SPECTRUM OF ENGINEERING SCIENCES
ISSN (E) 3007-3138 (P) 3007-312X VOLUME 4, ISSUE 3, 2026

# FROM AI-ENABLED ORGANIZATIONAL CAPITAL TO SUPPLY CHAIN PERFORMANCE: THE MEDIATING ROLE OF SUPPLY CHAIN ADAPTABILITY IN EMERGING ECONOMY MANUFACTURING FIRMS

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**DOI:** https://doi.org/10.5281/zenodo.21255850

**Keywords**
*Artificial intelligence, AI-enabled organizational capital, supply chain adaptability, supply chain performance, technology uncertainty, Dynamic Capability View, PLS-SEM, Pakistan*

**Article History**

*Received: 21 January 2026*
*Accepted: 16 March 2026*
*Published: 31 March 2026*


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## Abstract
*The increasing integration of artificial intelligence in supply chain management is reshaping how firms develop organizational capabilities to respond to dynamic and uncertain business environments. Drawing on the Dynamic Capability View, this study examines the effect of AI-enabled organizational capital on supply chain adaptability and supply chain performance, with technology uncertainty considered as a moderating condition. Using survey data collected from manufacturing firms and analyzed through partial least squares structural equation modeling, the findings show that AI-enabled organizational capital has a significant positive effect on supply chain adaptability. Supply chain adaptability also has a strong and significant positive effect on supply chain performance. However, the direct effect of AI-enabled organizational capital on supply chain performance is not significant. These results indicate that AI-enabled organizational capital improves supply chain performance primarily through the development of supply chain adaptability rather than through a direct performance effect. The mediation analysis further confirms that supply chain adaptability significantly mediates the relationship between AI-enabled organizational capital and supply chain performance. In contrast, the moderating effect of technology uncertainty on the relationship between AI-enabled organizational capital and supply chain performance is not significant. Firm size also does not show a significant effect on supply chain performance.This study contributes to the supply chain management literature by demonstrating that AI-enabled organizational capital functions as an important organizational resource for strengthening supply chain adaptability. It also extends the Dynamic Capability View by showing that adaptability is a critical mechanism through which AI-related organizational capabilities are translated into improved supply chain performance. From a managerial perspective, the findings suggest that firms should not expect AI-enabled organizational capital alone to directly enhance performance. Instead, managers should focus on using AI-related resources to build adaptive supply chain processes, flexible decision-making, and responsive operational capabilities.*

## 1.0 INTRODUCTION

Manufacturing firms in Pakistan are operating in an increasingly dynamic and uncertain business environment marked by demand volatility, supply disruptions, and rapid technological change. These challenges have intensified the need for firms to develop capabilities that enable timely and effective responses to environmental shifts. In recent years, the growing diffusion of advanced digital technologies has reshaped how organizations manage information, coordinate activities, and make strategic decisions across supply chains.

Among these developments, the integration of Machine Learning, Deep Learning, and Generative Artificial Intelligence has attracted considerable attention. These technologies allow firms to analyze large volumes of structured and unstructured data, improve forecasting accuracy, and support real-time decision-making. Recent studies indicate that such intelligent systems are increasingly transforming supply chain processes, enhancing coordination, and improving performance outcomes across industries (Culot et al., 2024). In the context of developing economies, emerging evidence further suggests that the adoption of AI-driven systems contributes positively to organizational efficiency and overall performance (Sheikh, 2025).

While the technological potential of artificial intelligence is widely acknowledged, its role as an embedded organizational resource remains insufficiently examined. From the perspective of Intellectual Capital, these technologies can be viewed as part of organizational (structural) capital when they are institutionalized within systems, routines, and databases. In this sense, machine learning, deep learning, and generative AI capabilities collectively represent a form of AI-enabled organizational capital that enhances a firm's ability to process information and generate actionable insights.

In supply chain settings, firms are increasingly required to move beyond efficiency-driven models toward more flexible and adaptive configurations. This has led to growing interest in Supply Chain Adaptability, which reflects a firm's ability to reconfigure internal operations, supplier relationships, and customer interactions in response to environmental changes. Advanced analytical technologies have been shown to strengthen such adaptive capabilities by enabling predictive analytics, real-time monitoring, and scenario-based planning (Jackson, 2024). In particular, generative AI has been recognized for its potential to support dynamic planning and innovative problem-solving in complex supply chain environments (Necula et al., 2025).

Drawing on the Dynamic Capability View, this study argues that AI-enabled organizational capital serves as a foundational resource that enhances a firm's adaptive capacity, which subsequently leads to improved supply chain performance. The dynamic capability perspective emphasizes that firms achieve superior performance not merely through resource possession, but through their ability to reconfigure and deploy those resources in response to changing conditions. In this regard, supply chain adaptability acts as a key mechanism linking AI-based organizational capital to performance outcomes.

Furthermore, the effectiveness of adaptive capabilities may depend on the level of uncertainty in the technological environment. In highly uncertain contexts, firms are required to process greater volumes of information and respond more rapidly to technological changes, thereby increasing the importance of both AI-enabled systems and adaptive capabilities. However, empirical evidence on how technological uncertainty influences these relationships remains limited, particularly in the context of Pakistan's manufacturing sector.

Against this backdrop, the present study examines the effect of AI-enabled organizational capital, conceptualized as a higher-order construct comprising machine learning, deep learning, and generative AI capabilities, on supply chain performance through the mediating role of supply chain adaptability. It further investigates the moderating role of technological uncertainty while controlling for firm size. By focusing on Pakistan's manufacturing firms, this study aims to provide context-specific insights into how advanced technological capabilities can be leveraged to enhance adaptability and performance in emerging economies.

### 1.1 Research Problem Statement

Although artificial intelligence technologies are increasingly being adopted by manufacturing firms, there is limited empirical evidence on how these technologies contribute to organizational outcomes in developing economies such as

Pakistan. Existing research has largely treated artificial intelligence as a standalone technological tool, without adequately positioning it within the framework of organizational capital.

Moreover, prior studies have often examined the direct relationship between technological adoption and firm performance, neglecting the intermediate processes through which such technologies exert their influence. In the context of supply chain management, the ability of firms to adapt to changing environmental conditions is critical for achieving superior performance. However, the role of AI-enabled organizational capital in enhancing supply chain adaptability remains insufficiently explored. Additionally, the influence of contextual factors such as technological uncertainty on the relationship between adaptability and performance has not been thoroughly investigated, particularly in the manufacturing sector of Pakistan. This creates a gap in understanding how firms can effectively leverage AI-based capabilities to enhance adaptability and, ultimately, performance under uncertain conditions.

Therefore, there is a need for a comprehensive empirical investigation that integrates AI-enabled organizational capital, supply chain adaptability, and supply chain performance within a unified theoretical framework.

### 1.3. Research Questions

Based on the above problem, the study seeks to address the following questions:

1. What is the impact of AIOC on Supply chain adaptability?
2. What is the impact of supply chain adaptability on supply chain performance?
3. Does AI-enabled organizational capital directly influence supply chain performance?
4. Does supply chain adaptability mediate the relationship between AI-enabled organizational capital and supply chain performance?
5. How does technological uncertainty affect the relationship between supply chain adaptability and supply chain performance?

### 1.4 Research Objectives

The main objective of this study is to examine the role of AI-enabled organizational capital in enhancing supply chain performance through supply chain adaptability.

Specific objectives are:

1. To assess the impact of AI-enabled organizational capital on supply chain adaptability.
2. To examine the effect of supply chain adaptability on supply chain performance.
3. To evaluate the direct relationship between AI-enabled organizational capital and supply chain performance.
4. To investigate the mediating role of supply chain adaptability.
5. To analyze the moderating effect of technological uncertainty on the adaptability–performance relationship.
6. To control the influence of firm size in the proposed model.

### 5. Scope of the Study

This study is confined to the manufacturing sector of Pakistan, which plays a vital role in the country's economic development but faces significant challenges related to supply chain disruptions, technological transformation, and market uncertainty. The study focuses on firms that are actively engaged in supply chain activities and have exposure to digital technologies.

The conceptual scope is limited to examining AI-enabled organizational capital as a higher-order construct comprising machine learning, deep learning, and generative AI capabilities. The study further focuses on supply chain adaptability as a multidimensional construct and its role in improving supply chain performance.

Methodologically, the study adopts a quantitative approach using survey data collected from managers involved in supply chain functions. The analysis is conducted using PLS-SEM, which is suitable for examining complex models involving higher-order constructs and mediation effects.

Geographically, the study is restricted to Pakistan, and therefore, the findings may not be directly generalizable to other contexts without considering institutional and environmental differences. However, the results are expected to provide valuable insights for similar developing economies.

## 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

### 2.1 AI-Enabled Organizational Capital

The increasing deployment of intelligent digital technologies has transformed the way organizations develop and utilize knowledge resources. Within the framework of Intellectual Capital, organizational (structural) capital represents the institutionalized knowledge embedded in systems, routines, databases, and processes that support value creation (Reed et al., 2006; Kianto et al., 2017). In recent years, advanced analytical technologies such as Machine Learning, Deep Learning, and Generative Artificial Intelligence have increasingly been integrated into these structures, thereby extending the traditional understanding of organizational capital.

Machine learning enables firms to identify patterns within large datasets and supports predictive decision-making, particularly in areas such as demand forecasting and risk assessment (Wamba et al., 2020). Deep learning, as a more advanced subset, enhances the firm's ability to process complex and unstructured data, enabling more accurate and real-time decision support (Min, 2010; Dubey et al., 2021). Generative AI, on the other hand, introduces new possibilities for scenario simulation, automated content generation, and innovative problem-solving, thereby supporting strategic and operational decision-making (Jackson, 2024; Dwivedi et al., 2023). When embedded within organizational systems, these technologies collectively form what can be conceptualized as AI-enabled organizational capital**,** which strengthens the firm's capacity to process information and respond to environmental changes.

Recent empirical studies suggest that the integration of AI technologies enhances operational efficiency, improves decision quality, and supports strategic alignment across supply chains (Culot et al., 2024; Sheikh, 2025). However, much of the existing literature has examined these technologies in isolation, without positioning them as a cohesive organizational resource. Conceptualizing machine learning, deep learning, and generative AI as dimensions of organizational capital provides a more comprehensive understanding of how firms institutionalize technological knowledge for sustained competitive advantage.

### 2.2 Dimensions of AIOC

#### 2.2.1 Deep Learning as Organizational Capital

Deep learning systems enhance operational decision-making by improving pattern recognition, anomaly detection, and real-time monitoring across supply chain activities (Khedr et al., 2024).

Deep learning—an advanced subset of Artificial Intelligence—is increasingly being conceptualized as a strategic component of **organizational capital** (e.g., forecasting systems, quality control, decision support) Within the framework of Intellectual Capital, organizational capital refers to the embedded knowledge residing in systems, processes, databases, routines, and culture that enhances a firm's ability to create value. When deep learning technologies are integrated into these structures, they transform organizational capital into a more adaptive, intelligent, and dynamic resource.

Thus, deep learning involves neural networks capable of learning from vast datasets, identifying patterns, and making predictions. Unlike traditional IT systems, deep learning systems continuously improve over time through data exposure.

Thus, deep learning contributes to organizational capital in three main ways:

- **Codification of Knowledge:** Converts tacit and explicit knowledge into algorithms and models
- **Process Enhancement:** Improves efficiency and accuracy of organizational processes
- **Institutional Memory:** Stores learned patterns that persist beyond individual employees

#### 2.2.2 Machine Learning Capability (MLC)

Machine learning capability refers to the organization's ability to utilize data-driven algorithms and predictive analytical systems to identify patterns, generate forecasts, and support decision-making processes. In supply chain contexts, machine learning is commonly applied in demand forecasting, inventory optimization, and risk identification (Wamba et al., 2020). These capabilities enable firms to improve predictive accuracy and strengthen their ability to anticipate environmental changes and operational disruptions (Dubey et al., 2021). Thus Machine Learning Capability

- Use of predictive analytics in forecasting
- Data-driven decision systems
- Automated risk identification

### 2.2.3 Generative Artificial Intelligence Capability (GAIC)

Generative AI capability refers to the organization's ability to use AI systems that generate new insights, simulate alternative scenarios, and support innovative problem-solving. Unlike traditional predictive systems, generative AI facilitates dynamic planning and process redesign through scenario-based analysis and automated content generation (Dwivedi et al., 2023). Recent studies highlight that generative AI enhances strategic flexibility and supports adaptive decision-making in complex supply chain environments (Jackson, 2024).

Collectively, these three dimensions operate in a complementary manner and form AI-enabled organizational capital, which strengthens the organization's ability to process information, adapt to environmental uncertainty, and improve supply chain outcomes. From the perspective of the Dynamic Capability View, machine learning supports sensing capabilities, deep learning enhances seizing capabilities, and generative AI facilitates resource reconfiguration and innovation (Teece, 2007).

**Thus, Generative AI Capability contributes to organizational capital in these ways:**

- Use of neural networks in operations
- Real-time intelligent decision systems
- Advanced analytics for process optimization
- AI-generated planning/scenarios
- Automated report/content generation
- AI-supported innovation in supply chain processes

ML, DL, and Generative AI are embedded in systems, databases, routines, and decision-support mechanisms. Therefore, they fit well within organizational capital**.**

AI-enabled Organizational Capital (AIOC) can be conceptualized as a higher-order organizational resource that reflects the extent to which firms embed advanced artificial intelligence capabilities within their systems, routines, databases, and decision-making processes. Drawing from the perspective of Intellectual Capital, these capabilities represent codified and institutionalized knowledge resources that enhance organizational learning, information processing, and strategic responsiveness (Kianto et al., 2017). In the present study, AIOC is conceptualized as a second-order construct composed of machine learning capability, deep learning capability, and generative AI capability.

### 2.3 Supply chain adaptability as mediator

Supply Chain Adaptability (including internal, supplier, and customer adaptability) partially or fully mediates the relationship between AI-enabled Organizational Capital (AIOC) and Supply Chain Performance (SCP) by translating AI-driven organizational capabilities into operational responsiveness and coordination effectiveness.

The AI-based capabilities help firms to sense changes in demand and supply conditions respond to disruptions, redesign operational processes, coordinate better with suppliers and customers. So, AI-enabled organizational capital improves internal adaptability, supplier adaptability, and customer adaptability**.**

- Internal Adaptability (ISCA): Enhances coordination through real-time analytics
- Supplier Adaptability (SSCA): Improves supplier selection and risk prediction
- Customer Adaptability (CSCA): Enables demand sensing and personalized responses

By embedding learning algorithms into supply chain processes, firms can dynamically adjust to disruptions, demand fluctuations, and technological uncertainty and enhance performance.

### 2.4 Dynamic Capability

The Dynamic Capability View provides a suitable theoretical lens to explain the role of AI-enabled organizational capital in shaping organizational outcomes (Teece, 2007). According to this perspective, firms achieve superior performance by developing capabilities that allow them to sense environmental changes, seize opportunities, and reconfigure resources accordingly.

AI-enabled organizational capital enhances the sensing capability of firms by enabling advanced data analytics and forecasting through machine learning (Wamba et al., 2020). It strengthens the seizing capability by supporting informed decision-making and optimization through deep learning applications (Dubey et al., 2021). Furthermore, generative AI contributes to the reconfiguration capability by facilitating scenario planning, process redesign, and innovation (Dwivedi et al., 2023; Jackson, 2024). These capabilities collectively enable firms to adapt their supply chain structures and operations in response to dynamic environmental conditions.

In this regard, AI technologies do not directly lead to improved performance; rather, they enhance the firm's ability to develop adaptive capabilities that subsequently influence performance outcomes. This argument is consistent with prior studies emphasizing that technological resources contribute to performance primarily through capability development (Dubey et al., 2019).

ML, DL, and Generative AI do not create performance merely by existing. They create performance when they are embedded in organizational routines and help the firm adapt to changing environments.

### 2.3 Supply Chain Adaptability as a Dynamic Capability

In contemporary supply chain environments, adaptability has emerged as a critical capability that enables firms to cope with uncertainty and complexity. Supply Chain Adaptability refers to the ability of a firm to modify its supply chain design and processes in response to changes in market conditions, technologies, and customer requirements (Lee, 2004; Eckstein et al., 2015).

Prior research conceptualizes supply chain adaptability as a multidimensional construct encompassing internal, supplier, and customer dimensions (Aslam et al., 2018). Internal adaptability reflects the firm's ability to reconfigure internal processes and resources, while supplier adaptability captures the flexibility of upstream relationships. Customer adaptability, in turn, reflects the firm's responsiveness to changing customer needs and market demands (Whitten et al., 2012).

The integration of AI-enabled systems significantly enhances these dimensions. Predictive analytics improves demand sensing and inventory management, real-time data processing strengthens coordination across supply chain partners, and scenario-based planning supports proactive decision-making (Culot et al., 2024). Recent studies indicate that advanced AI applications contribute to the development of adaptive and resilient supply chains by enabling firms to anticipate disruptions and respond effectively (Jackson, 2024).

### 2.4 Supply Chain Performance

Supply chain performance represents the extent to which a firm achieves its operational and strategic objectives through its supply chain activities. It is commonly assessed using both financial and non-financial indicators, including cost efficiency, delivery reliability, flexibility, responsiveness, and customer satisfaction (Beamon, 1999; Vickery et al., 2003).

In Pakistan's manufacturing sector, SCOR 13 is valuable for managing supply disruptions, demand fluctuations, and technological limitations. Its focus on reliability, responsiveness, agility, cost efficiency, and resource management help firms benchmark performance, address operational gaps, and improve both efficiency and competitiveness (Haider et al., 2025).

The literature suggests that adaptability plays a crucial role in enhancing performance outcomes. Firms that are able to adjust their supply chain structures and processes in response to environmental changes are better positioned to maintain operational continuity, reduce costs, and improve service quality (Eckstein et al., 2015; Dubey et al., 2019). In this sense, adaptability serves as a key mechanism through which organizational resources are translated into performance outcomes.

While previous studies have established a link between technological capabilities and performance, the underlying processes through which these effects occur remain underexplored. This highlights the importance of examining supply chain adaptability as a mediating variable in the relationship between AI-enabled organizational capital and supply chain performance.

This study used a Scale framed by D. Leończuk et al. (2019). Conducting an exploratory, and subsequently confirmatory, factor analysis, the results of which were described in a publication of D. Leończuk et al. (2019), allowed for distinguishing four factors that create a scale for measuring supply chain performance: responsiveness (RES), versatility (VER), visibility (VIS) and velocity (VEL).

Each of these factors portrays a different aspect of the performance of an adaptive supply chain, and variables connected with a given factor allow for measuring the level of a specific feature of a supply chain.

### 2.5 Technological Uncertainty as a Moderating Condition

Technological uncertainty refers to the rate and unpredictability of technological changes that affect organizational operations and decision-making (Srinivasan & Swink, 2018). In highly uncertain environments, firms are required to process greater volumes of information and respond more rapidly to technological developments.

From an information processing perspective, uncertainty increases the need for advanced analytical capabilities and adaptive mechanisms (Galbraith, 1974). AI-enabled systems enhance the firm's ability to process complex information, while adaptability enables the firm to respond effectively to changes. However, the effectiveness of these capabilities may vary depending on the level of technological uncertainty.

Empirical studies suggest that environmental and technological uncertainty strengthen the importance of dynamic capabilities in achieving performance outcomes (Queiroz et al., 2020). In environments characterized by high uncertainty, the value of adaptability is likely to be greater, as firms must continuously adjust their operations and strategies. Despite its importance, empirical evidence on the moderating role of technological uncertainty remains limited in developing country contexts, including Pakistan.

### 2.6 Research Gap

The foregoing discussion highlights several important gaps in the existing literature. First, although AI technologies are increasingly being adopted in supply chain management, their conceptualization as a form of organizational capital remains underdeveloped (Culot et al., 2024; Dwivedi et al., 2023). Second, prior studies have largely focused on direct relationships between technological adoption and performance, without adequately examining the intermediate role of adaptability (Dubey et al., 2019). Third, the moderating influence of technological uncertainty has not been sufficiently explored in empirical studies, particularly within the manufacturing sector of Pakistan.

To address these gaps, the present study integrates AI-enabled organizational capital, supply chain adaptability, and supply chain performance within a unified framework grounded in the dynamic capability perspective. By doing so, it seeks to provide a more comprehensive understanding of how firms can leverage advanced technological capabilities to enhance adaptability and achieve superior performance under conditions of uncertainty.

## 3.0 HYPOTHESIS DEVELOPMENT

### 3.1 AI-Enabled Organizational Capital and Supply Chain Adaptability

The integration of intelligent digital technologies into organizational systems has significantly enhanced firms' ability to process information and respond to environmental changes. When Machine Learning, Deep Learning, and Generative Artificial Intelligence are embedded within organizational routines, databases, and decision-support systems, they collectively form a knowledge-based resource that can be conceptualized as AI-enabled organizational capital. From the perspective of Intellectual Capital, such technologies represent codified knowledge that enhances the firm's information processing capability and supports strategic decision-making (Reed et al., 2006; Kianto et al., 2017).

AI-enabled organizational capital is inherently multidimensional, comprising machine learning, deep learning, and generative AI capabilities that differ in functionality but operate in a complementary manner. Machine learning capability enables firms to extract insights from large datasets and improve forecasting accuracy, thereby enhancing the ability to anticipate changes in demand and supply conditions. Empirical evidence suggests that data-driven decision systems improve responsiveness and coordination across supply chain activities (Wamba et al., 2020). Similarly, machine learning applications support proactive risk management and strengthen the firm's capacity to detect disruptions at an early stage (Dubey et al., 2021).

Deep learning capability extends these benefits by enabling the processing of complex and unstructured data through advanced neural networks. This capability allows firms to improve decision accuracy, enhance real-time monitoring, and strengthen coordination across supply chain networks. Studies indicate that deep learning contributes to improved operational responsiveness and efficiency by supporting timely and informed decision-making (Khedr et al., 2024).

Generative AI capability represents a more advanced form of artificial intelligence that enables organizations to simulate scenarios, generate alternative solutions, and support innovative decision-making. Unlike traditional predictive approaches, generative AI facilitates forward-looking analysis and dynamic planning. Recent studies highlight its role in enhancing supply chain planning, enabling scenario-based simulations, and supporting process innovation (Dwivedi et al., 2023; Jackson, 2024). These capabilities are particularly valuable in uncertain environments where firms must continuously redesign their processes and strategies.

From the standpoint of the Dynamic Capability View, these three dimensions collectively contribute to the firm's ability to sense, seize, and reconfigure resources (Teece, 2007). Machine learning supports sensing by identifying patterns and predicting changes, deep learning enhances seizing by enabling informed and timely decision-making, and generative AI facilitates reconfiguration by supporting innovation and process redesign. Together, these capabilities strengthen the firm's adaptive capacity.

In supply chain contexts, adaptability is reflected in the firm's ability to modify internal processes, adjust supplier relationships, and respond to changing customer demands. The integration of AI-enabled systems enhances these capabilities by improving information processing, coordination, and decision-making across supply chain activities. Empirical studies indicate that AI-based technologies contribute to supply chain flexibility and resilience by enabling firms to anticipate disruptions and respond effectively (Culot et al., 2024; Jackson, 2024).

Given the complementary and reinforcing nature of machine learning, deep learning, and generative AI capabilities, it is appropriate to conceptualize them as dimensions of a higher-order construct, namely AI-enabled organizational capital. When embedded within organizational systems and routines, these capabilities collectively enhance the firm's ability to adapt to environmental changes. This leads to following hypothesis:

**H1:** AI-enabled organizational capital positively influences supply chain adaptability.

### 3.2 Supply Chain Adaptability and Supply Chain Performance

In dynamic and uncertain environments, the ability to adapt supply chain structures and processes is a key determinant of performance. Supply Chain Adaptability reflects the firm's capacity to reconfigure internal operations, supplier relationships, and customer interactions in response to environmental changes (Eckstein et al., 2015).

The dynamic capability perspective posits that adaptive capabilities enable firms to align their resources and operations with changing environmental conditions, thereby improving performance outcomes (Teece, 2007). Firms that are able to respond quickly to demand fluctuations, adjust production systems, and maintain coordination with supply chain partners are more likely to achieve superior performance in terms of efficiency, reliability, and customer satisfaction.

Empirical evidence supports this relationship. Studies have shown that supply chain adaptability enhances both financial and non-financial performance by improving flexibility, responsiveness, and cost efficiency (Aslam et al., 2018). Furthermore, adaptable supply chains are better positioned to maintain performance during disruptions and environmental turbulence (Queiroz et al., 2020).

Based on these arguments, it is expected that higher levels of supply chain adaptability will lead to improved supply chain performance. Thus, we put forth:

**H2:** Supply chain adaptability positively influences supply chain performance.

### 3.3 AI-Enabled Organizational Capital and Supply Chain Performance

AI-enabled organizational capital enhances the firm's ability to process information, optimize operations, and support decision-making, which can contribute to improved performance outcomes. From an information processing perspective, organizations equipped with advanced analytical capabilities are better able to manage complexity and uncertainty, resulting in more efficient and effective operations (Galbraith, 1974; Srinivasan & Swink, 2018).

Empirical studies suggest that the adoption of AI-based systems improves operational efficiency, enhances responsiveness, and contributes to overall performance (Wamba et al., 2020; Sheikh, 2025). However, the extent to which these benefits are realized depends on the firm's ability to integrate these technologies into organizational processes and leverage them effectively.

Accordingly, AI-enabled organizational capital is expected to have a positive influence on supply chain performance. This leads to following hypothesis:

**H3:** AI-enabled organizational capital positively influences supply chain performance.

### 3.4 Mediating Role of Supply Chain Adaptability

The dynamic capability perspective emphasizes that resources alone are insufficient to generate superior performance; rather, firms must develop capabilities that enable the effective deployment and reconfiguration of these resources (Teece, 2007). In this context, supply chain adaptability serves as a key mechanism through which AI-enabled organizational capital is translated into performance outcomes. (Ghasemi et al., 2025)

AI technologies enhance the firm's ability to generate insights and support decision-making; however, these benefits are realized only when firms are able to adapt their processes and structures accordingly. Prior studies have highlighted the mediating role of dynamic capabilities in linking technological resources to performance outcomes (Dubey et al., 2019; Queiroz et al., 2020).

Therefore, it is expected that supply chain adaptability mediates the relationship between AI-enabled organizational capital and supply chain performance.

**H4:** Supply chain adaptability mediates the relationship between AI-enabled organizational capital and supply chain performance.

### 3.5 Moderating Role of Technological Uncertainty

Technological uncertainty reflects the extent to which technological changes are unpredictable and difficult to manage (Srinivasan & Swink, 2018). In such environments, firms face greater challenges in decision-making and must rely more heavily on adaptive capabilities.

From an information processing perspective, higher levels of uncertainty increase the need for advanced analytical capabilities and flexible organizational responses (Galbraith, 1974). Empirical studies suggest that environmental uncertainty strengthens the relationship between dynamic capabilities and performance outcomes (Dubey et al., 2020; Queiroz et al., 2020).

Accordingly, the effectiveness of supply chain adaptability in improving performance is expected to be greater under conditions of high technological uncertainty.

Thus, we hypothesize:

**H5:** Technological uncertainty moderates the relationship between supply chain adaptability and supply chain performance such that the relationship is stronger under higher levels of technological uncertainty.

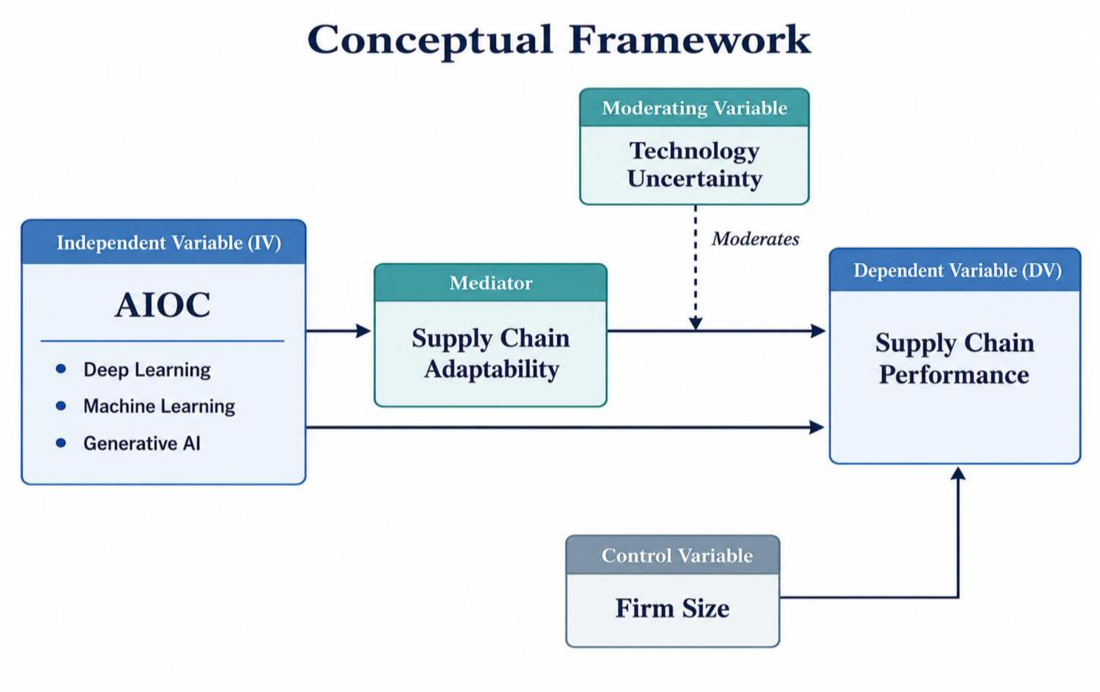
### 3.6 Firm Size as a Control Variable

Firm size is included as a control variable to account for heterogeneity in organizational scale that may systematically influence supply chain performance and related capability development. Larger firms typically benefit from greater resource availability, stronger technological infrastructure, and more developed managerial and analytical capabilities, which can facilitate the adoption and integration of advanced digital and AI-enabled systems within supply chain operations. Conversely, smaller firms often operate under resource constraints that may limit their ability to invest in technological transformation and advanced supply chain practices. These structural differences can independently shape organizational responsiveness, adaptability, and performance outcomes, thereby introducing potential bias in estimating the relationships among AI-enabled organizational capabilities, supply chain adaptability, and supply chain performance. Accordingly, firm size is controlled in the empirical model to ensure that the observed effects are not confounded by differences in organizational scale. In this study, firm size is operationalized using the natural logarithm of total employees or total assets, consistent with prior empirical research to reduce distributional skewness and improve model stability (Zheng et al., 2011).

### 3.7 Conceptual Framework

Based on the theoretical arguments and hypotheses developed, the study proposes a model in which **AI-enabled organizational capital** influences **supply chain performance** both directly and indirectly through **supply chain adaptability**, while **technological uncertainty** moderates the relationship between adaptability and performance. **Firm size** is included as a control variable.

**Diagrammatic Representation**




**Conceptual Explanation**

The model conceptualizes AI-enabled organizational capital as a higher-order construct comprising Machine Learning, Deep Learning, and Generative Artificial Intelligence capabilities. These capabilities are embedded within organizational systems and contribute to enhanced information processing and decision-making.

Drawing on the Dynamic Capability View, the model posits that AI-enabled organizational capital strengthens supply chain adaptability, which in turn improves supply chain performance. This reflects the mediating mechanism through which technological resources are translated into performance outcomes.

Furthermore, the model incorporates technological uncertainty as a boundary condition. Under conditions of high uncertainty, the value of adaptability is expected to increase, thereby strengthening its impact on performance. Conversely, in more stable environments, the effect may be less pronounced.

Firm size is included as a control variable, as larger firms may possess greater resources and capabilities that influence performance outcomes.

## 4.0 RESEARCH METHODOLOGY

### 4.1 Research Design

This study adopts a quantitative, cross-sectional research design to examine the relationships among AI-enabled organizational capital, supply chain adaptability, and supply chain performance in the manufacturing sector of Pakistan. A survey-based approach was employed to collect primary data from managers involved in supply chain and operational decision-making. The research design is consistent with prior studies in supply chain management and organizational research that examine complex relationships using perceptual data (Hair et al., 2021).

Given the exploratory nature of integrating advanced technological capabilities into organizational capital and the presence of higher-order constructs, partial least squares structural equation modeling (PLS-SEM) was considered appropriate for data analysis. PLS-SEM is particularly suitable for predictive models, complex relationships, and studies involving formative or higher-order constructs (Henseler et al., 2016).

### 4.2 Population and Sampling

The population of this study comprises manufacturing firms operating in Pakistan, which represent a critical sector of the national economy and are increasingly exposed to supply chain disruptions and technological transformation. Consistent with prior research, only firms actively engaged in supply chain activities were considered relevant for this study.

A combination of random and purposive sampling techniques was employed. Initially, manufacturing firms were identified from available industrial directories and listings. Subsequently, purposive sampling was used to select respondents with relevant knowledge and experience in supply chain operations, including supply chain managers, production managers, logistics managers, and operations executives.

A total of 256 usable responses were collected, which is considered adequate for PLS-SEM analysis and consistent with recommended sample size thresholds (Hair et al., 2021). This sample size also aligns with previous empirical studies conducted in similar contexts.

### 4.3 Data Collection Procedure

Data were collected using a structured questionnaire administered through both online (Google Forms) and in-person distribution methods. The use of multiple data collection channels helped increase response rates and ensured broader coverage across firms.

Respondents were assured of confidentiality and anonymity to reduce response bias and encourage accurate reporting. The questionnaire was designed in English, as it is commonly used in managerial and organizational communication within Pakistani firms.

### 4.4 Measurement of Variables

All constructs were measured using **multi-item scales** adapted from established studies, with modifications to fit the context of AI-enabled organizational capital and supply chain management. Responses were recorded using a **seven-point Likert scale** ranging from 1 ("strongly disagree") to 7 ("strongly agree").

**Table 1.0 Measurement of Variables**

| Construct | Code | Measurement Item | Source |
|---|---|---|---|
| **AI-Enabled Organizational Capital (Higher-Order)** | | Comprising ML, DL, Generative AI | Wamba et al. (2020); Dubey et al. (2021); Dwivedi et al. (2023) |

A. **Machine Learning Capability (MLC)**

| Construct | Code | Measurement Item | Source |
|---|---|---|---|
| Machine Learning Capability | MLC1 | Our firm uses data-driven models to forecast demand accurately | Wamba et al. (2020) |
| | MLC2 | Machine learning tools support operational decision-making | Dubey et al. (2021) |
| | MLC3 | Systems identify patterns in data to improve planning | Wamba et al. (2020) |
| | MLC4 | ML helps detect supply chain risks early | Dubey et al. (2021) |
| | MLC5 | Predictive analytics support inventory/logistics decisions | Wamba et al. (2020) |

B. **Deep Learning Capability (DLC)**

| | | | |
|---|---|---|---|
| Deep Learning Capability | DLC1 | Advanced AI models analyze complex data | Dubey et al. (2021) |
| | DLC2 | Deep learning supports real-time monitoring | Khedr et al. (2024) |
| | DLC3 | Intelligent systems improve decision accuracy | Dubey et al. (2021) |
| | DLC4 | AI detects anomalies in real time | Khedr et al. (2024) |

| | | | |
|---|---|---|---|
| | DLC5 | Deep learning improves coordination across functions | Dubey et al. (2021) |
| C. **Generative AI Capability (GAIC)** | | | |
| Generative AI Capability | GAIC1 | AI generates insights for planning | Dwivedi et al. (2023) |
| | GAIC2 | Supports scenario-based analysis | Jackson (2024) |
| | GAIC3 | AI explores alternative solutions | Dwivedi et al. (2023) |
| | GAIC4 | AI supports innovation in supply chain | Jackson (2024) |
| | GAIC5 | AI helps redesign processes | Dwivedi et al. (2023) |
| **D. Supply Chain Adaptability (SCA)** | | | |
| Construct | Code | No. of Measurement Item | Source |
| Internal Adaptability | ISCA | 7 | Yang et al. (2022) |
| Customer Adaptability | CSCA | 7 | |
| Supplier Adaptability | SSCA | 7 | |
| E**. Supply Chain Performance (SCP)** | | | |
| | **SCP** | 21 | Leończuk (2021) |
| F. **Technological Uncertainty (TU)** | | | |
| Technological Uncertainty | TU1 | Technological changes are rapid | Srinivasan & Swink (2018) |
| | TU2 | Future technologies are difficult to predict | Dubey et al. (2020) |
| | TU3 | New technologies disrupt operations | Srinivasan & Swink (2018) |
| | TU4 | Firm faces uncertainty due to technology | Dubey et al. (2020) |

## 5.0 DATA ANALYSIS TECHNIQUE

Data analysis was conducted using **SmartPLS (version 4.0)**. The analysis followed a two-step approach:



### 5.1 Measurement Model Assessment

**Internal Consistency Reliability (Cronbach's Alpha & Composite Reliability)**

**Table 2: Psychometric analysis**

| | Cronbach's alpha | Composite reliability (rho_a) | Average variance extracted (AVE) |
|---|---|---|---|
| AIOC | 0.918 | 0.927 | 0.540 |
| SCA | 0.941 | 0.946 | 0.479 |
| SCP | 0.973 | 0.974 | 0.673 |
| TE | 0.809 | 0.819 | 0.725 |

This table reports internal consistency reliability (Cronbach's alpha), composite reliability (rho_a), and convergent validity (AVE) for four constructs: AIOC, SCA, SCP, and TE.

All constructs show strong to excellent reliability.

Overall, the convergent validity assessment indicates that most constructs demonstrate acceptable to strong validity, with AVE values for AIOC (0.540), SCP (0.673), and TE (0.725) meeting or exceeding the recommended threshold of 0.50, while SCA (0.479) falls marginally below this criterion, suggesting a need for minor refinement of its measurement indicators to enhance construct representation.

Thus, measurement model is largely robust and reliable, supporting further structural analysis. However, SCA requires attention due to slightly weak convergent validity, and SCP may benefit from item review to reduce redundancy and improve construct efficiency.

**Table 3: Heterotrait-monotrait ratio (HTMT) – List**

| | Heterotrait-monotrait ratio (HTMT) |
|---|---|
| SCA <-> AIOC | 0.493 |
| SCP <-> AIOC | 0.369 |
| SCP <-> SCA | 0.804 |
| TE <-> SCA | 0.460 |
| TE <-> SCP | 0.372 |

The HTMT results confirm that all construct correlations remain below the recommended threshold of 0.85, indicating satisfactory discriminant validity across the model; however, the relatively higher value between SCP and SCA (0.804) suggests a moderate degree of conceptual proximity that may warrant careful theoretical review, although it does not violate established validity criteria.

### 5.2 Structural Model Assessment

**Table 4: Coefficient of determination ($R^2$)**

| R Square | R-square | R-square adjusted |
|---|---|---|
| SCA | 0.207 | 0.204 |
| SCP | 0.649 | 0.644 |

**Supply Chain Adaptability — SCA**

The R-square value for Supply Chain Adaptability is 0.207. This means that AI-enabled organizational capital explains 20.7% of the variance in supply chain adaptability.

In other words, deep learning, machine learning, and generative AI as dimensions of AIOC contribute to explaining changes in supply chain adaptability, but a large portion of adaptability is still influenced by other factors not included in the model.

The R-square value of SCA is 0.207, indicating that AIOC explains 20.7% of the variance in supply chain adaptability. The adjusted R-square value of 0.204 shows a minor difference from the original R-square, suggesting that the model has stable explanatory power. However, the explanatory power is relatively weak according to the criteria suggested by Hair et al. (2017).

**Supply Chain Performance — SCP**

The R-square value for Supply Chain Performance is 0.649. This means that 64.9% of the variance in supply chain performance is explained by the predictors in the model, including AIOC, supply chain adaptability, technology uncertainty, the interaction effect, and firm size.

This is a strong result because it shows that the model explains a large proportion of supply chain performance. Based on the PLS-SEM guideline, this value can be considered moderate to strong, because it is above 0.50 and close to 0.75 (Hair et al., 2017; Chin, 1998).

The adjusted R-square value is 0.644, which is very close to the R-square value of 0.649. The small difference between both values indicates that the model does not suffer from unnecessary predictors and has good explanatory stability.

The R-square value of SCP is 0.649, showing that the model explains 64.9% of the variance in supply chain performance. This indicates moderate to strong explanatory power. The adjusted R-square value of 0.644 is very close to the R-square value, suggesting that the model remains stable after adjustment for the number of predictors. Therefore, the model has strong predictive relevance for explaining supply chain performance.

**Conclusion**

The R-square results indicate that the model explains 20.7% of the variance in supply chain adaptability and 64.9% of the variance in supply chain performance. The R-square value for SCA is 0.207, suggesting weak explanatory power according to the criteria proposed by Hair et al. (2017). This implies that AI-enabled organizational capital explains a limited but meaningful portion of supply chain adaptability. In contrast, the R-square value for SCP is 0.649, indicating moderate to strong explanatory power. This shows that the predictors included in the model explain a substantial proportion of supply chain performance. Furthermore, the adjusted R-square values for SCA and SCP are 0.204 and 0.644 respectively, which are close to their original R-square values. This small difference indicates that the model has stable explanatory power and is not overly affected by the number of predictors. Therefore, the structural model demonstrates stronger explanatory power for supply chain performance than for supply chain adaptability.

### 5.3 Effect size ($f^2$)

**Table 5: f Square**

| Path | f-square | Effect Size | Interpretation |
|---|---|---|---|
| AIOC → SCA | 0.261 | Medium effect | Meaningful contribution |
| AIOC → SCP | 0.002 | No effect | Very weak contribution |
| SCA → SCP | 1.398 | Large effect | Very strong contribution |
| TE → SCP | 0.010 | No effect | Very weak contribution |
| TE × AIOC → SCP | 0.009 | No effect | Moderation effect is weak |

The f-square value of AIOC on supply chain adaptability is 0.261, indicating a medium effect size according to Cohen's (1988) criteria. This suggests that AI-enabled organizational capital has a meaningful explanatory contribution to supply chain adaptability.

The f-square value of AIOC on supply chain performance is 0.002, which is below the minimum threshold of 0.02. This indicates that AIOC has no meaningful direct effect on supply chain performance.

The f-square value of supply chain adaptability on supply chain performance is 1.398, indicating a large effect size. This shows that supply chain adaptability is the most influential predictor of supply chain performance in the model.

The f-square value of technology uncertainty on supply chain performance is 0.010, which is below the recommended threshold. Therefore, technology uncertainty has no meaningful direct effect on supply chain performance.

The f-square value of the interaction term between technology uncertainty and AIOC is 0.009, indicating no meaningful moderating effect. This suggests that technology uncertainty does not substantially change the relationship between AI-enabled organizational capital and supply chain performance.

**Conclusion**

The f-square results indicate that AIOC has a medium effect on supply chain adaptability, with an $f^2$ value of 0.261. This shows that AI-enabled organizational capital makes a meaningful contribution to explaining supply chain adaptability. However, the direct effect of AIOC on supply chain performance is very weak, with an $f^2$ value of 0.002, indicating no meaningful effect. The strongest effect in the model is found for supply chain adaptability on supply chain performance, with an $f^2$ value of 1.398, which represents a large effect size. This confirms that supply chain adaptability is the dominant predictor of supply chain performance. Furthermore, technology uncertainty has no meaningful direct effect on supply chain performance, as its $f^2$ value is 0.010. The interaction effect of technology uncertainty and AIOC also shows no meaningful effect, with an $f^2$ value of 0.009. Therefore, the f-square results support the conclusion that AIOC influences supply chain performance mainly through supply chain adaptability rather than through a direct or moderated relationship.

### 5.4 Model fit indices

**Table 6 :(SRMR, NFI)**

| Model fit indices: Fit Indices | Saturated model | Estimated model |
|---|---|---|
| SRMR | 0.044 | 0.045 |
| d_ULS | 0.039 | 0.038 |
| d_G | 0.070 | 0.070 |

| | | |
|---|---|---|
| Chi-square | 169.757 | 169.757 |
| NFI | 0.960 | 0.9610 |

These values indicate a **good and acceptable model fit**.

**Interpretation of Model Fit Indices**

The model fit assessment indicates that the proposed model demonstrates a strong and satisfactory fit to the observed data. The SRMR values for both the saturated model (0.044) and the estimated model (0.045) are well below the recommended threshold of 0.08, confirming a high level of fit between the model and empirical data. In addition, the NFI values (0.960 and 0.961) exceed the benchmark of 0.90, further supporting excellent comparative model fit. The d_ULS and d_G values are very low and closely aligned between the saturated and estimated models, indicating minimal discrepancy between the observed and model-implied correlation matrices. Although the Chi-square statistic is reported (169.757), it is sensitive to sample size and should be interpreted cautiously within SEM-based assessments. Overall, the results confirm that the measurement and structural model exhibit a good and acceptable fit, providing a solid foundation for interpreting the hypothesized relationships.

**5.5 Hypothesis testing using bootstrapping:**

**Table 7: Bootstrapping:**

| Hypothesis | Path Coefficient | β / Original Sample | T-value | P values | Decision |
|---|---|---|---|---|---|
| H1 | AIOC -> SCA | 0.455 | 5.396 | 0.000 | Supported |
| H2 | SCA -> SCP | 0.777 | 17.050 | 0.000 | Supported |
| H3 | AIOC -> SCP | -0.062 | 0.825 | 0.409 | Not supported |
| H4 | AIOC -> SCA -> SCP | 0.353 | 5.198 | 0.000 | Supported |
| H5 | TE x AIOC -> SCP | 0.03184 | 1.438978 | 0.150 | Not significant |
| | FR -> SCP | 0.050046 | 0.896039 | 0.370 | Not significant at 5% |

AIOC = Ai Enabled organizational Capital, SCA= Supply Chain Adaptability, SCP= Supply Chain Performance,
FR= Firm Size and TE= Technology uncertainty (Moderator)

In PLS-SEM, hypotheses are generally supported when the path coefficient is meaningful, the **t-value exceeds 1.96**, and the **p-value is below 0.05** at the 5% significance level, as recommended in bootstrapping-based structural model assessment (Hair et al., 2017; Kock, 2018).

**H1: AIOC → Supply Chain Adaptability**

The results show that AI-enabled organizational capital has a positive and significant effect on supply chain adaptability with a path coefficient of β = 0.455, t = 5.396, and p = 0.000. Therefore, H1 is supported.

This indicates that firms with stronger AI-enabled organizational capital, including deep learning, machine learning, and generative AI capabilities, are more capable of adapting their supply chain processes. This finding is consistent with the dynamic capabilities view, which argues that firms gain advantage when they can integrate, build, and reconfigure internal and external capabilities in changing environments (Teece, Pisano and Shuen, 1997).

In practical terms, AI-enabled organizational capital helps firms improve demand sensing, decision-making speed, operational flexibility, and responsiveness to market or supply disruptions. Similar evidence has been reported in supply chain analytics research, where analytics capabilities improve supply chain agility, adaptability, and operational performance (Wamba et al., 2020).

**H2: Supply Chain Adaptability → Supply Chain Performance**

The relationship between supply chain adaptability and supply chain performance is positive and highly significant, with β = 0.777, t = 17.050, and p = 0.000. Therefore, H2 is supported.

This is the strongest path in the model, suggesting that supply chain adaptability is a major driver of supply chain performance. Firms that can adapt their supply chain structure, logistics, supplier relationships, and operational decisions are more likely to achieve better performance outcomes. This aligns with Dubey et al. (2018), who explain that supply chain agility, adaptability, and alignment are important supply chain properties for achieving sustainable competitive advantage.

The result also supports the idea that performance improvement does not come only from technology ownership, but from the firm's ability to convert technology-enabled resources into adaptive supply chain capabilities.

**H3: AIOC → Supply Chain Performance**

The direct relationship between AIOC and supply chain performance is negative but statistically insignificant, with β = -0.062, t = 0.825, and p = 0.409. Therefore, H3 is not supported.

This means that AI-enabled organizational capital does not directly improve supply chain performance in this model. Although AIOC may provide advanced technological and knowledge-based resources, these resources do not automatically translate into performance gains unless they are converted into operational capabilities. This is consistent with the dynamic capabilities argument that resources alone are not enough; firms must deploy and reconfigure them effectively to generate performance outcomes (Teece, Pisano and Shuen, 1997).

Therefore, the insignificant direct effect suggests that AI capabilities such as deep learning, machine learning, and generative AI improve performance mainly through internal supply chain transformation rather than through a direct performance effect.

**H4: Mediating Effect of Supply Chain Adaptability**

The indirect effect of AIOC on supply chain performance through supply chain adaptability is positive and significant, with β = 0.353, t = 5.198, and p = 0.000. Therefore, H4 is supported.

Since the indirect effect is significant while the direct effect of AIOC on SCP is insignificant, the results indicate indirect-only mediation, often interpreted as full mediation. According to Zhao, Lynch and Chen (2010), this type of mediation occurs when the indirect path is significant but the direct path is not significant.

This means that supply chain adaptability fully explains how AIOC improves supply chain performance. In other words, AI-enabled organizational capital improves performance only when it strengthens the firm's ability to adapt its supply chain. This finding is also consistent with AI and supply chain research showing that AI contributes to supply chain resilience and performance through capability-building mechanisms under uncertain and dynamic environments (Belhadi et al., 2021).

**Technology Uncertainty as Moderator**

The direct effect of **technology uncertainty on supply chain performance** is positive but not significant at the 5% level, with **β = 0.124**, **t = 1.711**, and **p = 0.087**. This result may be considered marginal at the 10% level, but under the common 5% criterion, it is not statistically significant.

The moderation effect, represented by TE × AIOC → SCP, is also insignificant, with β = 0.03184, t = 1.438978, and p = 0.150313. Therefore, the moderating role of technology uncertainty is not supported.

Moderation is established when the interaction term significantly changes the strength or direction of the relationship between the independent and dependent variables (Hayes, 2017; Hayes and Montoya, 2017). In this case, the interaction term is insignificant, meaning technology uncertainty does not significantly strengthen or weaken the relationship between AIOC and supply chain performance.

**Firm Size as Control Variable**

The effect of firm size on supply chain performance is positive but insignificant, with β = 0.050, t = 0.896, and p = 0.370. This means firm size does not have a statistically significant control effect on supply chain performance in this model. In simple terms, larger firms in this sample do not necessarily perform better in supply chain outcomes than smaller firms. This suggests that supply chain performance depends more on adaptability and AI-enabled capability deployment than on firm size alone.

Also, because firm size is a control variable, it should normally be reported as a control path rather than as a formal hypothesis unless your study specifically hypothesizes its effect.

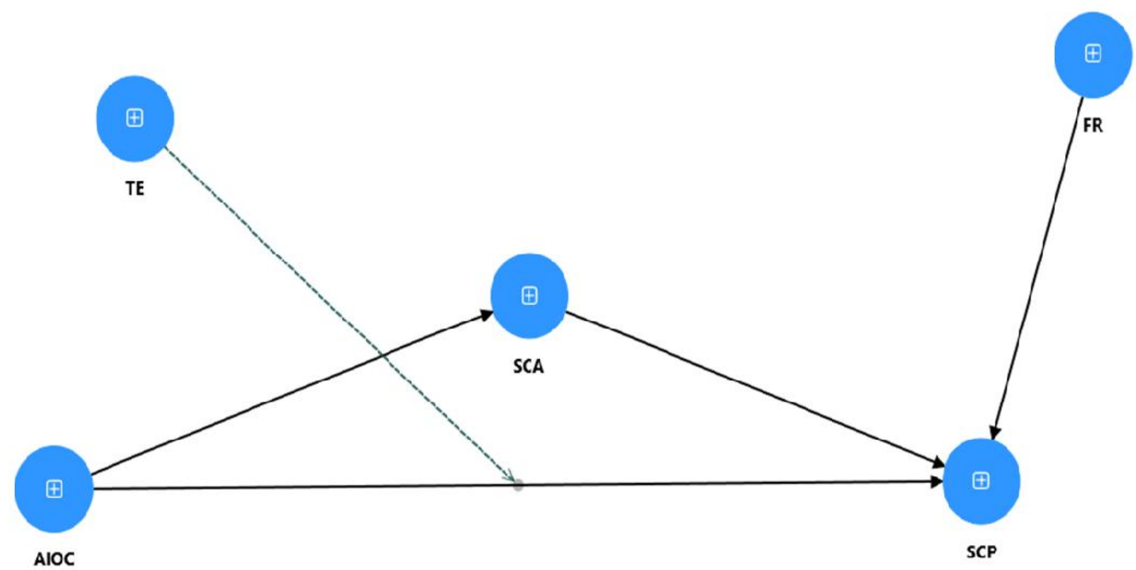
**Overall Interpretation**

Overall, the model shows that AI-enabled organizational capital significantly improves supply chain adaptability, and supply chain adaptability strongly improves supply chain performance. However, AIOC does not directly affect supply chain performance. This indicates that the value of AI-enabled organizational capital is realized through adaptability rather than through a direct performance route.

The most important finding is the significant mediation effect. The results suggest that firms should not focus only on adopting AI technologies such as deep learning, machine learning, and generative AI. Instead, they should use these technologies to build adaptive supply chain capabilities, including flexibility, responsiveness, rapid decision-making, and operational reconfiguration. Without adaptability, AI-enabled organizational capital may not produce meaningful performance outcomes.

Technology uncertainty does not moderate the AIOC–SCP relationship in this study, and firm size does not significantly control supply chain performance. Therefore, the final model mainly supports a capability-based explanation, where AIOC enhances SCP through SCA.

Therefore, Supply Chain Adaptability is the key mechanism through which AI-enabled organizational capital improves Supply Chain Performance.




## 6.0 DISCUSSION AND CONCLUSION

### 6.1 Introduction

This study empirically examined the structural relationships among AI-enabled organizational capital (AIOC), supply chain adaptability (SCA), supply chain performance (SCP), and technology uncertainty (TE), while controlling for firm size. The analysis was conducted using structural equation modeling (SEM), a widely established technique for validating complex causal frameworks in operations and information systems research (Hair et al., 2021; Kline, 2016).

The results demonstrate a robust explanatory framework, particularly for supply chain performance, consistent with prior research emphasizing the role of digital transformation in enhancing operational outcomes (Bharadwaj et al., 2013; Wamba et al., 2020).

### 6.2 Measurement Model Assessment

The measurement model demonstrates strong psychometric validity. Reliability indicators exceed established thresholds, confirming internal consistency (Nunnally & Bernstein, 1994; Hair et al., 2021).

Convergent validity is established as all constructs meet or approach the AVE threshold of 0.50, consistent with Fornell and Larcker's (1981) criterion. Discriminant validity is confirmed using the HTMT criterion, which remains below 0.85, aligning with Henseler et al. (2015), who recommend HTMT as a superior alternative to traditional Fornell-Larcker testing.

Model fit indices (SRMR < 0.05, NFI > 0.95) indicate strong structural adequacy, consistent with Hu and Bentler (1999), who emphasize SRMR as a sensitive model fit index in SEM applications.

### 6.3 Structural Model Evaluation

#### 6.3.1 AI-Enabled Organizational Capital and Supply Chain Adaptability

The positive and significant relationship between AIOC and SCA ($\beta = 0.455$, $p < 0.001$) confirms that AI capabilities enhance organizational responsiveness.

This aligns with the DCV, which posits that valuable and rare resources contribute to competitive advantage (Barney, 1991). Further, digital capability research suggests that AI enhances sensing and response capabilities in supply chains (Bharadwaj et al., 2013; Dubey et al., 2021).

#### 6.3.2 Supply Chain Adaptability and Supply Chain Performance

The strongest relationship is observed between SCA and SCP ($\beta = 0.777$, $p < 0.001$), indicating adaptability as the key performance driver.

This finding is consistent with **dynamic capability theory**, which argues that firms achieve sustained performance through reconfiguration and responsiveness (Teece, 2007; Eisenhardt & Martin, 2000). In supply chain contexts, adaptability is widely recognized as a core determinant of resilience and agility (Christopher, 2016; Ivanov, 2020).

#### 6.3.3 Direct Effect of AI-Enabled Capital on Performance

The insignificant direct effect of AIOC on SCP ($\beta = -0.062$, $p > 0.05$) suggests that AI capability alone does not generate performance outcomes.

This supports prior findings that digital technologies require organizational alignment to produce value (Nambisan et al., 2017). Technology value is therefore contingent upon complementary managerial and structural capabilities.

#### 6.3.4 Mediating Role of Supply Chain Adaptability

The significant indirect effect ($\beta = 0.353$, $p < 0.001$) confirms full mediation through SCA.

This aligns with Teece's (2007) framework, where dynamic capabilities act as transformation mechanisms converting resources into performance outcomes. Similar mediation effects have been reported in AI-enabled supply chain studies (Wamba et al., 2020; Dubey et al., 2021).

#### 6.3.5 Moderating Role of Technology Uncertainty

The non-significant moderating effect ($\beta = 0.031$, $p > 0.05$) indicates that technology uncertainty does not significantly influence the AI–performance relationship.

This finding contrasts with traditional uncertainty-performance theories (Milliken, 1987) but aligns with recent evidence suggesting that digital maturity reduces environmental sensitivity (Bharadwaj et al., 2013).

#### 6.3.6 Control Variable: Firm Size

Firm size is not significantly related to SCP ($\beta = 0.050$, $p > 0.05$), consistent with findings that organizational scale does not guarantee operational efficiency in digital environments (Choi et al., 2018). Instead, agility and capability development are stronger predictors of performance outcomes.

### 6.4 Theoretical Implications

This study contributes to three major theoretical streams:

First, it extends the Dynamic Capability View by demonstrating that AI-enabled organizational capital must be transformed into dynamic capabilities to create value.

Second, it strengthens Dynamic Capability Theory (Teece, 2007) by empirically validating supply chain adaptability as the key transformation mechanism.

Third, it contributes to **digital transformation literature** by confirming that technology does not directly enhance performance but operates through organizational capability layers (Nambisan et al., 2017; Vial, 2019).

Finally, it aligns with recent supply chain resilience research emphasizing adaptability as a core determinant of performance under uncertainty (Ivanov, 2020; Chowdhury et al., 2021).

### 6.5 Managerial Implications

From a managerial perspective, the findings highlight that AI investments should not be evaluated in isolation.
Managers must ensure:

- Integration of AI into operational decision systems
- Development of adaptive supply chain structures
- Investment in cross-functional coordination systems
- Strengthening of real-time analytics capability

These insights align with contemporary digital supply chain literature emphasizing agility, responsiveness, and resilience as key performance enablers (Christopher, 2016; Dubey et al., 2021).

### 6.6 Conclusion

This study confirms that AI-enabled organizational capital improves supply chain performance only through supply chain adaptability. The absence of a direct effect highlights the importance of organizational mechanisms in digital transformation.
Adaptability emerges as the central dynamic capability through which AI generates operational value, reinforcing established theoretical perspectives in DCV and dynamic capability theory (Teece, 2007; Barney, 1991).

### 7.7 Limitations and Future Research

The cross-sectional design limits causal inference. Future research should adopt longitudinal designs to capture capability evolution over time (Wamba et al., 2020).
Industry heterogeneity was not addressed; therefore, future studies should explore sector-specific dynamics. Additionally, future research should incorporate digital maturity, environmental turbulence, and organizational agility as additional moderators.
Cross-country comparative studies are also recommended to improve external validity and incorporate institutional differences in AI adoption.

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**Funder: SOCIOLOGY EDUCATIONAL NEXUS RESEARCH INSTITUTE**
**Disclosure:** The author(s) have participated in the research, authorship, and/or publication of this article as outlined in the disclosure statement on the previous page. The funder was not involved in the design, data collection, analysis, interpretation or writing of the paper.

**Declaration of conflicts of interest:**
The authors have no potential conflicts of interest to disclose in connection with the research, the writing, and/or the publication of this article.