improving customer satisfaction). In the questionnaire, firms were asked to specify the degree of their capacity for each item using a Likert scale from 1 "very limited capacity" to 5 "very extensive capacity".

- Degree of AI Adoption (AI_ADOPT): Our model presents this as a mediating variable. For operationalization, we selected ten items based on common AI applications in forecasting, drawing from recent work [16]: Three items associated with the *use of external data sources* for forecasting (market trends, economic indicators, weather data); four items associated with *specific AI techniques* (use of machine learning models, use of deep learning for time-series, use of predictive analytics for what-if scenarios, use of AI for real-time demand sensing); and three items associated with the *integration of AI outputs* (use of AI for automated inventory replenishment, use of AI to inform logistics planning, and use of AI to generate reports for management. In the questionnaire, companies were asked to indicate both their level of use and the perceived importance of these various applications. Each item was measured on a Likert scale ranging from 1 ("not at all important") to 5 ("extremely important").
- Supply Chain Performance (PERF): This dependent variable was measured using an indicator reflecting the degree of satisfaction with nine elements measuring overall supply chain performance. These elements were chosen based on pioneering work [4] and refer respectively to: forecast accuracy improvement; inventory turnover rates; reduction in stockout incidents; On-Time In-Full delivery rates; reduction in logistics and holding costs; lead time reduction; overall operational efficiency; customer satisfaction levels; and overall profitability of the supply chain. In the questionnaire, the degree of satisfaction with each item is specified according to the perception of company managers using a scale from 1 "very unsatisfactory" to 5 "very satisfactory".
- Control Variables: We also introduce in our model two control variables: the size (number of employees) and age of the firm.

D. Data Analysis Strategy

To analyze the collected data and validate the proposed research model, a three-stage statistical procedure was implemented. First, the unidimensionality of the measurement scales was assessed using Principal Component Analysis (PCA) with Varimax rotation, to confirm that each construct was adequately captured by a coherent set of indicators. This step was essential for ensuring the structural clarity of the latent variables. Second, reliability analyses were performed through the computation of Cronbach's alpha coefficients, verifying the internal consistency of each multi-item scale. These preliminary analyses were conducted using SPSS software. In the third phase, the hypotheses concerning the structural relationships among the variables were tested through Structural Equation Modeling (SEM), using the AMOS software package and the maximum likelihood estimation (MLE) method. To assess the overall model fit, we adopted the classification of fit indices proposed by Roussel et al. (2002), which includes absolute fit indices (χ^2/df, RMSEA), incremental fit indices (CFI, TLI), and parsimony fit indices (PNFI). Once model adequacy was established, the structural paths were assessed based on three main indicators: 1) the standardized regression weights, which indicate the relative strength of the relationships; 2) the critical ratio (CR) values, which test the statistical significance of each path; and 3) the sign of the coefficients, to confirm the expected directionality of the effects. Finally, to evaluate the mediating role of AI adoption in the relationship between organizational readiness and supply chain performance, we employed the procedure outlined by Baron and Kenny (1986), which enabled us to determine whether the mediation effect was statistically significant.

IV. Results

A. Reliability and Validity Analysis

To evaluate the unidimensionality and reliability of the measurement constructs, Table I presents the results of the PCA and internal consistency analysis. Each construct yielded a single dominant factor with a high proportion of total variance explained, ranging from 80.004% (AI Adoption) to 91.580% (Workforce Skills), confirming the unidimensionality of the measurement scales. The KMO values for all constructs exceed 0.80, with highly significant Bartlett's tests (p=0.000), indicating the suitability of the data for factor analysis. No items were removed during the analysis. Additionally, the reliability of the scales is supported by strong Cronbach's alpha coefficients, ranging from 0.879 (AI Adoption) to 0.937 (Data Infrastructure), demonstrating excellent internal consistency across all constructs.

TABLE I. Principal Component Analysis and Reliability

Variables Analysed	Number of items	Extracted Factors	KMO Indice	Total variance explained	Cronbach's Alpha
Data Infrastructure	6	DATA_INFRA	0.923 (0.000)*	84.110	0.937
Workforce Skills	4	SKILLS	0.875 (0.000) *	91.580	0.899
Management Support	3	SUPPORT	0.811 (0.000) *	82.002	0.905
AI Adoption	10	AI_ADOPT	0.828 (0.000) *	80.004	0.879
Supply Chain Performance	9	PERF	0.838 (0.000) *	81.002	0.892

* Bartlett Sphericity Test (Sig)

The confirmation of unidimensionality and the validation of the measurement scales provided a solid foundation for testing the proposed conceptual model. The outcomes of the hypothesis tests are detailed in the following section.

B. Verification and Validation of the Hypotheses

The results of testing our conceptual model represented in Fig. 2 and Tables II and III.

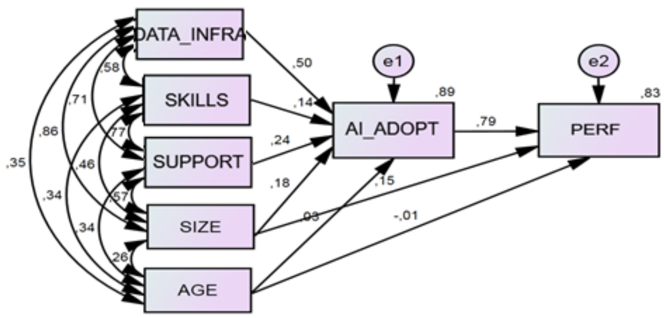

Fig. 2. Structural model – direct effects analysis.

To evaluate the direct relationships among variables in the research model (Fig. 2), the results summarized in Table II demonstrate a satisfactory model fit, providing robust empirical support for the hypothesized structural relationships.

TABLE II. FIT INDICES FOR THE STRUCTURAL MODEL ASSESSING DIRECT EFFECTS

Absolute indices			Incremental indices			Parsimony indices		
GFI	*AGFI*	*RMSEA*	*NFI*	*CFI*	*TLI*	*DMIN/DF*	*AIC*	*CAIC*
0.995	0.961	0.017	0.998	1.000	0.999	3.216/3 = 1.072 *P*=0.351	55.021	165.732

TABLE III. RESULTS OF DIRECT EFFECTS ANALYSIS USING STRUCTURAL EQUATION MODELING

Structural relations	Structural parameters		
	Direct effects	*CR*	*Sig. P*
DATA_INFRA → AI_ADOPT	0.496	9.704	0.000
SKILLS → AI_ADOPT	0.145	4.201	0.000
SUPPORT → AI_ADOPT	0.236	5.972	0.000
SIZE → AI_ADOPT	0.174	4.065	0.000
AGE → AI_ADOPT	0.030	1.212	0.226
AI_ADOPT → PERF	0.789	16.400	0.000
SIZE → PERF	0.152	3.285	0.001
AGE → PERF	-0.006	-0.207	0.836

As presented in Table III, the SEM results provide empirical evidence on the direct associations between organizational enablers and the adoption of AI within firms. Among the examined factors, data infrastructure emerges as the most influential determinant ($\beta = 0.496$; $p = 0.000$), highlighting the pivotal role of digital capabilities in facilitating AI integration. In parallel, both employee skillsets ($\beta = 0.145$; $p = 0.000$) and executive support ($\beta = 0.236$; $p = 0.000$) exhibit significant and positive effects on AI adoption, though their relative impacts are less substantial compared to that of data infrastructure. These findings provide empirical support for hypotheses H1a, H1b, and H1c, indicating that these internal organizational factors are critical drivers of AI adoption.

Regarding the control variables, the analysis reveals that firm size exerts a statistically significant positive effect on AI adoption ($\beta = 0.174$; CR = 4.065; $p = 0.000$), indicating that larger firms may possess greater resources and capabilities to invest in advanced technologies. In contrast, firm age does not appear to have a significant influence ($\beta = 0.030$; CR = 1.212; $p = 0.226$), suggesting that organizational maturity alone is insufficient to drive AI implementation.

Furthermore, the model validates a strong and significant relationship between AI adoption and firm performance ($\beta = 0.789$; CR = 16.400; $p = 0.001$), thereby supporting hypothesis H2. This result highlights the strategic relevance of AI integration as a performance-enhancing factor in contemporary organizational settings. The positive and significant effect of firm size on performance ($\beta = 0.152$; CR = 3.285; $p = 0.001$) reinforces this trend, whereas firm age remains non-significant ($\beta = -0.006$; CR = –0.207; $p = 0.836$), indicating that innovation outcomes are more likely to be associated with firm scalability rather than longevity.

To examine the presence of indirect effects, a second structural model was estimated following the mediation analysis framework proposed by Baron and Kenny (1986). This model was designed to evaluate both the direct and indirect pathways connecting dynamic organizational capabilities to innovation performance, incorporating the degree of openness to inbound open innovation practices as a mediating variable. The conceptual framework of this mediation model is depicted in Fig. 3.

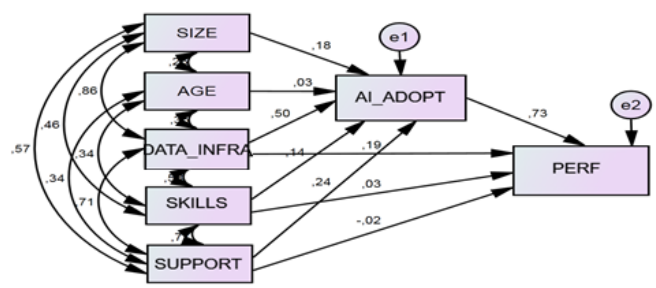

Fig. 3. Structural model assessing the mediating role of AI adoption.

Table IV presents the model fit indices associated with the mediation analysis, which confirm the adequacy of the model and support its suitability for representing the data structure.

TABLE IV. CONCEPTUAL FRAMEWORK FOR THE MEDIATING ROLE OF AI ADOPTION

Absolute indices			incremental indices			Parsimony indices		
GFI	*AGFI*	*RMSEA*	*NFI*	*CFI*	*TLI*	*DMIN/DF*	*AIC*	*CAIC*
0.994	0.910	0.084	0.997	0.998	0.979	5.191/2 = 2.595 P=0.075	57.192	172.355

Table V summarizes the direct and indirect effects derived from the mediation model, which examines how organizational enablers influence firm performance through the intermediary role of AI adoption. The preceding analyses confirmed that data infrastructure, employee skills, and top management support have significant positive effects on the adoption of AI technologies. In parallel, the findings revealed a robust and statistically significant association between AI adoption and organizational performance, thereby supporting Hypothesis H2.

To explore the mediating dynamics more comprehensively, a second model was estimated using AMOS, allowing for simultaneous evaluation of both direct and indirect paths. In this expanded framework, AI adoption remains a robust predictor of performance ($\beta = 0.726$; CR = 9.092; $p = 0.000$), confirming its central role as a mediating construct in the relationship between internal organizational factors and performance outcomes.

The estimates shown in Table V indicate that data infrastructure continues to exhibit a direct and statistically significant influence on performance ($\beta = 0.195$; $p = 0.003$), in addition to a notable indirect effect ($\beta = 0.360$) via AI adoption. This pattern is consistent with partial mediation, wherein the effect of data infrastructure is only partially channeled through the mediator. Conversely, the direct effects of skills ($\beta = 0.027$; $p = 0.547$) and support ($\beta = –0.016$; $p = 0.757$) on performance are no longer statistically significant when accounting for the mediating role of AI adoption. These findings point to full mediation, suggesting that the influence of these two factors on performance operates entirely through the adoption of AI technologies.

TABLE V. DIRECT AND INDIRECT RELATIONSHIPS BY STRUCTURAL EQUATION MODELING

Structural relations	Structural Parameters			
	direct Effects (β)	*CR*	*Sig. P*	*indirect Effects (β)*
DATA_INFRA → PERF	0.195	2.967	0.003	0.360
SKILLS → PERF	0.27	0.602	0.547	0.105
SUPPORT → PERF	-0.016	-0.310	0.757	0.171
AI_ADOPT → PERF	**0.726**	9.092	0.000	-

The results show that in the presence of the mediator (AI_ADOPT), the direct effects of Workforce Skills and Management Support on Supply Chain Performance become insignificant ($p=0.547$ and $p=0.757$, respectively). This indicates perfect mediation. However, the direct relationship between Data Infrastructure and Supply Chain Performance remains significant ($\beta=0.195$, $p=0.003$), indicating partial mediation.

We can therefore confirm hypothesis H3a through the presence of partial mediation and hypotheses H3b and H3c through perfect mediation. This confirms that organizational readiness factors, Data Infrastructure, Workforce Skills, and Management Support, have a significant relationship with supply chain performance indirectly through the degree of adoption of AI-enabled demand forecasting.

V. DISCUSSION

This study sought to examine the factors influencing supply chain performance by integrating the Resource-Based View with the Technology Adoption Theory. By empirically examining both direct and mediated relationships, the analysis contributes to a deeper understanding of how organizational readiness factors, Such as data infrastructure, workforce skills, and top management support, influence AI adoption and, in turn, supply chain performance. In addition to validating direct linkages, the results deliver compelling evidence confirming AI adoption as a significant mediator in the proposed relationship framework.

Specifically, the statistical analysis reveals that technological and organizational readiness have a positive impact on the level of AI adoption, which subsequently exerts a strong and significant influence on supply chain performance. These outcomes are consistent with prior theoretical and empirical research [9-11]. For example, global logistics firms equipped with mature data infrastructures tend to adopt AI-enabled forecasting tools more proactively. The observation of partial mediation in the case of data infrastructure suggests a dual mechanism: while a solid technological foundation facilitates AI implementation, it may also directly enhance performance outcomes, potentially through improved reporting systems, real-time analytics, or other non-AI digital capabilities.

The results also indicate that skills and managerial support are fully mediated by AI adoption in their relationship with performance. This finding implies that the presence of skilled personnel or supportive leadership, while necessary, is not sufficient to improve supply chain outcomes in isolation. Their true value is realized when these capabilities are mobilized to support and implement AI technologies effectively. In this sense, skills and support function as enablers of technological transformation, with AI adoption serving as the operative mechanism that translates readiness into performance gains.

By empirically validating the proposed conceptual model, this study advances the existing literature on AI deployment within supply chain management. The analytical approach, focusing on both direct and mediating effects, adds methodological and theoretical value, offering a nuanced view of how internal organizational capabilities interact with emerging digital technologies. This multi-layered perspective on causality is relatively novel in supply chain research, where mediation models remain underexplored.

From a managerial standpoint, the findings underscore the importance of building AI readiness across multiple dimensions. Executives should recognize that the mere acquisition of AI tools does not guarantee performance improvements. Instead, value creation from AI depends on foundational investments in data systems, workforce development, and sustained leadership commitment. These factors collectively determine whether AI adoption efforts yield tangible returns in operational performance.

VI. Conclusion

This study demonstrates that organizational readiness, captured through data infrastructure, workforce skills, and top management support, exerts its influence on supply chain performance primarily through the adoption of AI-enabled demand forecasting. While data infrastructure shows both direct and mediated effects, skills and managerial support improve performance only indirectly via AI adoption.

These findings highlight the pivotal role of AI adoption as the mechanism translating organizational capabilities into operational performance gains. For practitioners, the results stress the need for holistic readiness, encompassing not only technological investments but also human capital and leadership commitment.

Despite its contributions, this study is subject to certain limitations. First, the exclusive focus on demand forecasting as the examined AI application may restrict the breadth and generalizability of the findings across other supply chain functions. To enhance external validity, future research should investigate additional AI-driven applications, such as inventory optimization, predictive maintenance, and warehouse automation, that may reveal complementary or divergent patterns of mediation. Moreover, the current model primarily emphasizes internal readiness factors, overlooking external contingencies. Future studies would benefit from incorporating environmental dimensions, including market competition, industry maturity, and regulatory frameworks, to provide a more holistic understanding of AI adoption and its performance implications.

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