Journal of Business Insight and Innovation
Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

# THE IMPACT OF AI BIG DATA CAPABILITIES AND SUPPLY CHAIN AGILITY ON SUPPLY CHAIN PERFORMANCE: THE MEDIATING ROLES OF SUPPLY CHAIN INTEGRATION AND CAPABILITIES WITH MODERATED EFFECTS

**Sadaqat Ullah [1], Hammad Zafar [2], Sarah Anjum [3]**

**DOI:** https://doi.org/10.63544/jbii.v5i9.191

**Affiliations:**

[1] Karachi University Business School, University of Karachi, Pakistan
Email: sadaqatullahm@gmail.com
ORCID: https://orcid.org/0009-0002-4945-3222

[2] Karachi University Business School, University of Karachi, Pakistan
Email: hammad.zafar@uok.edu.pk
ORCID: https://orcid.org/0009-0000-1067-1439

[3] Assistant Professor, Karachi University Business School, University of Karachi, Pakistan
Email: anjum.sar@uok.edu.pk
ORCID: https://orcid.org/0009-0009-7437-9539

**Corresponding Author's Email:**

[1] sadaqatullahm@gmail.com



**Article History:**
Received: 01.08.2026
Accepted: 17.08.2026
Published: 02.09.2026

## Abstract

***Purpose:*** *The growing complexity of global supply chains, driven by digital transformation and increasing competition, requires a better understanding of the factors influencing Supply Chain Performance (SCP). Grounded in the Resource-Based View (RBV) and Dynamic Capabilities perspectives, this study examines the direct and indirect effects of Artificial Intelligence Big Data Capabilities (AIBDA), Supply Chain Agility (SCA), Supply Chain Collaboration (SCC), Supply Chain Ethical Leadership (SCEL), and Supply Chain Management Practices (SCMP) on SCP.*

***Design/Methodology/Approach.*** *Using a cross-sectional design, data were collected from 380 supply chain professionals through a structured questionnaire and analyzed using PLS-SEM in SmartPLS 4. Supply Chain Integration (SCI) and Supply Chain Capabilities (SCCap) were examined as mediators, while AIBDA and SCA were tested as moderators.*

***Findings.*** *Results indicate that AIBDA ($\beta$=0.125), SCA ($\beta$=0.154), SCEL ($\beta$=0.187), SCMP ($\beta$=0.194), and SCCap ($\beta$=0.243) significantly enhance SCP. The mediating roles of SCCap are supported, whereas SCI does not mediate the relationships. The moderating effects of AIBDA ($\beta$=0.023) and SCA ($\beta$=0.065) are insignificant. The model explains 64.7% of the variance in SCP, providing theoretical and practical implications for digitally enabled supply chains.*

***Research Limitations.*** *The cross-sectional design limits causal inferences, and convenience sampling restricts generalizability. Future studies should employ longitudinal designs and probability sampling.*

***Practical Implications.*** *The findings guide managers in prioritizing investments in AI capabilities, agility, ethical leadership, and management practices to enhance supply chain performance, while recognizing that integration alone may not directly translate to performance without capability development.*

***Originality/Value.*** *This study offers an integrated framework examining AIBDA and SCA alongside traditional supply chain constructs, providing empirical evidence on their direct, mediating, and moderating effects on SCP.*

**Keywords:** Supply Chain Agility, Supply Chain Performance, Supply Chain Integration, Supply Chain Capabilities, PLS-SEM, AI Big Data Capabilities

## 1. Introduction

The modern business world is becoming more complex, more technologically disruptive, and more competitive around the world. The concept of supply chain management (SCM) has become a key strategic focus of organizations that aim to maintain competitive edge and customer value delivery (Chopra and Meindl, 2022). The concept of supply chain performance (SCP) which can be broadly described as the extent to which a supply chain meets the end-customer demands such as the ability to deliver products in time, of acceptable quality and at an acceptable cost has been cited as a key determinant of organizational success (Qrunfleh & Tarafdar, 2014).

### *1.1 Problem Statement*

There are still a few crucial gaps in the supply chain management literature. To begin with, the interaction of AIBDA with SCA, as well as other conventional supply chain constructs, has not been extensively studied (Dubey et al., 2022; Fosso Wamba et al., 2020). Second, the moderating effects of AIBDA and SCA on the relationships between SCI, SCCap and SCP have not been empirically validated on an integrative framework. Third, the mediation mechanisms by which SCC, SCEL and SCMP eventually affect SCP through SCI and SCCap should be more systematically studied. Such gaps all make it difficult to make evidence-based strategic decisions about technology adoption and supply chain design by the practitioners.

## 2. Literature Review

### *2.1 Theoretical Foundations*

**2.1.1 Resource-Based View (RBV) Theory.** Resource-Based View (RBV) is a position by Wernerfelt (1984) and further developed by Barney (1991), which assumes that sustained competitive advantage is attained by a firm through tapping valuable, rare, inimitable, and non-substitutable (VRIN) resources. Information processing capabilities, collaboration, and integration are among the strategic resources in the supply chain setting that distinguish successful supply chains and their counterparts (Soosay and Hyland, 2015). AIBDA is one of the strongest types of strategic assets in the digital era, allowing companies to handle large amounts of both structured and unstructured data to derive actionable intelligence (Fosso Wamba et al., 2020; Khan et al., 2026).

**2.1.2 Dynamic Capabilities Framework.** The RBV is further expanded by the Dynamic Capabilities framework, proposed by Teece et al. (1997), which places more emphasis on the capability of an organization to sense, seize and reconfigure resources in reaction to changes in the environment. Dynamic capability is illustrated by supply chain agility, which is the ability of an organization to identify changes in the market and respond to them within a short time (Gligor et al., 2019). The framework outlines how SCA, with the help of AIBDA, helps firms to constantly reconfigure their supply chains to respond to demand fluctuations, disruptions, and competition (Dubey et al., 2022).

**2.1.3 AI Big Data Capabilities and Digital Transformation.** This AI and big data functionality allows organisations to handle complex information, make better strategic decisions and build data-driven capabilities. In terms of advanced analytical capabilities, AI-based solutions are capable of helping organizations identify patterns and optimize their operations, which can in turn boost performance outcomes (Iram et al. 2025). Likewise, AI's adoption enhances organizational capabilities by supporting intelligent decision-making processes and elevating service quality through the use of technology in management practices (Malik & Rafiq-uz-Zaman, 2025).

Artificial Intelligence integrated with organizational processes not only boosts productivity and resource utilization but also revolutionizes traditional practices, enabling organizations to become digitally empowered for performance enhancement (Rafiq-uz-Zaman, 2025a). Yet, to overcome the hurdles of AI adoption and maximize its technological advantages, it is crucial to have suitable policies, organizational preparedness, and strategic alignment (Rafiq-uz-Zaman, 2025b). Moreover, big data analytics can help organizations derive valuable information from vast amounts of data, which can further facilitate enhanced decision-making and capability building (Rafiq-uz-Zaman & Ameer, 2025).

**2.1.4**. **Stakeholder Theory and Ethical Leadership.** According to Freeman (1984), as developed further by other researchers, stakeholder theory states that in order to maintain the long-term performance, organizations should strike a balance between the interests of various stakeholders, such as suppliers, employees, customers, and communities. Supply chain ethical leadership (SCEL) is a paradigm that functions at the interplay of ethical decision-making and stakeholder theory because ethical leaders have the ability to foster trust between supply chain partners by focusing more on fairness, transparency, and integrity (Wang and Feng, 2023). This credibility is a relational base that promotes collaboration, integration and eventually performance (Gosling et al., 2016; Khan et al., 2025).

### *2.2 Key Constructs and Prior Research*

**2.2.1 AI Big Data Capabilities (AIBDA).** Artificial intelligence big data capabilities are the ability of an organization to gather, process, analyze, and take actions on large amounts of data with artificial intelligence-based tools and algorithms (Fosso Wamba et al., 2020). Machine learning, predictive analytics, natural language processing, and intelligent automation are all part of AIBDA with far-reaching consequences regarding supply chain operations. A study by Dubey et al. (2022) has shown that AI-enables supply chains have a better responsiveness, demand forecasting, and inventory optimization. Equally, Queiroz et al. (2021) concluded that the capabilities associated with big data analytics have a positive predictive power of operational performance in both manufacturing and logistics companies.

**2.2.2 Supply Chain Agility (SCA).** The concept of supply chain agility can be characterized as the capacity of a supply chain to swiftly detect and react to any alterations in the external environment such as demand variations, supply shocks, and competitive alterations (Gligor et al., 2019). SCA involves product flexibility, volume flexibility and new product introduction flexibility. These are three of the dimensions that capture responsiveness of a supply chain in various contexts of operation (Arawati, 2011). The role of SCA has been increased during the post-pandemic period when global supply chains were challenged by unparalleled disruptions numerous times (Ivanov & Dolgui, 2021).

**2.2.3 Supply Chain Collaboration (SCC).** Supply chain collaboration is the process of collaborative planning, decision making, and resource sharing by the parties to the supply chain with the goal of producing mutually advantageous results (Soosay & Hyland, 2015). Based on the transaction cost economics and the relational perspective of the firm, collaborative relationship lowers transaction cost, increases the quality of information and generates shared value (Cao and Zhang, 2011; Dash et al., 2026). SCC occurs in the form of information exchange, collaboration in forecasting, coordination in production programs and development of new products and services together.

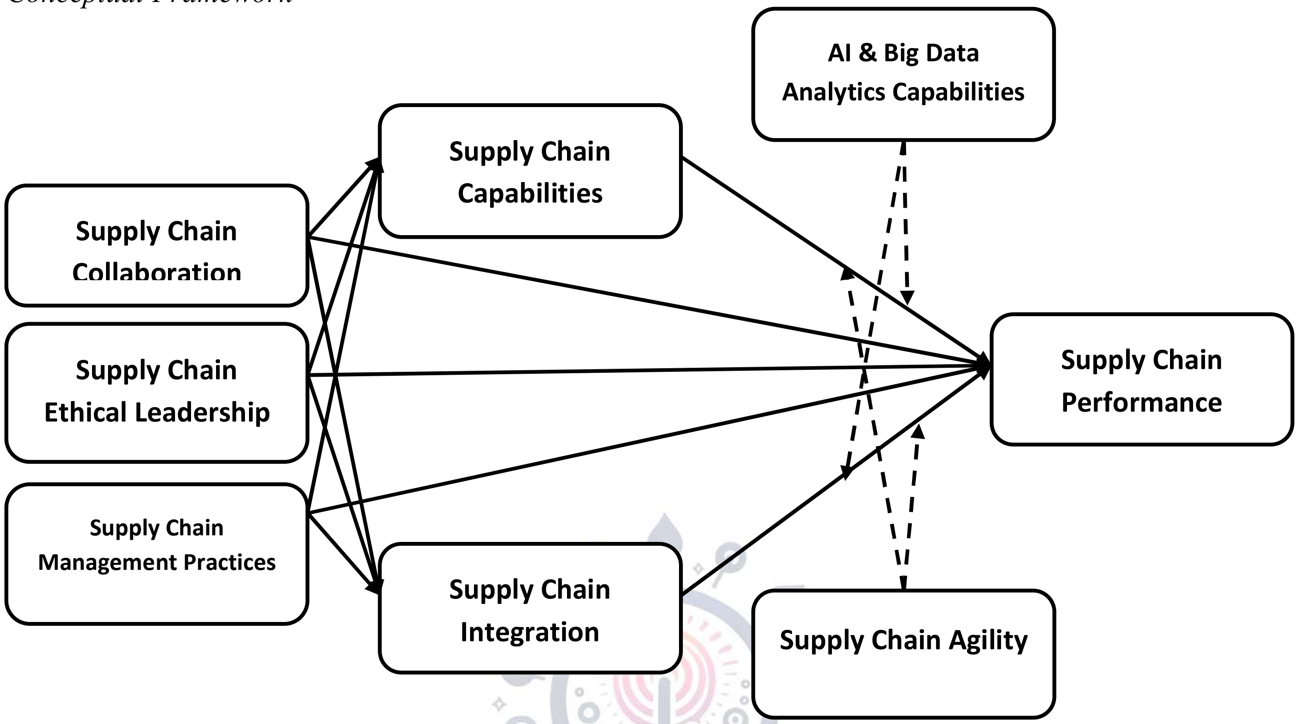
**2.2.4 Supply Chain Ethical Leadership (SCEL).** Ethical leadership in supply chains can be defined as the display of normatively desirable behavior in either personal or interpersonal relationships in the context of supply chain management (Wang and Feng, 2023). SCEL includes actions like telling the truth, making equitable decisions, caring about the welfare of the supply chain partners, and establishing ethical principles that govern supply chain activities. Ethical behaviors in leaders foster a positive organizational climate of trust and psychological safety, contributing to the knowledge sharing, risk-taking, and innovation in supply chain networks (Gosling et al., 2016).

**2.2.5 Supply Chain Management Practices (SCMP).** The practices in supply chain management include the documented actions and routine that are used to handle the relations with the suppliers, the optimization of inventory, the demand prediction, and the coordination of logistics (Karmaker et al., 2023). SCMP relies on the RBV and transaction cost economics in the explanation of how standardized supplier management, quality assessment, and strategic partnerships result in operational efficiencies (Rajaguru and Matanda, 2019). Significant dimensions of SCMP are supplier selection, which is done according to quality criteria, a dependence on a trusted supplier base, the long-term relationship development, the clarity of specification, and the ability evaluation.

**2.2.6 Supply Chain Integration (SCI).** Supply chain integration can be defined as the levels of strategic collaboration and coordination between the focal firm and its supply chain participants - upstream suppliers, and downstream customers - in order to control intra- and inter-organizational processes, information, and resources (Flynn et al., 2010). SCI includes exchange of information, rapid ordering, strategic alliances, and common production planning. A well-coordinated supply chain is a smooth mechanization, and partners exchange information in real-time and have unified goals.

**2.2.7. Supply Chain Capabilities (SCCap).** Supply chain capabilities are the capacity of an organization to effectively design and mobilize supply chain resources to address the demands in the market (Dubey et al., 2023). These are responsiveness, agility, innovation, reliability and cost efficiency. Based on the Dynamic Capabilities paradigm, companies that design better SCCap can quickly re-architect their operations of the supply chain in reaction to market shifts, disruptions, and competitive pressures (Asamoah et al., 2021).

**Figure 1**
*Conceptual Framework*




### *2.3 Hypothesis Development*

#### 2.3.1 Direct Effects on Supply Chain Performance

**H1:** The positive effect of AIBDA on SCP is significant. AI and big data can be used to sense demand in real-time, optimize inventory, predictive logistics, and it can, in turn, improve the performance of the supply chain (Dubey et al., 2022; Queiroz et al., 2021).

**H2:** SCA produces a great positive effect on SCP. Agile supply chain responds faster to environmental changes, maintains a higher level of services and efficiency of operations (Gligor et al., 2019; Hohenstein et al., 2015).

**H3:** SCC exerts a large positive impact on SCP. Information flow and coordination is improved through direct and indirect cooperation with the supply chain partners, increasing performance (Baah et al., 2022; Oubrahim et al., 2023).

**H4:** SCEL has a strong positive influence on SCP. Ethical leadership promotes trust and collaborations between the supply chain partners and improves the overall performance outcomes (Wang & Feng, 2023; Alabdullah & AL-Qallaf, 2023).

**H5:** There is a strong positive impact of SCMP on SCP. The best management practices ensure the optimization of supplier relationships and also cut down the cost of transactions, enhancing performance (Karmaker et al., 2023; Ibrahim & Hamid, 2014).

**H6:** SCI positively impacts on SCP significantly. The supply chain of the future is integrated, which has better operational performance due to the improved sharing and coordination of information (Flynn et al., 2010; Cui et al., 2023).

**H7:** SCCap positively significantly influences SCP. Companies exhibiting a well-developed supply chain have a greater responsiveness and better performance results (Asamoah et al., 2021; Bag & Rahman, 2023).

#### 2.3.2 Antecedents of Supply Chain Integration and Capabilities

**H8:** SCC provides a great positive impact on SCI. The integrative relations through collaboration enable the sharing of information and making decisions together, which facilitates integration (Mofokeng & Chinomona, 2019; Anderson & Thomas, 2024).

**H9:** SCEL makes a large positive impact on SCI. Trust-based relationships established by ethical leadership provide an opportunity to communicate freely and align the processes (Wang & Feng, 2023).

**H10:** SCMP affect SCI significantly and positively. Best management practices encourage stakeholders to share information and coordinate processes in supply chains among partners (Saragih et al., 2020; Jahanbakhsh Javid & Amini, 2023).

**H11:** SCC positively influences SCCap to a great extent. The relationships capabilities such as responsiveness and flexibility are promoted through collaborative partnerships (Friday et al., 2021; Baah et al., 2022).

**H12:** SCEL has a significant positive effect on SCCap. Ethical leadership fosters the establishment of trust and collaboration, which contributes to the ability building (Gosling et al., 2016; Hameed et al., 2023).

**H13:** SCMP positively impact on SCCap significantly. Advanced management practices help the firms to build and improve operational and relational capabilities (Rajaguru & Matanda, 2019; Asamoah et al., 2021).

#### 2.3.3 Mediation Hypotheses

**H14:** SCI stands in between the correlation between SCC and SCP. Teamwork can help to improve integration, and, therefore, the performance (Oubrahim et al., 2023; Salah et al., 2023).

**H15:** SCI is a mediator of the relationship between SCEL and SCP. The conditions of integration created through ethical leadership lead to better performance results (Wang & Feng, 2023).

**H16:** There is a mediating effect of SCI on the SCMP and SCP. Performance is increased due to improved integration mechanisms through management practices (Saragih et al., 2020; Sundram et al., 2016).

**H17:** SCCap mediates the effect of SCC and SCP. The capacity-building process through collaboration improves performance (Madhiyarsi & Nambirajan, 2015; Asamoah et al., 2021).

**H18:** SCCap is an intermediary of the association between SCEL and SCP. Ethical leadership increases the capability development, which is a predictor of performance (Hameed et al., 2023; Wang & Feng, 2023).

**H19:** There is a mediating effect of SCCap between SCMP and SCP. Capabilities are enhanced by management practices that consequently promote the supply chain (Rajaguru & Matanda, 2019).

#### 2.3.4 Moderation Hypotheses

**H20:** AIBDA moderates the SCCap–SCP relationship. The performance returns of supply chain capabilities are amplified through AI big data tools, which allow making decisions based on data (Fosso Wamba et al., 2020; Dubey et al., 2022).

**H21:** AIBDA moderates the SCI-SCP relationship. The AI features can add value to the performance of integration by means of real-time data processing and predictive analytics (Queiroz et al., 2021).

**H22:** SCA moderates the SCCap–SCP relationship. Agility increases the effects of capabilities on performance because it allows mobilizing the resources faster (Gligor et al., 2019; Hohenstein et al., 2015).

**H23:** SCA moderates the SCI–SCP relationship. Agile companies take advantage of integration infrastructure more effectively to convert coordination into performance results (Ivanov & Dolgui, 2021).

### *2.4. Research Objectives*

The study is guided by the following objectives:

RO1. To examine the direct effects of AIBDA, SCA, SCC, SCEL, SCMP, SCI, and SCCap on SCP.
RO2. To investigate the indirect effects of SCC, SCEL, and SCMP on SCP mediated by SCI and SCCap.
RO3. To explore the moderating effects of AIBDA and SCA on the SCI–SCP and SCCap–SCP relationships.
RO4. To provide theoretical and managerial recommendations based on empirical findings.

### *2.5 Research Questions*

Correspondingly, the study poses four research questions:

RQ1. Do AIBDA, SCA, SCC, SCEL, SCMP, SCI, and SCCap significantly and directly influence SCP?

Journal of Business Insight and Innovation
Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

RQ2: Do SCI and SCCap mediate the relationships between SCC, SCEL, SCMP, and SCP?
RQ3: Do AIBDA and SCA moderate the relationships between SCI, SCCap, and SCP?

### *2.6 Gap Analysis*

The central research gap lies in the absence of an integrated framework that simultaneously examines Artificial Intelligence and Big Data Capabilities (AIBDA), Supply Chain Agility (SCA), Supply Chai Ethical Leadership (SCEL), Supply Chain Collaboration (SCC), Supply Chain Management Practice (SCMP), Supply Chain Integration (SCI), and Supply Chain Capabilities (SCCap) as predictors of Suppl Chain Performance (SCP). Previous studies have largely investigated these constructs individually or through limited relationships, leaving their combined direct, mediating, and moderating effects insufficiently understood. In particular, AIBDA remains a relatively emerging construct, and its role as both a direct predictor and moderator of SCP-related relationships requires further empirical validation.

## 3. Research Methodology

### *3.1 Research Design and Philosophical Orientation*

The study is based on the deductive, cross-sectional, and quantitative research design. The study uses the deductive approach due to the conceptual model grounded on the existing theories of the Resource-Based View (RBV) and Dynamic Capabilities frameworks being tested empirically with the help of hypotheses (Saunders et al., 2019). The quantitative design enables measurement of the latent constructs and estimation of structural relationship using standardized self-report scales. The cross-sectional type allows collecting the data on all the constructs simultaneously at a single point in time and is appropriate in situations when the constructs are stable organizational traits and not quickly changing phenomena (Hair et al., 2021).

### *3.2 Population and Sampling*

The target population of the study is the supply chain professionals in various organizational settings, including manufacturing, logistics, retail, and service industries. The analysis unit is the individual professional who has knowledge on the supply chain operations, integration practices and organizational capabilities of his or her organization.

The sample was recruited using convenience sampling which was then supplemented by snowball sampling with the help of professional networks. Although the use of probability sampling is theoretically desirable, convenience and snowball methods are more popular in supply chain studies where the sampling frame is not available as comprehensive and where the construct of interest does not need a random cross-section of the population, but informed respondents (Sarstedt et al., 2018).

### *3.3 Instrument Development*

A structured, self-administered questionnaire, which contained two major sections, was used to collect the data. Part A included demographic questions on gender, age category, the level of education, and occupation. Section B was comprised of multi-item reflective scales of the eight latent constructs. All items were rated using a 5-point Likert scale (Strongly Disagree to Strongly Agree).

To guarantee content validity, all measures were modified based on already tested instruments. The 5 items used to measure AI Big Data Capabilities were modified after Fosso Wamba et al. (2020). The measurement of Supply Chain Agility used 4 items according to Arawati (2011) and Gligor et al. (2019). Supply Chain Collaboration was assessed using 4 scale items that are modified after Cao and Zhang (2011). The measurement of Supply Chain Capabilities was done using 5 items as indicated by Bag and Rahman (2023). 10 items of Supply Chain Ethical Leadership were based on Wang and Feng (2023). The 10 items of Supply Chain Integration were assessed according to Flynn et al. (2010). The response was measured using 5 items that were modified based on Karmaker et al. (2023). Measurement of Supply Chain Performance was done using 10 items as per Qrunfleh and Tarafdar (2014).

### *3.4 Data Collection Procedure*

The data was gathered during six weeks by distribution online in professional networks (LinkedIn), portal of industry associations, and direct contact with the organizations. A cover letter was provided before each questionnaire that described the scholarly intent of the research, voluntary participation, and documenting confidentiality and anonymity. The non-respondents were also reminded two weeks after the initial distribution to receive a follow up to enhance response rates. Items were randomized to eliminate common method bias and attention-check items were incorporated to detect careless responses.

### *3.5 Data Analysis Techniques*

Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4 was used to analyze data (Ringle et al., 2024). The main analytical method was selected as PLS-SEM due to several reasons. First, it suits intricate models incorporating numerous mediators, numerous moderators, and interaction conditions (Hair et al., 2021). Second, PLS-SEM does not assume multivariate normality and so it is suitable with survey data that do not follow normal distribution. Third, PLS-SEM has high statistical power to conduct theory-building and prediction-focused studies (Sarstedt et al., 2022).

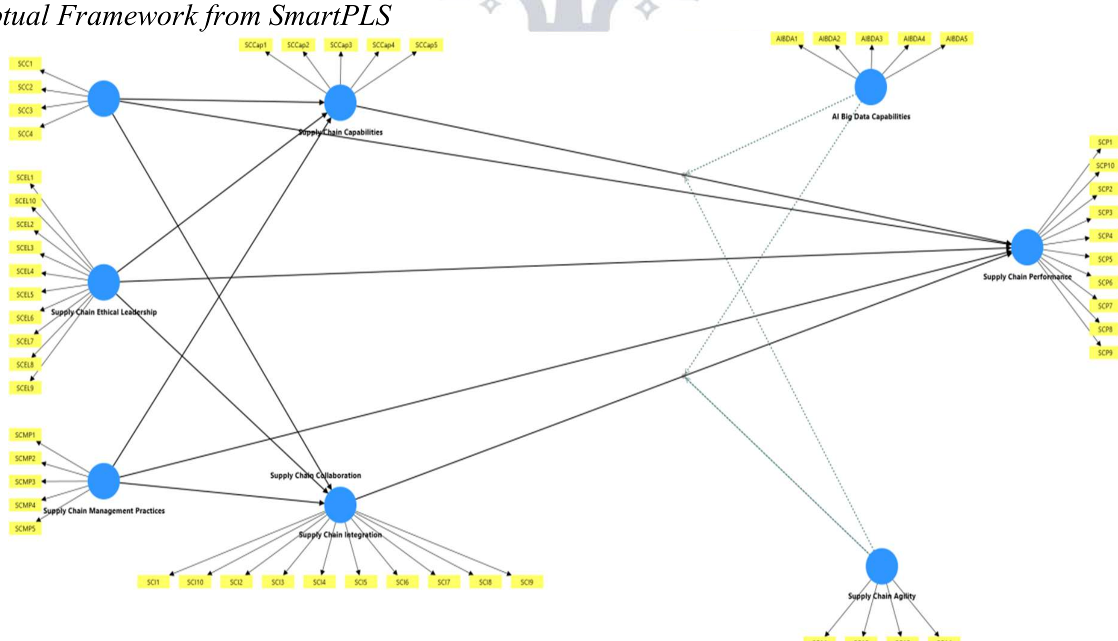
The two-stage analysis approach as suggested by Anderson and Gerbing (1988) was used. Stage 1 involved measurement (outer) model measurement of indicator reliability (outer loadings ≥ 0.70), internal consistency reliability (Cronbach's α and composite reliability rho_c ≥ 0.70), convergent validity (Average Variance Extracted, AVE ≥ 0.50) and discriminant validity (Heterotrait-Monotrait ratio, HTMT < 0.85). Stage 2 involved the structural (inner) model, which was evaluated by evaluating path coefficients (5,000 subsamples), bootstrap t-statistics, p-values, 95% bias-corrected confidence intervals, Cohen $f^2$ effect sizes, and the explained variance $R^2$ of each endogenous construct. The specific indirect effects approach was used in SmartPLS to test the hypotheses of mediation, whereas the product-indicator approach was used to test the moderation hypotheses (Henseler & Chin, 2010).

### 4. Findings of the Study

This chapter shows the empirical results of the research. These findings are presented as four key parts namely: (1) demographic profile of the respondents, (2) measurement model assessment in terms of reliability, convergent validity, and discriminant validity, (3) structural model assessment in terms of $R^2$, direct effects and, (4) moderation analysis. All findings are a PLS-SEM analysis with SmartPLS 4 with N = 380 and bootstrapping, 5,000 subsamples.

**Figure 2**

*Conceptual Framework from SmartPLS*




### *4.1 Demographic Profile*

Table 1 presents the demographic characteristics of the respondents (380 individuals). The sample is male dominated (74%), with the females comprising 26% of the sample. The largest age group is 36–40 years (28.9%), followed closely by 31–35 years (26.3%). In terms of education level, most of them have a Master's degree (44.7%), followed by a Bachelor of degree (27.6%). Regarding job position, most people are the entry-

Journal of Business Insight and Innovation
Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

level workers (42.1%), followed by the supervisory-level (34.2%), and middle-level management (23.7%) workers.

**Table 1**

*Demographic profile*

| Variable | Category | n | % |
|---|---|---|---|
| Gender | Male | 280 | 74.0% |
| | Female | 100 | 26.0% |
| Age Group | 25–30 years | 90 | 23.7% |
| | 31–35 years | 100 | 26.3% |
| | 36–40 years | 110 | 28.9% |
| | More than 40 years | 80 | 21.1% |
| Education | Bachelor's Degree | 105 | 27.6% |
| | Master's Degree | 170 | 44.7% |
| | Professional Qualification | 30 | 7.9% |
| | Other | 75 | 19.7% |
| Job Position | Entry Level | 160 | 42.1% |
| | Supervisory Level | 130 | 34.2% |
| | Middle Management | 90 | 23.7% |

*Note. N = 380.*

***4.2 Measurement Model Assessment***

Measurement model testing was conducted in accordance with the two steps of a PLS-SEM procedure as suggested by Hair et al. (2021). Factor loadings, composite reliability (rho_c), Cronbach's alpha and Average Variance Extracted (AVE) were used to check convergent validity. The Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker criterion were used to test the discriminant validity

***4.2.1 Convergent Validity.*** Table 2 presents the construct reliability and validity statistics. All the alpha values are higher than the standard level of 0.70 (Hair et al., 2021), with a value of 0.868 (Supply Chain Collaboration) to 0.944 (Supply Chain Ethical Leadership). All composite reliability (rho_c) values exceed 0.90, with 0.909 to 0.952, which is a strong internal consistency. The AVE values are all greater than the 0.50 cutoff with a range of 0.630 (SCP) to 0.737 (SCA) which means that each of the constructs explains over 50% of the variance in its corresponding indicators. These findings are good indications of convergent validity of all the eight constructs.

**Table 2**

*Construct Reliability and Validity*

| **Construct** | **Cronbach's α** | **rho_a** | **rho_c** | **AVE** |
|---|---|---|---|---|
| AI Big Data Capabilities (AIBDA) | 0.875 | 0.876 | 0.909 | 0.667 |
| Supply Chain Agility (SCA) | 0.881 | 0.881 | 0.918 | 0.737 |
| Supply Chain Capabilities (SCCap) | 0.893 | 0.894 | 0.921 | 0.701 |
| Supply Chain Collaboration (SCC) | 0.868 | 0.871 | 0.910 | 0.716 |
| Supply Chain Ethical Leadership (SCEL) | 0.944 | 0.944 | 0.952 | 0.664 |
| Supply Chain Integration (SCI) | 0.941 | 0.942 | 0.949 | 0.652 |
| Supply Chain Management Practices (SCMP) | 0.906 | 0.907 | 0.930 | 0.728 |
| Supply Chain Performance (SCP) | 0.935 | 0.935 | 0.945 | 0.630 |

*Note. rho_a = composite reliability (rho_a); rho_c = composite reliability (rho_c); AVE = average variance extracted. All values meet Hair et al. (2021) thresholds: α > 0.70, rho_c > 0.70, AVE > 0.50.*

**Journal of Business Insight and Innovation**
**Volume 5 Issue 9, 2026**
**ISSN-p: 3006-2284, ISSN-e: 3006-0982**
**https://insightfuljournals.com/**

Each of the eight constructs has above the minimum thresholds suggested by Hair et al. (2021). The values of Cronbach's α are all equal or above 0.868, composite reliability (rho_c) are all equal or above 0.90, and AVE values are in the range of 0.630 to 0.737, which is significantly higher than the 0.50 mark, indicating strong convergent validity across the measurement model. The outer loading of all the retained indicators was greater than 0.70 with the minimum indicator loading of 0.721 (SCP3) and the maximum indicator loading of 0.872 (SCMP2).

**4.2.2 Discriminant Validity.** The Heterotrait-Monotrait (HTMT) ratio was used to measure discriminant validity. Hair et al. (2021) suggests that values of HTMT must be less than 0.85 to achieve sufficient discriminant validity. The HTMT matrix can be found in Table 3. The values of all HTMT are smaller than 0.85 with the largest one of 0.730 between SCCap and SCP, which is a positive indication of sufficient discriminant validity among all pairs of constructs. This implies that all the constructs used in the model are empirically different.

**Table 3:**
*Heterotrait-Monotrait (HTMT) Ratio Matrix*

| Construct | AIBDA | SCA | SCCap | SCC | SCEL | SCI | SCMP |
|---|---|---|---|---|---|---|---|
| AIBDA | — | | | | | | |
| SCA | 0.591 | — | | | | | |
| SCCap | 0.593 | 0.612 | — | | | | |
| SCC | 0.538 | 0.524 | 0.519 | — | | | |
| SCEL | 0.547 | 0.578 | 0.603 | 0.639 | — | | |
| SCI | 0.545 | 0.601 | 0.671 | 0.638 | 0.661 | — | |
| SCMP | 0.506 | 0.575 | 0.636 | 0.546 | 0.627 | 0.712 | — |
| SCP | 0.628 | 0.671 | 0.730 | 0.596 | 0.693 | 0.678 | 0.699 |

*Note. HTMT = Heterotrait-Monotrait ratio. All values < 0.85, confirming discriminant validity (Hair et al., 2021). AIBDA = AI Big Data Capabilities; SCA = Supply Chain Agility; SCCap = Supply Chain Capabilities; SCC = Supply Chain Collaboration; SCEL = Supply Chain Ethical Leadership; SCI = Supply Chain Integration; SCMP = Supply Chain Management Practices; SCP = Supply Chain Performance.*

The highest eight ratios, SCCap-SCP 0.730 and SCM-PSCI 0.712 are less than 0.85, and the remaining eight ratios are all less than 0.60, which proves that all eight constructs are empirically different. There is no two that comes close to the problematic area (>0.85), which is a good sign of discriminant validity throughout the model. The Fornell-Larcker criterion was also met: the square root of the AVE of each construct was larger than its correlations with all the rest of the constructs in the model, which were convergent to validate the discriminant validity.

**4.2.3 Model Fit.** Table 4 shows the model fit indices. The saturated model has the Standardized Root Mean Square Residual (SRMR) equal to 0.047, which is much less than the 0.08 criterion suggested by Hu and Bentler (1999), so that the model fits exceptionally well. The SRMR of the estimated model is 0.057 which is also less than 0.08 hence fit is acceptable. The differences between d_ULS and d_G lie within the bootstrap-based cutoff.

**Table 4:**
*Model Fit Indices*

| Fit Index | Saturated Model | Estimated Model | Threshold |
|---|---|---|---|
| SRMR | 0.047 | 0.057 | < 0.08 |
| d_ULS | 3.113 | 4.667 | — |
| d_G | 2.512 | 2.570 | — |
| Chi-square | 4972.50 | 5026.32 | — |
| NFI | 0.731 | 0.728 | > 0.90 (indicative) |

*Note.* SRMR = Standardized Root Mean Square Residual; d_ULS = squared Euclidean distance; d_G = geodesic distance; NFI = Normed Fit Index.

### 4.3 Structural Model Assessment

**4.3.1 Variance Explained ($R^2$).** Table 5 shows the $R^2$ and adjusted $R^2$ of the three endogenous constructs. The model has the largest value of $R^2 = 0.647$ (adjusted $R^2 = 0.636$) indicating that the predictors in the model explain a combined 64.7% of SCP. The adjusted $R^2 = 0.555$ with respect to SCC, SCEL and SCMP to explain the supply chain is 0.558 ($R^2 = 0.558$). Supply Chain Capabilities has an $R^2$ of 0.413 (adjusted $R^2 = 0.409$). These values are found to be significant ($R^2 > 0.25$) explanatory power according to Cohen (1988) and they affirm the predictive relevance of the model.

**Table 1**

*R-Square Values for Endogenous Constructs*

| Endogenous Construct | $R^2$ | Adjusted $R^2$ |
|---|---|---|
| Supply Chain Capabilities (SCCap) | 0.413 | 0.409 |
| Supply Chain Integration (SCI) | 0.558 | 0.555 |
| Supply Chain Performance (SCP) | 0.647 | 0.636 |

*Note.* $R^2$ values indicate the proportion of variance in endogenous constructs explained by the model.

**4.3.2 Direct Effects.**Table 6 presents the direct path coefficients, bootstrap standard errors, t-statistics, p-values and Cohen $f^2$ effect sizes of all the hypothesized direct relationships, using 5,000 bootstrap subsamples. AIBDA has a positive and significant effect on SCP ($\beta = 0.125$, $t = 3.444$, $p < 0.001$), supporting H1. SCA also significantly predicts SCP ($\beta = 0.154$, $t = 3.578$, $p < 0.001$), supporting H2. SCEL has a substantial direct effect on SCP ($\beta = 0.187$, $t = 4.102$, $p < 0.001$), confirming H4. SCMP exerts a significant impact on SCP ($\beta = 0.194$, $t = 4.265$, $p < 0.001$), supporting H5. SCCap demonstrates the strongest direct effect ($\beta = 0.243$, $t = 5.715$, $p < 0.001$), supporting H7. The direct effect of SCC on SCP is positive but non-significant ($\beta = 0.062$, $t = 1.476$, $p = 0.140$), failing to support H3. The direct effect of SCI on SCP is also non-significant ($\beta = 0.060$, $t = 1.199$, $p = 0.231$), failing to support H6. Turning to the antecedents of the mediating variables, SCMP exhibits the strongest impact on both SCI ($\beta = 0.394$, $t = 10.077$, $p < 0.001$) and SCCap ($\beta = 0.350$, $t = 8.055$, $p < 0.001$), supporting H10 and H13. SCEL significantly influences both SCI ($\beta = 0.257$, $t = 5.701$, $p < 0.001$) and SCCap ($\beta = 0.278$, $t = 5.129$, $p < 0.001$), supporting H9 and H12. SCC significantly predicts both SCI ($\beta = 0.238$, $t = 5.398$, $p < 0.001$) and SCCap ($\beta = 0.128$, $t = 2.530$, $p = 0.011$), supporting H8 and H11.

**Table 2**

*Direct Path Coefficients and Significance Tests*

| Hypothesis / Path | β | Std. Error | t | p | $f^2$ | Decision |
|---|---|---|---|---|---|---|
| H1: AIBDA → SCP | 0.125 | 0.036 | 3.444 | < 0.001*** | 0.026 | Supported |
| H2: SCA → SCP | 0.154 | 0.043 | 3.578 | < 0.001*** | 0.037 | Supported |
| H3: SCC → SCP | 0.062 | 0.042 | 1.476 | 0.140 | 0.006 | Not Supported |
| H4: SCEL → SCP | 0.187 | 0.046 | 4.102 | < 0.001*** | 0.046 | Supported |
| H5: SCMP → SCP | 0.194 | 0.045 | 4.265 | < 0.001*** | 0.051 | Supported |
| H6: SCI → SCP | 0.060 | 0.050 | 1.199 | 0.231 | 0.004 | Not Supported |
| H7: SCCap → SCP | 0.243 | 0.043 | 5.715 | < 0.001*** | 0.083 | Supported |
| H8: SCC → SCI | 0.238 | 0.044 | 5.398 | < 0.001*** | 0.081 | Supported |
| H9: SCEL → SCI | 0.257 | 0.045 | 5.701 | < 0.001*** | 0.082 | Supported |
| H10: SCMP → SCI | 0.394 | 0.039 | 10.077 | < 0.001*** | 0.222 | Supported |
| H11: SCC → SCCap | 0.128 | 0.051 | 2.530 | 0.011* | 0.018 | Supported |
| H12: SCEL → SCCap | 0.278 | 0.054 | 5.129 | < 0.001*** | 0.072 | Supported |
| H13: SCMP → SCCap | 0.350 | 0.043 | 8.055 | < 0.001*** | 0.131 | Supported |

Journal of Business Insight and Innovation
Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

*Note. β = standardized path coefficient; t-statistics based on 5,000 bootstrap subsamples; $f^2$ = Cohen's effect size. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.*

SCCap (β = 0.243), SCMP (β = 0.194) and SCEL (β = 0.187) can be seen as the three most powerful predictors out of the seven direct paths to Supply Chain Performance. The SCI → SCP (β = 0.060) and the SCC → SCP (β = 0.062) are not significant, which implies that integration and collaboration do not have a direct effect on performance but it has an indirect effect. The SCC, SCEL and SCMP to SCI and SCCap directions are all very important ($p < 0.05$ or greater) and SCMP is the most important antecedent of both mediators (β = 0.394 to SCI; 0.350 to SCCap). The largest $f^2$ in the model is SCMP → SCI ($f^2 = 0.222$), indicating a large effect size by Cohen's (1988) benchmarks ($f^2 \geq 0.15$ is medium, ≥ 0.35 is large).

**4.3.3 Indirect (Mediation) Effects.** The specific indirect testing of mediation hypothesis (H14-H19) is reported in Table 7. The presence of indirect effect is statistically significant with the support of mediation is supported by the bootstrap-based 95% bias-corrected confidence interval that does not include zero (Hair et al., 2021).

The indirect effect of SCC on SCP via SCCap is significant (β = 0.031, t = 2.294, p = 0.022), supporting H17. The impact of SCEL on SCP through SCCap is large and significant (β = 0.068, t = 3.660, p = 0.001), which proves H18. The strongest mediation effect is SCMP → SCCap → SCP (β = 0.085, t = 4.725, $p < 0.001$), supporting H19. By contrast, none of the indirect paths through SCI achieved statistical significance: SCC → SCI → SCP (β = 0.014, p = 0.261), SCEL → SCI → SCP (β = 0.016, p = 0.244), and SCMP → SCI → SCP (β = 0.024, p = 0.239), failing to support H14, H15, and H16. These findings affirm that SCCap is the most predominant mediating factor in the model, and that SCI does not mediate the effects of antecedents to SCP.

**Table 3.**

*Specific Indirect Effects (Mediation Results)*

| Indirect Path | β (Indirect) | t | p | Decision |
|---|---|---|---|---|
| H14: SCC → SCI → SCP | 0.014 | 1.125 | 0.261 | Not Supported |
| H15: SCEL → SCI → SCP | 0.016 | 1.166 | 0.244 | Not Supported |
| H16: SCMP → SCI → SCP | 0.024 | 1.177 | 0.239 | Not Supported |
| H17: SCC → SCCap → SCP | 0.031 | 2.294 | 0.022* | Supported |
| H18: SCEL → SCCap → SCP | 0.068 | 3.660 | < 0.001*** | Supported |
| H19: SCMP → SCCap → SCP | 0.085 | 4.725 | < 0.001*** | Supported |

Note. Indirect effects estimated via 5,000 bootstrap subsamples. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Supply Chain Capabilities (SCCap) turns out to be the most prevalent mediating mechanism: all indirect effects via SCCap are statistically significant, with the largest coefficient (β= 0.085, $p < 0.001$) being SCMP → SCCap →SCP. In comparison, all the three indirect effects through SCI are no significant ($p > 0.23$) which implies that integration by itself does not turn supply chain practices, ethical leadership, and collaboration into performance without the capability bridge. This trend of findings indicates that integration can be a facilitator of capability building, but not a pathway to performance in this sample.

**4.4 Moderation Analysis**

The results of Table 8 indicate the moderation effects of AIBDA and SCA on the SCI-SCP and SCCap-SCP relationships that were estimated using the product-indicator method of SmartPLS 4.

The interaction AIBDA × SCCap on SCP yields β = 0.023 (t = 0.515, p = 0.607), failing to support H20. The interaction AIBDA × SCI on SCP yields β = −0.025 (t = 0.527, p = 0.598), failing to support H21. The interaction SCA × SCCap on SCP yields β = 0.065 (t = 1.240, p = 0.215), failing to support H22. The interaction SCA × SCI on SCP yields β = −0.039 (t = 0.815, p = 0.415), failing to support H23. All the four terms of interaction are not statistically significant (all $p > 0.05$), which means that the moderating variables of AIBDA and SCA to the SCI-SCP and SCCap-SCP relationships are not supported in this sample. The $f^2$ values are all realized to be close to zero (≤ 0.006) indicating insignificant interaction effects.

Journal of Business Insight and Innovation
Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

**Table 4.**

*Moderation Effects (Interaction Terms)*

| Hypothesis / Interaction | β | t | p | f² | Decision |
|---|---|---|---|---|---|
| H20: AIBDA × SCCap → SCP | 0.023 | 0.515 | 0.607 | 0.001 | Not Supported |
| H21: AIBDA × SCI → SCP | −0.025 | 0.527 | 0.598 | 0.001 | Not Supported |
| H22: SCA × SCCap → SCP | 0.065 | 1.240 | 0.215 | 0.006 | Not Supported |
| H23: SCA × SCI → SCP | −0.039 | 0.815 | 0.415 | 0.002 | Not Supported |

*Note. Interaction terms estimated using the product-indicator approach in SmartPLS 4. *p < 0.05.*

The four terms of interaction are all non-significant. The biggest interaction (SCA × SCCap, β = 0.065) is nearly significant without being significant, and the interactions based on AIBDA are practically null. These findings indicate that AIBDA and SCA are direct and additive predictors of SCP as opposed to being a boundary condition that enhances or attenuates the effects of SCI or SCCap on performance

## 5. Discussion

This chapter puts the empirical results presented in Chapter 4 into the perspective of the theoretical background and the existing literature discussed in Chapter 2. The three sets of hypotheses tested, direct effects, mediation effects, and moderation effects, are discussed.

### *5.1 AI Big Data Capabilities and Supply Chain Performance*

*T*he observation that AIBDA is a positive and significant predictor of SCP (β = 0.125, p < 0.001) is consistent with the accumulating amount of research indicating that digital intelligence capabilities are related to high-quality supply chain performance (Dubey et al., 2022; Fosso Wamba et al., 2020). AIBDA allows organizations to work with high volumes of real-time data to improve the accuracy of demand forecasting, supplier performance monitoring, and optimization of logistics. Similar results were provided by Queiroz et al. (2021), who also proved that the more developed the big data analytics capabilities of organizations, the higher their operational performances. The present results add to the literature on the AIBDA by confirming its direct value in relation to SCP in a multi-construct model where other established predictors are held constant simultaneously.

### *5.2 Supply Chain Agility and Supply Chain Performance*

A strong correlation between supply chain agility and SCP (β= 0.154, p < 0.001) supports the claim that it is a dynamic capability that assists organizations to maintain performance amid demand variability and supply uncertainty. Hohenstein et al. (2015) determined that agile supply chains have better recovery performance following disruptions. Agility performance relevance is especially salient in the post-pandemic business environment, which is marked by global supply chain shocks (Ivanov and Dolgui, 2021). The effect size ($f^2$ = 0.037) is low, yet SCA accounts a significant portion of variance in SCP. This observation is in line with that of Arawati (2011) who determined that the product, volume, and new-product flexibility are joint predictors of supply chain and business performance. The managers then are advised to invest in agility by having flexible manufacturing system, diversified supplier base and responsive logistics capabilities.

### *5.3 Discussion of Mediation Effects*

The findings show that SCCap is a significant mediator between the SCEL → SCP (β= 0.068, p < 0.001) and SCMP and SCP (β =0.085, p < 0.001) and partially between SCC → SCP( β =0.031, p = 0.022). The findings demonstrate that the performance effects of ethical leadership, practices in management, and teamwork are achieved in part because of the development of supply chain capabilities. The strongest mediation effect in the model is the mediation of SCMP → SCCap → SCP (β = 0.085). This means that the performance advantages of advanced supplier management, supplier selection based on quality, and supplier relationship development that is long-run in nature are, in part, attained due to the capability development that the practices bring about. Evidence in support of the mentioned is provided by Rajaguru and Matanda (2019) and Madhiyarsi and Nambirajan (2015), who have revealed that management practices improve capabilities, which subsequently forecast performance. Of management interest is the direct implication of this finding:

the investments of SCMP may not necessarily produce the greatest performance returns unless combined with deliberate capability building.

Unexpectedly, SCI does not play an important role in all the three indirect effects considered (SCC→ SCI→ SCP, SCEL→ SCI→ SCP, SCMP→ SCI→ SCP). This null mediation finding can be attributed to the non-significant direct effect of SCI on SCP: with a weak relationship between the distal outcome and the mediator, a null mediation is mathematically constrained irrespective of the strength of the antecedent-mediator relationships (Hair et al., 2021). The strong correlation of SCMP, SCEL, and SCC with SCI (β = 0.394, 0.257, and 0.238, respectively) confirms the fact that the mentioned antecedents have a positive effect on integration, which, in this case, does not directly result in SCP.

### *5.4 Discussion of Moderation Effects*

Moderation hypotheses (H2O-H23) of the study were not proved. The SCI, SCCap are not significantly moderated by AIBDA –SCA, nor the SCCap –SCP. These can be intriguing null results which should be interpreted closely. First, the findings imply that AIBDA and SCA can be used as primary-effect predictors instead of being closed-end conditions of integration- or capability-performance associations. Both AIBDA and SCA have substantial direct impacts on SCP, suggesting that they additive contributions to performance and not an amplification of the impact of integration or capabilities. This aligns with the perspective that AI big data and agility are core digital and organizational assets, which directly cause performance regardless of the degree of SCI or SCCap.

## 6. Conclusion and Recommendations

The paper has explored an inclusive model of the supply chain performance that incorporates AI Big Data Capabilities and Supply Chain Agility with traditional constructs of the supply chain in a PLS-SEM model. According to the results of the analysis of 380 supply chain professionals conducted with the help of SmartPLS 4 and 5,000 bootstrap subsamples, it can be concluded that AIBDA (β = 0.125), SCA (β = 0.154), SCEL (β = 0.187), SCMP (β = 0.194), and SCCap (β = 0.243). The model is very explanatory with 64.7% of the variance in SCP explained in the model.

The strongest predictor of SCI (SCMP β = 0.394) and SCCap (SCMP β = 0.350) among the antecedents of the mediating variables is SCMP. SCEL is the second-strongest predictor of SCCap (β = 0.278) and SCI (β = 0.257), and SCC is the third (β = 0.128 to SCCap; β = 0.238 to SCI). SCCap turns out to be the hegemony mediating mechanism, relaying the impacts of SCEL and SCMP and partly that of SCC to SCP. Although it has been strongly predicted by all the three antecedents, SCI does not mediate any of the indirect correlations to SCP. The moderation hypotheses are rejected; the role of AIBDA and SCA as direct performance drivers and none as a boundary condition on the capability-performance and integration-performance relationships are rejected.

### *6.1 Limitations and Future Research Directions*

There are several limitations of this study. First, the cross-sectional type of research does not allow making causal conclusions and studying dynamic relationships during a period. Longitudinal designs would offer more solid evidence of causal mechanisms and possibly look at the effect of the adoption patterns of AIBDA on supply chain performance over time. Second, the convenience and snowball sampling are practical and are frequently used in supply chain research but restrict the extrapolation of the results to larger groups of people. The probability sampling should be utilized in the future studies in well-established industries to allow more representative conclusions.

Third, the non-significant moderation results could be due to the similarity of the samples and limited statistical power to identify small interactions. Further studies must also be able to test the moderation hypotheses with larger samples or experimental designs with intentionally different levels of AIBDA adoption. Fourth, the paper considers the collaboration of the supply chain as a unidimensional construct. Further studies might consider breaking down SCC into different types (e.g., information sharing, joint planning, co-investment) and how each collaborative activity correlates most with SCI, SCCap and SCP.

**Author Contributions**

Journal of Business Insight and Innovation
Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

All authors participated in ideation, development, and writing the manuscript. All authors read and approved the final manuscript.

**Conflict of Interest Statement**

The authors declare that there is no conflict of interest regarding the publication of this article.

**Funding Statement**

The authors did not receive financial support from any funding agency or external organization for the research, authorship, or publication of this article.

**Informed Consent**

Informed consent was obtained from all participants prior to data collection. Participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without any consequences. The confidentiality and anonymity of respondents were guaranteed throughout the research process.

**Data Availability**

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request. The SmartPLS output files, including measurement and structural model results, can be shared for verification and further research purposes. Due to privacy and confidentiality agreements with participants, raw survey data may not be publicly distributed but can be accessed through the corresponding author with appropriate data use agreements. The authors are committed to transparency and will provide detailed methodological information and analysis protocols upon request.

**References**

Akhavan, P., & Philsoophian, M. (2023). Improving of supply chain collaboration and performance by using blockchain technology as a mediating role and resilience as a moderating variable. Journal of the Knowledge Economy, 14(4), 4561–4582. https://doi.org/10.1007/s13132-022-01085-9

Alabdullah, T. T. Y., & AL-Qallaf, A. J. M. (2023). The impact of ethical leadership on firm performance in Bahrain: Organizational culture as a mediator. CASHFLOW: Current Advanced Research on Sharia Finance and Economic Worldwide, 2(4), 482–498. https://doi.org/10.55047/cashflow.v2i4.736

Al-Doori, J. A. (2019). The impact of supply chain collaboration on performance in automotive industry: Empirical evidence. Journal of Industrial Engineering and Management, 12(2), 241–253. https://doi.org/10.3926/jiem.2835

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 103(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Anderson, J., & Thomas, R. (2024). Supply chain integration: Enhancing collaboration for competitive advantage. EasyChair Preprints. https://easychair.org/publications/preprint_download/GtvR

Arawati, A. (2011). Supply chain management, supply chain flexibility and business performance. Journal of Global Strategic Management, 9(1), 134–145. https://www.acarindex.com/dosyalar/makale/acarindex-1423906231.pdf

Asamoah, D., Agyei-Owusu, B., Andoh-Baidoo, F. K., & Ayaburi, E. (2021). Inter-organizational systems use and supply chain performance: Mediating role of supply chain management capabilities. International Journal of Information Management, 58, 102195. https://doi.org/10.1016/j.ijinfomgt.2020.102195

Aslam, H., Blome, C., Roscoe, S., & Azhar, T. M. (2018). Dynamic supply chain capabilities: How market sensing, supply chain agility and adaptability affect supply chain ambidexterity. International Journal of Operations & Production Management, 38(12), 2266–2285. https://doi.org/10.1108/IJOPM-09-2017-0555

Baah, C., Acquah, I. S. K., & Ofori, D. (2022). Exploring the influence of supply chain collaboration on supply chain visibility, stakeholder trust, environmental and financial performances: A partial least square approach. Benchmarking: An International Journal, 29(1), 172–193. https://doi.org/10.1108/BIJ-10-2020-0519

Bag, S., & Rahman, M. S. (2023). The role of capabilities in shaping sustainable supply chain flexibility and enhancing circular economy-target performance. Supply Chain Management: An International Journal, 28(1), 162–178. https://doi.org/10.1108/SCM-05-2021-0246

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Bhatti, A. A., Bhatti, S. H., & Saif, S. (2022). A moderated-mediation analysis of supply chain efficiency, flexibility, integration, and risk management. Pakistan Business Review, 24(3). https://doi.org/10.22555/pbr.v24i3.770

Cahyono, Y., Purwoko, D., Koho, I., Setiani, A., Supendi, S., Setyoko, P., Sosiady, M., & Wijoyo, H. (2023). The role of supply chain management practices on competitive advantage and performance of halal agroindustry SMEs. Uncertain Supply Chain Management, 11(1), 153–160. http://dx.doi.org/10.5267/j.uscm.2022.10.012

Cao, M., & Zhang, Q. (2011). Supply chain collaboration: Impact on collaborative advantage and firm performance. Journal of Operations Management, 29(3), 163–180. https://doi.org/10.1016/j.jom.2010.12.008

Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: Moving toward new theory. International Journal of Physical Distribution & Logistics Management, 38(5), 360–387. https://doi.org/10.1108/09600030810882816

Cheng, Y., Farooq, S., & Jajja, M. S. S. (2021). Does plant role moderate relationship between internal manufacturing network integration, external supply chain integration, operational performance in manufacturing network? Journal of Manufacturing Technology Management, 32(6), 1267–1289. https://doi.org/10.1108/JMTM-06-2019-0237

Chopra, S., & Meindl, P. (2022). Supply chain management: Strategy, planning, and operation (7th ed.). Pearson Education.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.

Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications.

Cui, L., Wu, H., Wu, L., Kumar, A., & Tan, K. H. (2023). Investigating the relationship between digital technologies, supply chain integration and firm resilience in the context of COVID-19. Annals of Operations Research, 327(2), 825–853. https://doi.org/10.1007/s10479-022-04735-y

Dash, A., Samantray, B. S., Reddy, K. H. K., Amin, F., & Mishra, S. K. (2026). *A secure framework for smart waste management using IoT, machine learning, and blockchain*. In *2026 1st International Conference on Emerging Trends in Advancements and Applications of Computational Intelligence Techniques (ETAACT)* (pp. 1-7). IEEE. https://doi.org/10.1109/ETAACT69135.2026.11541497

Delic, M., & Eyers, D. R. (2020). The effect of additive manufacturing adoption on supply chain flexibility and performance: An empirical analysis from the automotive industry. International Journal of Production Economics, 228, 107689. https://doi.org/10.1016/j.ijpe.2020.107689

Deshpande, A. (2012). Supply chain management dimensions, supply chain performance and organizational performance: An integrated framework. International Journal of Business and Management, 7(8), 2–19. http://dx.doi.org/10.5539/ijbm.v7n8p2

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., Foropon, C., & Papadopoulos, T. (2023). Dynamic digital capabilities and supply chain resilience: The role of government effectiveness. International Journal of Production Economics, 258, 108790. https://doi.org/10.1016/j.ijpe.2023.108790

Dubey, R., Gunasekaran, A., Childe, S. J., Roubaud, D., Wamba, S. F., Giannakis, M., & Foropon, C. (2022). Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. International Journal of Production Economics, 251, 108535. https://doi.org/10.1016/j.ijpe.2022.108535

Flynn, B. B., Huo, B., & Zhao, X. (2010). The impact of supply chain integration on performance: A contingency and configuration approach. Journal of Operations Management, 28(1), 58–71. https://doi.org/10.1016/j.jom.2009.06.001

Fosso Wamba, S., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2020). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Freeman, R. E. (1984). Strategic management: A stakeholder approach. Pitman.

Friday, D., Savage, D. A., Melnyk, S. A., Harrison, N., Ryan, S., & Wechtler, H. (2021). A collaborative approach to maintaining optimal inventory and mitigating stockout risks during a pandemic. Journal of Humanitarian Logistics and Supply Chain Management, 11(2), 248–271. https://doi.org/10.1108/JHLSCM-07-2020-0061

Ghaleb, M. M. S., & Alshiha, F. A. (2023). Effects of supply chain management practices on organizational supply chain performance: A mediated model. International Journal of Construction Supply Chain Management, 13(2), 1–22. https://doi.org/10.14424/ijcscm2023230101

Gligor, D., Feizabadi, J., Russo, I., Win, M. A., & Whiteside, M. (2019). An examination of logistics versus supply chain management foundations. International Journal of Logistics Management, 30(4), 1142–1167. https://doi.org/10.1108/IJLM-06-2018-0155

Gosling, J., Jia, F., Gong, Y., & Brown, S. (2016). The role of supply chain leadership in the learning of sustainable practice: Toward an integrated framework. Journal of Cleaner Production, 137, 1458–1469. https://doi.org/10.1016/j.jclepro.2014.10.029

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2021). When to use and how to report results of PLS-SEM (2nd ed.). European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hameed, Z., Naeem, R. M., Mishra, P., Chotia, V., & Malibari, A. (2023). Ethical leadership and environmental performance: The role of green IT capital, green technology innovation, and technological orientation. Technological Forecasting and Social Change, 194, 122739. https://doi.org/10.1016/j.techfore.2023.122739

Hohenstein, N. O., Feisel, E., Hartmann, E., & Giunipero, L. (2015). Research on the phenomenon of supply chain resilience: A systematic review and paths for further investigation. International Journal of Physical Distribution & Logistics Management, 45(1/2), 90–117. https://doi.org/10.1108/IJPDLM-05-2013-0128

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1–55. https://doi.org/10.1080/10705519909540118

Huo, B., Gu, M., & Wang, Z. (2018). Supply chain flexibility concepts, dimensions and outcomes: An organisational capability perspective. International Journal of Production Research, 56(17), 5883–5903. https://doi.org/10.1080/00207543.2018.1456694

Ibrahim, S. B., & Hamid, A. A. (2014). Supply chain management practices and supply chain performance effectiveness. International Journal of Science and Research, 3(8), 187–195.

Iram, S., Rafiq-uz-Zaman, M., & Malik, N. (2025). Advancing strategic decision-making through artificial intelligence: A critical review of methods, applications, barriers, and emerging trends. Contemporary Journal of Social Science Review, 3(3), 3025–3044. https://doi.org/10.63878/cjssr.v3i3.2289

Ivanov, D., & Dolgui, A. (2021). OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications. International Journal of Production Economics, 232, 107921. https://doi.org/10.1016/j.ijpe.2020.107921

Jahanbakhsh Javid, N., & Amini, M. (2023). Evaluating the effect of supply chain management practice on implementation of halal agroindustry and competitive advantage for small and medium enterprises. International Journal of Computer Science and Information Technology, 15, 8997–9008. https://ssrn.com/abstract=4348136

Khan, A., Amin, F., & Imtiaz, U. (2026). *SecurePulse-GRID: Trust-aware predictive load balancing and rapid cyber containment in distributed smart microgrids*. *The Asian Bulletin of Big Data Management, 6*(1), 697-708. https://doi.org/10.62019/smxj7m37

Khan, A., Imtiaz, U., & Amin, F. (2025). *Honeytoken-augmented AI model for insider threat detection using cyber deception and isolation forest*. *Kashf Journal of Multidisciplinary Research, 2*(9), 294-313. https://doi.org/10.71146/kjmr625

Karmaker, C. L., Al Aziz, R., Ahmed, T., Misbauddin, S., & Moktadir, M. A. (2023). Impact of industry 4.0 technologies on sustainable supply chain performance: The mediating role of green supply chain management practices and circular economy. Journal of Cleaner Production, 419, 138249. https://doi.org/10.1016/j.jclepro.2023.138249

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. Educational and Psychological Measurement, 30(3), 607–610. https://doi.org/10.1177/001316447003000308

Lamba, K., & Singh, S. P. (2017). Big data in operations and supply chain management: Current trends and future perspectives. Production Planning & Control, 28(11–12), 877–890. https://doi.org/10.1080/09537287.2017.1336533

Liao, S. H., Hu, D. C., & Shih, Y. S. (2021). Supply chain collaboration and innovation capability: The moderated mediating role of quality management. Total Quality Management & Business Excellence, 32(3–4), 298–316. https://doi.org/10.1080/14783363.2018.1552515

Madhiyarsi, S., & Nambirajan, T. (2015). Marketing capability of farmers in agribusiness: A link between supply chain management components and performance. ZENITH International Journal of Business Economics & Management Research, 5(10), 1–14.

Malik, N., & Rafiq-uz-Zaman, M. (2025). The role of artificial intelligence in educational leadership and management for service quality in Pakistani higher education: A narrative review. Journal of Applied Linguistics and TESOL (JALT), 8(2), 1–18. https://doi.org/10.63878/jalt2080

Mofokeng, T. M., & Chinomona, R. (2019). Supply chain partnership, supply chain collaboration and supply chain integration as the antecedents of supply chain performance. South African Journal of Business Management, 50(1), 1–10. https://hdl.handle.net/10520/EJC-14cea8be2a

Oubrahim, I., Sefiani, N., & Happonen, A. (2023). The influence of digital transformation and supply chain integration on overall sustainable supply chain performance: An empirical analysis from manufacturing companies in Morocco. Energies, 16(2), 1004. https://doi.org/10.3390/en16021004

Piprani, A. Z., Mohezar, S., & Jaafar, N. I. (2020). Supply chain integration and supply chain performance: The mediating role of supply chain resilience. International Journal of Supply Chain Management, 9(3), 58–73.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Qrunfleh, S., & Tarafdar, M. (2014). Supply chain information systems strategy: Impacts on supply chain performance and firm performance. International Journal of Production Economics, 147, 340–350. https://doi.org/10.1016/j.ijpe.2012.09.018

Queiroz, M. M., Wamba, S. F., Machado, M. C., & Telles, R. (2021). Smart production systems drivers for business process management improvement: An empirical investigation. Business Process Management Journal, 27(5), 1525–1541. https://doi.org/10.1108/BPMJ-06-2020-0264

Rafiq-uz-Zaman, M. (2025a). Artificial intelligence-driven human resource management: A strategic review of workforce productivity and organizational performance. Al-Aasar, 2(4), 1–24. https://doi.org/10.63878/aaj1711

Rafiq-uz-Zaman, M. (2025b). Between Adoption and Ambiguity: Navigating the AI Policy Vacuum in Pakistani Higher Education. Research Journal for Social Affairs, 3(6), 877–885. https://doi.org/10.71317/RJSA.003.06.0523

Rafiq-uz-Zaman, M., & Ameer, A. (2025). Learning analytics and educational data mining: Transforming student success in higher education. The Study of Religion and History, 3(3), 1–36. https://doi.org/10.63163/srh434

Rajaguru, R., & Matanda, M. J. (2019). Role of compatibility and supply chain process integration in facilitating supply chain capabilities and organizational performance. Supply Chain Management: An International Journal, 24(2), 301–316. https://doi.org/10.1108/SCM-05-2017-0187

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). SmartPLS 4. SmartPLS. https://www.smartpls.com

Ruzo-Sanmartín, E., Abousamra, A. A., Otero-Neira, C., & Svensson, G. (2023). The impact of the relationship commitment and customer integration on supply chain performance. Journal of Business & Industrial Marketing, 38(4), 943–957. https://doi.org/10.1108/JBIM-07-2021-0349

Salah, A., Çağlar, D., & Zoubi, K. (2023). The impact of production and operations management practices in improving organizational performance: The mediating role of supply chain integration. Sustainability, 15(20), 15140. https://doi.org/10.3390/su152015140

Saragih, J., Tarigan, A., Silalahi, E. F., Wardati, J., & Pratama, I. (2020). Supply chain operational capability and supply chain operational performance: Does the supply chain management and supply chain integration matters. International Journal of Supply Chain Management, 9(4), 1222–1229.

Sharma, M., Luthra, S., Joshi, S., Kumar, A., & Jain, A. (2023). Green logistics driven circular practices adoption in industry 4.0 era: A moderating effect of institution pressure and supply chain flexibility. Journal of Cleaner Production, 383, 135284. https://doi.org/10.1016/j.jclepro.2022.135284

Soosay, C. A., & Hyland, P. (2015). A decade of supply chain collaboration and directions for future research. Supply Chain Management: An International Journal, 20(6), 613–630. https://doi.org/10.1108/SCM-06-2015-0217

Sundram, V. P. K., Chandran, V., & Bhatti, M. A. (2016). Supply chain practices and performance: The indirect effects of supply chain integration. Benchmarking: An International Journal, 23(6), 1445–1471. https://doi.org/10.1108/BIJ-03-2015-0023

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Tiwari, A. K., Tiwari, A., & Samuel, C. (2015). Supply chain flexibility: A comprehensive review. Management Research Review, 38(7), 767–792. https://doi.org/10.1108/MRR-08-2013-0194

Truong, H. Q., Sameiro, M., Fernandes, A. C., Sampaio, P., Duong, B. A. T., Duong, H. H., & Vilhenac, E. (2017). Supply chain management practices and firms' operational performance. International Journal of Quality & Reliability Management, 34(2), 176–193. https://doi.org/10.1108/IJQRM-05-2015-0072

Wang, J., & Feng, T. (2023). Supply chain ethical leadership and green supply chain integration: A moderated mediation analysis. International Journal of Logistics Research and Applications, 26(9), 1145–1171. https://doi.org/10.1080/13675567.2021.2022640

Wernerfelt, B. (1984). A resource-based view of the firm. Strategic Management Journal, 5(2), 171–180. https://doi.org/10.1002/smj.4250050207

Yang, J., Xie, H., Yu, G., & Liu, M. (2021). Antecedents and consequences of supply chain risk management capabilities: An investigation in the post-coronavirus crisis. International Journal of Production Research, 59(5), 1573–1585. https://doi.org/10.1080/00207543.2020.1856958

Yousefi, S., & Tosarkani, B. M. (2023). Exploring the role of blockchain technology in improving sustainable supply chain performance: A system-analysis-based approach. IEEE Transactions on Engineering Management. https://doi.org/10.1109/TEM.2022.3231217

Zhang, W., Siyal, S., Riaz, S., Ahmad, R., Hilmi, M. F., & Li, Z. (2023). Data security, customer trust and intention for adoption of fintech services: An empirical analysis from commercial bank users in Pakistan. SAGE Open, 13(3). https://doi.org/10.1177/21582440231181388