

# The Impacts of Big Data Analytics and Artificial Intelligence on Supply Chain Strategic Performance: An Empirical Study

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## ABSTRACT

The present paper investigates the impacts of Big Data Analytics and Artificial Intelligence (BDA-AI) technologies on the Supply Chain Strategic Performance (SCSP), focusing on reliability, environmental and social performance. It also examines the moderating role of Organizational Culture (OC). Using the Supply Chain Operations Reference (SCOR) model and Dynamic Capabilities Theory (DCT) as theoretical frameworks, the study employed a structured questionnaire distributed to Supply Chain (SC) professionals across various industrial sectors essentially based in Morocco. In fact, a total of 200 professionals were initially targeted using the virtual snowball sampling method. That is, 97 survey responses were effectively collected and then analyzed. Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM). The obtained results demonstrate that BDA-AI technologies positively and significantly influence Supply Chain Reliability (SCRE). However, while a positive impact on Environmental Performance (ENPER) and Social Performance (SOPER) was observed, it was not statistically significant. Moreover, OC significantly moderates the effect of BDA-AI on SCRE. To sum up, this paper contributes to the existing literature by providing empirical evidence of the strategic benefits of BDA powered by AI in Supply Chain Management (SCM). Furthermore, it sheds light on the importance of OC as a critical factor in realizing the full potential of such technologies in digital transformation context.

**Keywords:** *artificial intelligence, big data analytics, dynamic capabilities theory, organizational culture, PLS-SEM, supply chain strategic performance*

## 1. INTRODUCTION

In an increasingly globalized and digitized industrial environment, SCs face growing challenges in terms of complexity, responsiveness, and adaptability to rapidly changing market condition. As companies operate across multiple regions and time zones, the need for real-time visibility, seamless coordination, and efficient resource allocation has become paramount. SC networks are no longer linear but are evolving into intricate, interconnected systems that require a higher level of precision and agility to manage effectively (Dubey *et al.*, 2019a).

In this context, traditional approaches to SCM often fall short in addressing the ever-growing volume of data generated from diverse sources, ranging from customer transactions to IoT-enabled devices across logistics operations. Emerging technologies such as BDA-AI offer transformative solutions by leveraging advanced algorithms and computational power to manage and analyze these vast data streams. BDA enables organizations to handle large, unstructured datasets, providing deeper insights into patterns, trends, and anomalies that were previously undetectable using conventional methods (Wamba *et al.*, 2015). AI, on the other hand, augments decision-making processes by automating complex tasks such as demand forecasting, inventory management, and predictive maintenance, ensuring that SC processes are not only optimized but also predictive and proactive (Gunasekaran *et al.*, 2017).

Together, BDA and AI technologies enable SCs to move from reactive models to predictive and prescriptive frameworks. This shift allows for real-time decision-making, enhancing the responsiveness of SCs to sudden disruptions, such as fluctuations in demand or unforeseen delays. For example, AI-driven algorithms can recommend adjustments in inventory levels or reroute shipments based on real-time data, thereby reducing lead times and minimizing operational

costs. Similarly, BDA can track customer preferences and predict market trends, allowing for more accurate demand planning and reducing stockouts or overstocking. According to Bag *et al.* (2020b), BDA management capabilities significantly improve green product innovation and sustainable SC outcomes. Additionally, BDA talent capabilities contribute to employee development and sustainability, while innovation and learning performance play a key role in enhancing SCSP.

Moreover, these technologies facilitate continuous process optimization by fostering a data-driven culture within organizations, encouraging a shift toward proactive strategies rather than relying on historical data or manual interventions. By integrating BDA-AI into SCM, companies can enhance their competitive edge, increase operational efficiency, and improve SCSP. As these technologies continue to evolve, they are likely to play an even more critical role in shaping the future of SCs, providing businesses with the tools to navigate the complexities of the global market while maintaining a trans of service and efficiency (Gunasekaran *et al.*, 2017).

Furthermore, BDA-AI can be used as powerful technological tools for facilitating the decision-making process by automating the most complex tasks throughout the SC, which ensures an efficient and proactive management of induced logistical activities (Gunasekaran *et al.*, 2017). These technologies enable firms to anticipate market fluctuations and operational disruptions, allowing for a transition from reactive to anticipatory SC strategies. The integration of BDA-AI into SCM holds considerable potential to enhance key performance dimensions. Notably, research highlights improvements in reliability ensuring consistent and dependable performance (Wang *et al.*, 2020), in responsiveness enabling swift reactions to market changes and disruptions (Zhang *et al.*, 2017), and in agility allowing rapid adaptation to unforeseen events (Gupta *et al.*, 2020). However, while substantial progress has been made in understanding the technological impact on operational outcomes, the influence of BDA-AI on the broader performance dimensions, particularly ENPER and SOPER, remains underexplored. Recent studies suggest that these technologies could contribute to sustainability initiatives by optimizing resource usage, reducing waste, and improving transparency in social practices (Belhadi *et al.*, 2021). Nonetheless, empirical evidence remains sparse, and there is a need for further investigation into how AI and BDA can support SCs in meeting sustainability goals without compromising operational efficiency.

Despite the growing body of literature on BDA-AI in SCs, their comprehensive impact on SCSP, especially when measured through established frameworks such as the SCOR model, is not yet fully understood. The SCOR model offers a robust and structured approach to evaluating SCP across eight key dimensions: reliability, responsiveness, agility, cost, profit, asset management efficiency, environmental, and social. However, the specific influence of AI and BDA on these dimensions, particularly from a strategic viewpoint, requires more empirical analysis (Dubey *et al.*, 2021). Furthermore, the role of OC as a potential moderator in this relationship is under-researched. Studies have suggested that OC, particularly in terms of openness to innovation, collaboration, and data-driven decision-making, could

significantly influence the success of AI and BDA implementations in SCs contexts (Dubey *et al.*, 2019c).

This study aims to address these research gaps by investigating the impacts of BDA-AI on the SCSP, specifically focusing on three key SCOR performance metrics: SCRE, ENPER, and SOPER. Additionally, we explore the moderating role of OC on the relationship between these advanced technologies and SCRE (Roden & Lawson, 2014). That is, understanding how cultural factors influence the success of AI and BDA implementations will provide deeper insights into the organizational readiness required for technology-driven SC transformations.

The findings of this study offer critical insights for SC managers and decision-makers on how to effectively leverage BDA-AI to enhance SCSP across multiple dimensions. Beyond technological investments, the research highlights the importance of cultivating a supportive OC that aligns with the adoption of advanced digital technologies. The study also emphasizes the relevance of human resource management strategies that foster digital skills and organizational flexibility to maximize the full potential of BDA-AI implementations (Hazen *et al.*, 2016).

The remainder of this paper is organized as follows. We first present the theoretical framework underpinning this research while justifying its choice based on the existing literature. We then formulate the starting hypotheses of our study. We next provide a detailed description of the research methodology, including data collection and analytical techniques. The results of the statistical analysis are then presented and discussed in depth, considering both theoretical and practical implications with a mention of the main limitations. Finally, we conclude by summarizing the key findings and giving some future research directions. The body of the paper should be anonymous and provides no attributes of authors' identity. The Introduction should emphasize the research background and motivation, the research gap, and the objectives of the study. Author(s) should be able to be positioning the current paper with the existing literature in the field. Therefore, the introduction should be well connected to the existing literature.

## 2. LITERATURE REVIEW

### 2.1 DCT and the SCOR Model for SCSP

DCT and the SCOR model offer complementary approaches for analyzing SCP, particularly in the context of emerging technologies such as BDA and AI. DCT provides a robust theoretical framework to understand how firms can develop, integrate, and reconfigure resources to adapt to environmental changes and maintain a sustainable competitive advantage (Teece *et al.*, 1997). It has been extensively adopted to explore organizational capabilities in various fields, including SCM (Eisenhardt & Martin, 2000). Studies have demonstrated how dynamic capabilities (DC) can enhance SCP, particularly through the adoption of BDA. For instance, Dubey *et al.* (2018) found that DC can moderate the effect of analytical capabilities on SCP, while Mishra *et al.* (2021) emphasized its importance in improving ecological and social dimensions of SCP through BDA adoption. For their part, Rehman *et al.* (2024) showed the interest of using DCT to illustrate the impact of BDA on the green SCP. In addition, Augier and Teece (2009) have

highlighted the role of DC in fostering innovation and competitiveness, reinforcing their strategic relevance.

The choice of DCT for this study is justified by the need to understand the direct effects of BDA-AI adoption on SCP and how these effects can be influenced by OC, particularly on SCRE. Aspects such as innovation, transparency, investment in innovative technologies, and open communication are key elements of OC that can moderate the impact of DC on reliability (Rashid *et al.*, 2025). By integrating these moderating variables, this study offers a more comprehensive view of the conditions under which DC can be optimized to improve the SCSP.

On the other hand, the SCOR model -developed by the SC Council- serves as a comprehensive framework for assessing and improving SCP across key performance measures: reliability, responsiveness, agility, cost, profit, asset management efficiency, or even environmental and social effects (Arzu Akyuz & Erman Erkan, 2010; Es-satty *et al.*, 2020; Lemghari *et al.*, 2019; Lima-Junior & Carpinetti, 2019). Its relevance is widely recognized in academic research and empirical studies for measuring logistics performance (Aem-on *et al.*, 2024). That is, numerous studies have employed the SCOR model to evaluate the impact of emerging technologies like BDA-AI on SCP. For example, Persson and Araldi (2009) demonstrated how the SCOR model can align BDA-AI with SC strategic objectives, while Alshawabkeh *et al.* (2022) confirmed that BDA technologies can enhance SCP by using such a framework. In the same vein, Ziaee *et al.* (2023) achieved a study based on SCOR model to highlight benefits of BDA adoption for pharmaceutical SC in Australia.

In this study, the SCOR model is instrumental in providing a standardized approach for assessing the impact of BDA-AI technologies on SCSP, particularly regarding their potential to drive improvement within the industrial value chain. By combining the theoretical insights of DCT with the practical efficiency of the SCOR model, this study aims to deliver a comprehensive understanding of how BDA-AI adoption influences SCP, providing a more strategic and operationally focused analysis of SC dynamics.

## 2.2 Use of BDA-AI in SCs

The integration of BDA-AI technologies in SCs has transformed operations by enabling firms to process and analyze vast amounts of data from various sources (Darbanian *et al.*, 2024; Es-satty *et al.*, 2024). The types of data commonly processed include transactional data, financial data, inventory data, customer data, and supplier data (Dubey *et al.*, 2017). Unstructured data, such as customer reviews on social media, multimedia data, and textual data, are also used (Chen *et al.*, 2014). In addition, firms exploit semi-structured data like IoT sensor data and server logs, as well as temporal and geospatial data (Wang *et al.*, 2016).

Data analysis conducted in this context cover a wide range of techniques. Descriptive analysis is used to describe and interpret existing data, while predictive analysis helps forecast future trends and outcomes (Wamba *et al.*, 2015). Prescriptive analysis recommends specific actions based on descriptive and predictive analysis results, and real-time analysis enables instantaneous decision-making, which is crucial for SC responsiveness (Dubey *et al.*, 2017).

AI tools and techniques used in SCs include machine and deep learning, which enables systems to boost their performance automatically and autonomously by running smart algorithms on large datasets (Kusiak, 2017). Natural language processing (NLP) helps understand and generate human language, facilitating textual data analysis (Choi & Linton, 2011). Computer vision enables machines to interpret and understand images, which is useful for optimizing logistics operations, especially inventory management (Abosuliman & Almagrabi, 2021). Chatbots use AI to interact with users in real time (Huang *et al.*, 2017).

Studies have demonstrated the significant impact of these technologies on SCP (Riad *et al.*, 2024). Indeed, Dubey *et al.* (2019b) showed that predictive BDA can improve SC sustainability from an environmental and social perspective. Belhadi *et al.* (2024) investigated the AI capabilities to strengthen SC resilience.

## 3. CONCEPTUAL MODEL AND HYPOTHESIS

### 3.1 Conceptual Model

The proposed conceptual model incorporates hypothetical relationships among the variables studied: BDA-AI technologies, logistics performance defined by the SCOR model, and OC as a moderating variable. This framework allows for a comprehensive exploration of how DC, supported by an innovative OC, can enhance SCSP by adopting emerging technologies.

### 3.2 Development of Hypotheses

This section outlines the hypotheses related to the impact of BDA-AI technologies on SCSP, framed through the lens of DCT. This theory emphasizes an organization's ability to sense, seize, and transform opportunities in a rapidly changing environment. In the context of BDA-AI utilization, it provides a robust framework for understanding how organizations can leverage technological innovations to enhance SCSP, particularly SCRE, SOPER, and ENPER.

#### 3.2.1 Direct Effects of BDA-AI Technologies on SCSP

Strategic reliability refers to the ability of a SC to maintain consistent performance, minimizing disruptions and maximizing order accuracy and timeliness. The adoption of BDA-AI technologies equips organizations with advanced predictive and prescriptive analytics that enhance their ability to anticipate and mitigate disruptions, forecast demand fluctuations, and optimize SC operations. According to DCT, the capability to sense external threats and opportunities (e.g., demand changes, supply disruptions) is crucial to maintaining strategic reliability. BDA-AI enable organizations to enhance this sensing capability, allowing them to proactively address uncertainties and ensure operational continuity. Moreover, the seizing capability of BDA-AI allows firms to act on insights from real-time data, optimizing inventory management, order fulfillment, and logistics, thus contributing to enhanced reliability.

In addition, BDA-AI's role in dynamic decision-making and real-time adjustments aligns with DCT's emphasis on organizational agility, which is critical for maintaining SCRE under volatile conditions (Teece *et al.*, 1997). Thus, we hypothesize that BDA-AI technologies will positively influence strategic reliability by enhancing an

organization's responsiveness to internal and external challenges:

**Hypothesis 1 (H1):** BDA-AI positively and significantly impact SCORE.

ENPER refers to a SC's ability to reduce its ecological footprint by improving energy efficiency, reducing waste, and optimizing resource utilization. BDA-AI technologies, through advanced analytics and optimization algorithms, can help firms achieve these goals by improving the efficiency of operations such as inventory management, logistics, and production processes. By leveraging AI to optimize transportation routes, reduce energy consumption, and minimize waste generation, organizations can significantly lower their environmental impact.

DCT underscores the importance of sensing environmental challenges (e.g., carbon emissions, energy consumption) and seizing opportunities for environmental optimization (e.g., adopting green technologies). With BDA-AI, firms can develop a more sustainable SC by transforming their operations to align with environmental goals (Zhang *et al.*, 2017). Therefore, we hypothesize that the integration of BDA-AI technologies will positively affect ENPER by enabling more efficient use of resources and reducing the SC's ecological impact:

**Hypothesis 2 (H2):** BDA-AI has a positive and significant impact on the ENPER of the SC.

SOPER encompasses key elements such as fair labor practices, employee welfare, ethical sourcing, and corporate social responsibility. The adoption of BDA-AI technologies has the potential to improve these social dimensions by providing insights into SC operations that foster greater transparency and accountability. For instance, AI-powered tools can monitor and optimize labor conditions across the SC, ensuring compliance with ethical labor standards and promoting diversity and inclusion.

From a DCT perspective, the transforming capability of AI allows organizations to adapt their internal practices and workforce strategies in response to evolving social norms and regulatory pressures. Through AI-enhanced data analytics, firms can sense labor market trends and seize opportunities to improve employee engagement and well-being. By doing so, organizations can not only improve their SOPER but also align their practices with emerging societal expectations, thus reinforcing the strategic role of BDA-AI in fostering sustainability (Hazen *et al.*, 2016).

Thus, we hypothesize that BDA-AI will enhance SOPER by enabling firms to optimize their workforce management and ethical sourcing practices, leading to more sustainable and socially responsible SC operations:

**Hypothesis 3 (H3):** BDA-AI has a positive and significant impact on the SOPER of the SC.

### 3.2.2 Moderating Effect of OC on SCORE

The moderating role of OC is essential in determining how effectively BDA-AI technologies can be leveraged to enhance SCORE. OC influences how technology is adopted, implemented, and integrated into daily operations. Cultures that prioritize innovation, data-driven decision-making, and technological adaptability are better positioned to maximize the benefits of BDA-AI.

According to DCT, a culture that promotes openness to change and collaborative innovation strengthens organizations' detection, capture and transformation capabilities, which are which are critical for improving

SCORE. In firms with a culture that values technological integration and data transparency, BDA-AI can be utilized more effectively to anticipate disruptions and optimize operational processes. In contrast, companies with a rigid or siloed culture may struggle to fully capitalize on the potential of BDA-AI, leading to less reliable SCP.

Thus, we hypothesize that a supportive OC will consolidate the positive effects of BDA-AI on strategic reliability by fostering an environment that is conducive to continuous improvement and technological adoption.

**Hypothesis 4 (H4):** OC moderates the impact of BDA-AI on SCORE.

## 3.3 Research Design

A survey was used to collect data to test our research hypotheses. The questionnaire was pre-tested with three academics and three SC managers. Based on their feedback, we refined the wording to improve clarity and ensure that the survey length was appropriate. The final questionnaire was then ready for data collection. Our target sample consisted of organizations operating in the industrial sector. Thus, developing a psychometrically reliable survey instrument was the most crucial step.

### 3.3.1 Operationalization of Constructs

The survey instrument was developed by identifying measures from our literature review. All constructs used in our theoretical framework are operationalized as reflective constructs. The operationalization of each construct is presented in the following table (see Table 1).

### 3.3.2 Data Collection

This study aimed to assess the impact of BDA-AI technologies on SCSP across multiple industrial sectors. The target population comprised SC professionals from key industries, including aerospace, automotive, pharmaceuticals, electronics, energy, and chemicals. They were selected for their reliance on AI-driven data technologies in SCM, aligning closely with the study's objectives.

To ensure access to senior-level professionals with domain expertise, a snowball sampling technique was employed (Parker *et al.*, 2019). This method was particularly suitable for reaching high-ranking professionals, including SC managers, operations directors, logistics specialists, and IT experts, whose specialized knowledge was essential. The sampling process began with key informants identified through diverse professional networks (e.g., LinkedIn, industry-specific forums, industry-specific WhatsApp groups), based on their strategic roles, experience, and geographical distribution. These participants, drawn from firms across diverse sectors, were then encouraged to refer other qualified professionals within their networks, expanding the sample pool. This iterative process enabled access to a broader, more heterogeneous group, particularly those who might have been difficult to reach through conventional methods due to geographic or sectoral dispersion.

A structured questionnaire was developed using Google Forms (Bag *et al.*, 2020a). Strict confidentiality and anonymity were guaranteed to encourage participation, thus fostering trust and encouraging candid responses. A total of 200 potential respondents were identified through the snowball sampling process.

While no universal guideline exists for determining sample size saturation in snowball sampling (Saunders *et al.*, 2019), the final sample size was shaped by practical considerations, including time constraints, available resources, geographic factors, and logistical context. These elements were carefully balanced, ensuring that the sample size was robust enough to meet the study's objectives while remaining feasible within the given constraints. The study achieved a response rate of 48.5%, yielding 97 valid responses, emphasize that a sufficient sample size is essential for ensuring representativeness and statistical validity.

Although no specific thresholds are prescribed, specialized studies (Saunders *et al.*, 2019) suggest that the sample must adequately capture participant diversity to address the research questions. To ensure compliance with this recommendation, we consulted both statistical and academic experts. This collaborative approach enabled us to ensure that the collected data sufficiently reflected the diversity of professionals' perspectives and practices, confirming that the dataset was both comprehensive and representative for the study's objectives.

**Table 1** Operationalization of Constructs

Construct	Description	References
<b>Use of BDA-AI</b>		
Use_BDA_AI1	The use of advanced methods to analyze large amounts of data to identify trends and useful information in the SC.	Belhadi <i>et al.</i> (2024) Cannas <i>et al.</i> (2024) Dubey <i>et al.</i> (2018)
Use_BDA_AI2	Utilization of technologies capable of simulating human intelligence, such as natural language processing, pattern recognition, and recommender systems	Gunasekaran <i>et al.</i> (2017) Ivanov & Dolgui (2021) Wamba <i>et al.</i> (2024)
<b>SCRE (Supply chain reliability)</b>		
Reliability1	Improvement in order accuracy for customers.	Benzidia <i>et al.</i> (2021) Dubey <i>et al.</i> (2017)
Reliability2	Management of supplier orders to ensure seamless delivery.	N. P. Singh & S. Singh (2019) Tseng <i>et al.</i> (2019)
Reliability3	Management of returns for perfect execution.	
<b>ENPER (Environment performance)</b>		
Environment1	Reduction in material usage.	Belhadi <i>et al.</i> (2020)
Environment2	Reduction in energy consumption.	Benzidia <i>et al.</i> (2021)
Environment3	Reduction in water consumption.	Dubey <i>et al.</i> (2019b)
Environment4	Reduction in greenhouse gas emissions.	Lin <i>et al.</i> (2024) Mishra <i>et al.</i> (2021)
<b>OC (Organizational culture)</b>		
Org_culture1	Promotes innovation and technology adoption.	Dubey <i>et al.</i> (2019c) Hazen <i>et al.</i> (2014)
Org_culture2	Regular investments in innovation and new technologies.	Upadhyay & Kumar (2020) Wamba <i>et al.</i> (2024)
Org_culture3	Open and transparent communication.	
<b>SOPER (Social performance)</b>		
Social1	Promotion of diversity and inclusion.	Dubey <i>et al.</i> (2019b)
Social2	Maintenance of competitive salary levels.	Mishra <i>et al.</i> (2021)
Social3	Strengthening of training and development programs.	Roßmann <i>et al.</i> (2018) Wang <i>et al.</i> (2020)

## 4. METHODOLOGICAL APPROACH

To test our research hypotheses, we will use PLS-SEM method (Vishnoi *et al.*, 2024). This method can be simplistically defined as an advanced data analysis technique that allows using the aggregate variance of latent variables to evaluate the scores of the model's constructs, while considering the potential complex relationships between the underlying factors. The choice of this approach lies first and foremost in the nature of our data. Our items are measured on a 5-point Likert scale. These items are designed to assess how companies use BDA-AI. They also measure the performance of companies' logistics operations, considering factors like reliability, social impact, and environmental impact, as well as their organizational structure. Another reason lies in the fact that we want to study the impact of the

use of BDA-AI on several endogenous variables simultaneously, namely reliability, ENPER and SOPER.

We also want to investigate whether OC positively moderates the impact of BDA-AI implementation on SCRE. The complexity of the interrelations we want to study requires the use of a latent variable structural equation model. In fact, this approach is commonly used in literature reviews under such circumstances. Another advantage of the PLS-SEM approach is that it is less demanding in terms of application conditions. For example, normality is not assumed as a condition when applying this approach.

In the diagram below (see Figure 1), we present our conceptual model to reflect the different relationships between the constructs to be investigated. Each arrow originates from an exogenous variable and leads to an endogenous variable. For example, the arrow between the "Use\_BDA\_AI" construct and the "Reliability" construct

will enable us to study the impact of using BDA-AI on SCORE.

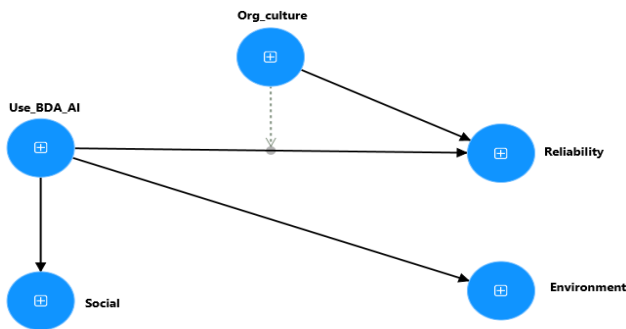


Figure 1 Conceptual model.

In this study, we will use SmartPLS software (v.4.1.0.9) to produce PLS-SEM results. To carry out this study, we will first use a measurement model to evaluate the constructs' quality. Based on this measurement model, such a quality will be assessed through the items' factor loadings, using indicators that will enable us to study the constructs' reliability. The most used indicators are Cronbach's alpha and composite reliability.

We will also use this measurement model to study the convergent validity of our constructs, using a well-known and widely used indicator: the Average Variance Extracted (AVE) indicator. A final analysis of construct quality, namely the analysis of construct discriminant validity, will be carried out. For this purpose, we will focus on the following commonly used indicators: the Fornell and Larcker criterion (Fornell and Larcker, 1981), the Heterotrait-Monotrait ratio (HTMT) indicator (Roemer *et al.*, 2021), and cross-loadings of items on constructs (Vichi, 2017).

We will then proceed with evaluating the structural model, which will enable us to carry out hypothesis testing. This model is evaluated using two commonly used indicators:  $R^2$  and  $Q^2$  (Vishnoi *et al.*, 2024).  $R^2$  is the coefficient of determination used to measure the percentage of variability in an endogenous variable explained by the exogenous variable(s). The coefficient of determination  $R^2$  is always between 0 and 1. The closer this indicator is to 1, the greater the explanatory power for the endogenous variable under consideration. According to Cohen (1988),  $R^2$  values for latent endogenous variables can be evaluated as follows:

- When  $R^2 \geq 0.26$ , the explanatory power for the corresponding endogenous variable is said to be substantial.
- When  $0.13 \leq R^2 < 0.26$ , the explanatory power for the corresponding endogenous variable is said to be moderate.
- When  $0.02 \leq R^2 < 0.13$ , the explanatory power for the corresponding endogenous variable is said to be low.
- Finally, when  $R^2 < 0.02$ , the explanatory power of the corresponding endogenous variable is said to be very low.

The  $Q^2$  indicator is used to study the predictive relevance of an endogenous variable by the exogenous variable(s) under consideration. Predictive power is said to be relevant when  $Q^2$  is strictly positive.

The final step is to carry out hypothesis testing. This step enables us to validate or reject our research hypotheses.

We use the bootstrapping method in SmartPLS to produce standard deviations,  $t$ -statistics and  $p$ -values associated with the path coefficients. Using these  $p$ -values and the signs of the coefficients, we can accept or reject a research hypothesis by comparing its corresponding  $p$ -value with a fixed risk of error threshold of 1%, 5% or 10%. More precisely, if the positive sign of the impact is preserved and the test value associated with the research hypothesis being tested is below the risk of error threshold of either 1%, 5% or 10%, the considered hypothesis is validated. Otherwise, it will not be validated.

## 5. RESULT DESCRIPTION AND ANALYSIS

Firstly, we present descriptive statistics on the characteristics of the respondents in our sample. Our sample comprises a total of 97 respondents. In the table below (see Table 2), we present the respondents' distribution (i.e., number  $N$  and percentage %) according to their current positions. According to these results, 51.5% hold SCE (SC Engineer), SCA (SC Analyst), DA (Data Analyst) and BA (Business Analyst) positions, and 38.1% hold SCM positions. Finally, 5.2% hold CEO (Chief Executive Officer) positions and 5.2% hold HSC (Head of SC) positions. The results also show that 69% of respondents have between 2 and 5 years of experience, and 15.5% have between 5 and 10 years of experience. Finally, the remaining 15.5% of respondents have more than 10 years of experience. The table below also shows that 45.5% of our respondents work in very large organizations (over 1000 employees), 26.8% in large organizations (251 to 1000 employees), 14.4% in medium-sized organizations (51 to 250 employees) and 13.4% in small organizations (1 to 50 employees).

Before moving on to the hypothesis testing, it is crucial to carry out an evaluation analysis of the measurement model in a first stage, and an evaluation analysis of the structural model in a second stage.

### 5.1 Measurement Model Results

In the context of our study, it is important to first assess the quality of our constructs. To do this, we will evaluate the measurement model using the method based on items' factor loadings, construct reliability analysis, and construct validity analysis.

#### 5.1.1 Operationalization of Constructs

Factor loadings show the extent to which each item in a construct correlates with the corresponding principal component. Factor loadings are always between -1 and 1. When the absolute value of a factor loading for a given item is high, this indicates a strong correlation (linkage relationship) between the item in question and the main component identified (Pett *et al.*, 2003). According to the results in the table below (see Table 3), no factor loading is below 0.50 which is the minimum recommended threshold (Hair *et al.*, 2016). It is advisable to remove items whose factor loadings are below 0.50. In our case, we don't fall into this situation, and indeed it's easy to see that the majority of our items' factor loadings are even above the 0.70 threshold (the frequently recommended threshold).

#### 5.1.2 Construct Reliability Analysis

Construct reliability is a situation in which a measurement instrument is stable and consistent. The notion of construct reliability is based on the idea that if a

measurement instrument is administered repeatedly under the same conditions, it should produce the same results (Mark, 1996). In addition, the reliability of a construct ensures the accuracy and consistency of the items making up

the construct. In other words, it's a way of assessing the credibility that can be attributed to the measures used to represent a particular concept in the considered model.

**Table 2** Descriptive statistics on respondents' characteristics.

		<b>N</b>	<b>(%)</b>
Position held	CEO	5	5.2
	HSC	5	5.2
	SCE/SCA/DA/BA	50	51.5
	SCM	37	38.1
	<i>Total</i>	97	100.0
Experience years	2-5 years	67	69
	5-10 years	15	15.5
	More than 10 years	15	15.5
	<i>Total</i>	97	100.0
Organization size	Large (251-1000 employees)	26	26.8
	Medium (51-250 employees)	14	14.4
	Small (1-50 employees)	13	13.4
	Very large (over 1000 employees)	44	45.4
	<i>Total</i>	97	100.0

**Table 3** Factor loadings of items.

	<b>Org_culture</b>	<b>Environment</b>	<b>Reliability</b>	<b>Social</b>	<b>Use_BDA_AI</b>
Org_culture1	0.889				
Org_culture2	0.870				
Org_culture3	0.931				
Environment1		0.837			
Environment2		0.755			
Environment3		0.856			
Environment4		0.921			
Reliability1			0.854		
Reliability2			0.826		
Reliability3			0.860		
Social1				0.933	
Social2				0.793	
Social3				0.827	
Use_BDA_AI1					0.947
Use_BDA_AI2					0.879

Two methods are frequently used to study item reliability: the method based on Cronbach's alpha and the method based on the composite reliability measure. The results of these two methods are summarized in the table below (see Table 4). When the Cronbach's alpha and composite reliability values of the items are above the 0.70 threshold (Hair *et al.*, 2016), we conclude that there is item reliability. We find that Cronbach's alpha and composite item reliability values are all above 0.70. We therefore conclude that our items are reliable.

**Table 4** Results of item reliability analysis based on Cronbach's alpha and composite reliability measure.

<b>Constructs</b>	<b>Cronbach's alpha</b>	<b>Composite reliability</b>
Org_culture	0.879	0.925
Environment	0.881	0.908
Reliability	0.805	0.884
Social	0.818	0.888
Use_BDA_AI	0.808	0.910

**5.1.3 Convergent Validity Analysis**

According to Bagozzi *et al.* (1991), convergent validity is the degree of agreement between several attempts to measure the same concept. In other words, two or more measures of the same concept should covary if they are valid

measures of the concept in question (i.e., they should converge to measure together the same concept they actually claim to measure).

In order to study the convergent validity of our constructs, we will use a commonly used indicator: the AVE indicator. When the AVE value for a given construct is above the 0.50 threshold, the corresponding items converge to measure the construct under consideration, and we can conclude that the construct's convergent validity is accepted. The table below (see Table 5) summarizes the AVE results for the considered constructs. From these results, we can see that all the constructs' AVE values are above the 0.50 value (the recommended threshold). We thus accept that there is convergent validity for all our constructs.

**Table 5** AVE values for convergent construct validity analysis.

<b>Constructs</b>	<b>Average variance extracted (AVE)</b>
Org_culture	0.804
Environment	0.713
Reliability	0.717
Social	0.727
Use_BDA_AI	0.834

**5.1.4 Discriminant Validity Analysis**

According to Bagozzi *et al.* (1991), discriminant validity is the degree to which measures of different constructs are distinct. In other words, if two or more constructs are unique, the valid measures of each should not be highly correlated with each other. To carry out this analysis, we will use three frequently used methods: the Fornell and Larcker criterion-based method, the cross-loading analysis-based method and the HTMT criterion-based method.

**5.1.4.1 Discriminant Validity Analysis Using Fornell and Larcker Criterion**

According to this criterion, discriminant validity is said to exist for a given construct when the square root of the

AVE value associated with the construct under consideration is greater than all correlations with the other constructs in the study (Fornell and Larcker, 1981). In the table below (see Table 6), we present the square roots of the AVE values of the constructs and the correlation coefficients between the constructs. The square roots of the constructs’ AVE values are found on the diagonal of the matrix. The correlations between the constructs can be read by crossing row and column of the matrix. From the results, we see that for each given construct the square root of the AVE value for the construct under consideration is greater than all the correlations with the other constructs. We thus accept that there is discriminant validity for all considered constructs.

**Table 6** Discriminant validity based on Fornell and Larcker criterion.

	Org_culture	Environment	Reliability	Social	Use_BDA_AI
Org_culture	0.897				
Environment	0.282	0.844			
Reliability	0.334	0.399	0.847		
Social	0.353	0.704	0.486	0.853	
Use_BDA_AI	0.480	0.099	0.345	0.119	0.913

**5.1.4.2 Discriminant Validity Analysis Using Cross-Loadings**

Discriminant validity can also be analyzed using cross-loadings of the items. This type of analysis allows us to see whether the items of a construct are strongly correlated with the construct they are intended to measure, rather than being correlated with constructs they are not intended to measure.

In the table below (see Table 7), we present the cross-loadings of items for the different constructs. It can be seen from the results that the items for each construct are only strongly correlated with the construct they measure. We therefore accept from the cross-loading analysis the evidence of discriminant validity.

**Table 7** Discriminant validity based on cross-loading analysis.

	Org_culture	Environment	Reliability	Social	Use_BDA_AI
Org_culture1	0.889	0.239	0.319	0.275	0.517
Org_culture2	0.870	0.268	0.259	0.386	0.369
Org_culture3	0.931	0.256	0.314	0.303	0.394
Environment1	0.268	0.837	0.381	0.567	0.073
Environment2	0.197	0.755	0.306	0.514	0.015
Environment3	0.273	0.856	0.292	0.675	0.064
Environment4	0.224	0.921	0.364	0.624	0.116
Reliability1	0.313	0.369	0.854	0.463	0.326
Reliability2	0.179	0.272	0.826	0.370	0.273
Reliability3	0.331	0.356	0.860	0.391	0.273
Social1	0.358	0.622	0.457	0.933	0.135
Social2	0.246	0.669	0.346	0.793	0.076
Social3	0.274	0.531	0.434	0.827	0.075
Use_BDA_AI1	0.417	0.123	0.344	0.173	0.947
Use_BDA_AI2	0.476	0.043	0.278	0.016	0.879

**Table 8** Discriminant validity based on HTMT criterion.

	Org_culture	Environment	Reliability	Social	Use_BDA_AI
Org_culture					
Environment	0.320				
Reliability	0.381	0.459			
Social	0.408	0.825	0.589		
Use_BDA_AI	0.573	0.084	0.417	0.123	
Org_culture X Use_BDA_AI	0.112	0.142	0.103	0.148	0.162

**5.1.4.3 Discriminant Validity Analysis Using HTMT criterion**

The HTMT criterion is a ratio calculated based on the estimated correlations between the different constructs. Concerning the decision threshold for concluding on discriminant validity, there is no unanimity. For example, according to Kline (2011), when the HTMT ratios are less

than or equal to 0.85, we can conclude that there is discriminant validity, whereas according to Teo *et al.* (2008), we accept discriminant validity when the HTMT ratios are less than or equal to the threshold 0.90. In the table below (see Table 8), we present all the HTMT ratios for all our constructs. From the results, we can see that all ratios are

below 0.85. We therefore accept that there is discriminant validity.

### 5.2 Structural Model Results

Having evaluated the measurement model, we now turn to hypothesis testing and interpretation of the direct path and moderator effect coefficients. However, before doing so, it is essential to carry out an evaluation of the structural model under consideration.

#### 5.2.1 Evaluation of the Structural Model

To evaluate the structural model, we will use the  $R^2$  and  $Q^2$  indicators mentioned previously (see Section 4). Let us remember that  $R^2$  is the determination coefficient used for evaluating the variability percentage in an endogenous variable explained by the exogenous variable(s), whereas  $Q^2$  is the indicator used for investigating the predictive relevance of an endogenous variable by the exogenous variable(s).

**Table 9** Structural model evaluation indicators.

Paths	$R^2$	$Q^2$
Use_BDA_AI → Environment	0.010	-0.020
Use_BDA_AI → Reliability	0.180	0.112
Use_BDA_AI → Social	0.014	-0.017

From the results in the table above (see Table 9), we can see that the  $R^2$  values associated with the latent endogenous variable “reliability” is equal to 0.180. Consequently, we can say that the explanatory power of this endogenous variable is beyond being at a low level and it is said to be moderate (Cohen, 1988). However, for the other two endogenous variables (i.e. social and environment), the respective  $R^2$  values are 0.014 and 0.010. All these values are below 0.020. Consequently, the explanatory power for these two endogenous variables is negligible (Cohen, 1988).

Furthermore, by examining the  $Q^2$  values reported in Table 9, we can see that the predictive power is positive for the endogenous variable “reliability”. However, the

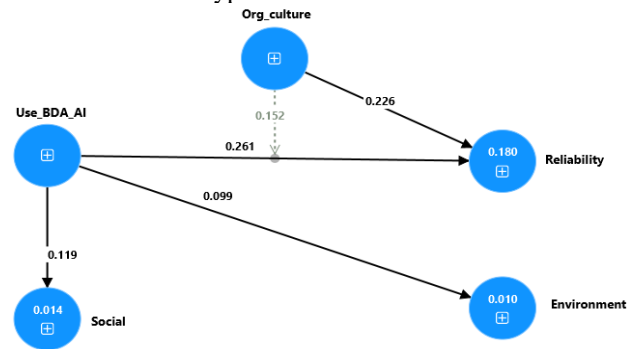
predictive power is negative for two endogenous variables: social and environment.

#### 5.2.2 Hypothesis Testing Results

In order to test our research hypotheses, we run 5000 bootstrapping trials on SmartPLS. The bootstrapping results are summarized in the table below (see Table 10).

From the results in Table 10 and Figure 2 (the figure of path coefficients in the conceptual model), we can see that:

- The use of BDA-AI has a positive and significant impact on SC reliability ( $\beta = 0.261$ ,  $p$ -value = 0.032). Our research hypothesis  $H1$  is therefore validated.



**Figure 2** Estimation of model path coefficients.

- OC positively and significantly moderates the relationship between BDA-AI utilization and SCORE ( $\beta = 0.152$ ,  $p$ -value = 0.085) at the 10% significance level. We thereby validate the research hypothesis  $H4$  of our study.
- However, we find that the impact of using BDA-AI is certainly positive on ENPER ( $\beta = 0.099$ ,  $p$ -value = 0.510) and on SOPER ( $\beta = 0.119$ ,  $p$ -value = 0.382), but this impact is insignificant. Therefore, hypotheses  $H2$  and  $H3$  of our research cannot be validated. That is, in the context of the data and results of this study, we can say that the impact of using BDA-AI is not significant on ENPER and SOPER.

**Table 10** Results of hypothesis testing.

Hypothesis	$\beta$ -Coefficients	Standard deviation	t-Statistics	p-Values
Org_culture → Reliability	0.226	0.117	1.929	0.054
Use_BDA_AI → Environment	0.099	0.150	0.659	0.510
Use_BDA_AI → Reliability	0.261	0.122	2.145	0.032
Use_BDA_AI → Social	0.119	0.137	0.874	0.382
Org_culture X Use_BDA_AI → Reliability	0.152	0.088	1.723	0.085

## 6. DISCUSSION

The results of our data analysis reveal that the implementation of BDA-AI technologies significantly enhances SCORE, particularly in areas such as order accuracy, supplier order management, and return execution. This finding extends the work of Dubey *et al.* (2020) who emphasized the role of BDA-AI in improving operational performance through entrepreneurial orientation. While their research primarily focused on operational performance, our study advances these findings by positioning SCORE as a key strategic benefit of BDA-AI technologies.

Furthermore, we demonstrate that OC -especially the one that fosters innovation, prioritizes technological investments, and encourages open communication- plays a significant moderating role in enhancing the impact of BDA-AI on SCORE. This finding aligns with the broader body of literature, which underscores the importance of OC in successfully integrating advanced technologies into SC processes. Our study resonates with the work of Upadhyay and Kumar (2020), who also emphasized the mediating role of OC in the relationship between BDA capabilities and firm performance. They found that a supportive OC positively influences the firm performance. Our findings echo this by demonstrating that OC serves as a critical factor in leveraging BDA-AI technologies for enhanced SCORE.

While Upadhyay and Kumar (2020) focused on firm performance at a broader level, our study contributes by specifically examining how OC interacts with BDA-AI to improve SCORE. Nevertheless, both studies collectively underscore the necessity of cultivating a strong internal culture that not only facilitates the adoption of new technologies but also maximizes their strategic impact. This highlights the importance for companies to nurture a culture that supports technological adoption, continuous innovation, and agility, ultimately strengthening their competitive advantage in an increasingly data-driven and technology-enabled business environment.

Furthermore, our study underscores the moderating role of OC for enhancing the effectiveness of BDA-AI technologies to improve SCORE. While prior research has acknowledged the significance of OC in technology adoption and performance outcomes (Mandal, 2018; Wamba *et al.*, 2024), our findings offer more granular insights into how specific cultural attributes (e.g., strong commitment to innovation, sustained technological investments, and fostering transparent communication) act as key enablers in this relationship. This extends the work of (Hallikas *et al.*, 2021), who observed that a supportive OC is critical for the successful integration of new technologies into SC. Unlike other studies, however, our research highlights the active, moderating influence of culture, where a culture of continuous innovation and proactive communication amplifies the positive effects of BDA-AI on SCORE. This suggests that organizations must not only focus on acquiring and implementing BDA-AI technologies, but also prioritize the development of a robust OC that encourages openness to change and a commitment to continuous learning, thus ensuring the long-term success of these technological advancements in driving SCP.

While this study demonstrates a positive but statistically insignificant impact of BDA-AI technologies on ENPER and SOPER, it aligns with the findings of (Benzidia *et al.*, 2021), who argue that the adoption of emerging technologies faces substantial challenges in achieving sustainability objectives. That is, both investigations highlight that immediate gains in areas such as reduced carbon footprints or enhanced social responsibility are improbable without long-term investments and systemic organizational transformations. Additionally, (Dubey *et al.*, 2019b) find that while BDA and predictive analytics significantly affect social and environmental performance, their full potential is contingent upon OC, strategy, and DC. This underscores the need for a comprehensive and long-term organizational change to effectively leverage advanced technologies for sustainable outcomes.

Moreover, the insignificant impact of BDA-AI on ENPER and SOPER could reflect the degree of technological maturity of the firms under study. That is, organizations in the early stages of adopting these technologies may prioritize immediate performance improvements, such as cost reduction and operational efficiency, over long-term sustainability goals. This underlines the need for future research to investigate how technology maturity and the evolution of SC digitalization influence the achievement of environmental and social objectives. In addition, the contextual factors such as industry type, regulatory environment, and stakeholder pressure may play a significant

role in shaping the relationship between BDA-AI adoption and sustainability outcomes.

On the other hand, the moderating role of OC on the relationship between BDA-AI use and SCORE is a particularly salient finding of this study. Our results demonstrate that firms with a strong culture of innovation and proactive technology adoption are better positioned to leverage BDA-AI for enhancing SCORE. This corroborates the work of (Hazen *et al.*, 2014) who emphasized that an OC supportive of technological innovation fosters the successful deployment of emerging technologies. Moreover, a culture that prioritizes openness to change, collaboration, and continuous learning enables firms to fully exploit the potential of BDA-AI in SC contexts.

These findings also align with the DCT, which posits that firms with strong DC -such as the ability to seize opportunities, sense innovations, and reconfigure resources- are more likely to achieve sustained competitive advantages (Teece *et al.*, 1997). In this context, OC acts as an enabler of DC, allowing firms to adapt quickly to market changes and capitalize on new technologies. In other words, companies that foster a culture of transparency, innovation, and collaborative decision-making can better align their technological investments with broader strategic goals, thereby improving the reliability of their SCs. Future research should explore the interaction between OC and technological capabilities in greater depth to identify specific cultural attributes that enhance the effectiveness of BDA-AI.

It can thus be argued that the present study contributes to further enriching the literature on the role of BDA-AI in SCM by providing empirical evidence of their positive impact on SCORE. However, the lack of significant impact on ENPER and SOPER highlights the need for further research on how firms can align their technological investments with long-term sustainability objectives. Additionally, the moderating role of OC underscores the importance of cultivating a culture that supports technological innovation and DC to fully leverage the potential of BDA-AI. Future studies should also investigate how different cultural frameworks, technological maturity, and contextual factors such as industry dynamics influence the success of BDA-AI implementations in achieving broader sustainability goals.

### **6.1 Managerial Implications**

From a practical standpoint, managers should prioritize BDA-AI investments to enhance SCP, especially in terms of reliability. Training personnel and developing the necessary technological infrastructure are key steps in this process. Additionally, companies should foster an OC that promotes openness, innovation, and investment in emerging technologies. These cultural aspects significantly amplify the benefits of BDA-AI technologies, helping organizations to remain competitive in dynamic market environments.

### **6.2 Academic Implications**

This research contributes to academic literature by reinforcing the validity of the DCT in modern SCs. It demonstrates that BDA-AI technologies can enhance SOPER, particularly when aligned with a supportive OC. The study also provides a new perspective on the conditions under which these technologies can yield substantial benefits. These findings enrich our understanding of how DC are operationalized in the digital era.

### **6.3. Research Limitations**

While our study makes significant contributions, it has several limitations. First, data collection was limited to a relatively modest number of organizations, which may restrict the generalizability of our results. Second, the study focuses on the immediate and/or short-term impacts of BDA and AI adoption, without evaluating the long-term effects. Furthermore, it is worth noting that our study did not investigate the impact of BDA and AI on some other SC's crucial dimensions such as agility, responsiveness, costs, assets, and profits.

## 7. CONCLUSION

This study explores the impact of BDA-AI on SCSP, using the SCOR model and DCT. The results confirm that BDA-AI adoption significantly enhances key dimensions of SCSP, particularly SCORE. These technologies help organizations optimize operations, improve order accuracy, manage supplier orders, and execute returns more effectively, thereby contributing to more reliable and efficient supply chains.

However, the influence of BDA-AI on ENPER and SOPER remains statistically insignificant in the short term, suggesting that technological benefits must be coupled with sustained efforts to achieve long-term sustainability. Companies must then integrate environmental and social goals into their technology strategies, recognizing the need for deeper organizational shifts.

An important finding is the role of OC as a critical moderator. Firms that foster innovation and collaboration are better equipped to harness the full potential of BDA-AI technologies. This emphasizes the need for companies to cultivate environments that support continuous improvement and technological adaptability.

In conclusion, this study affirms that BDA and AI are powerful catalysts for improving the SCSP. Moreover, the moderating role of OC emphasizes the importance of creating an environment conducive to innovation and adaptability. However, realizing the potential benefits on environmental and social fronts requires long-term commitment and profound organizational changes.

Future research should extend the scope to cover the long-term effects of BDA-AI adoption, exploring its influence on SCSP indicators such as costs, profits, and assets efficiency. It would also be interesting to investigate contextual factors like organizational size and technological maturity. In addition, future studies should examine the moderating effect of OC, with a particular focus on innovative culture and organizational commitment, on the impact of BDA-AI across various dimensions of SCP. These include agility, responsiveness, cost, profit, asset efficiency, as well as social and environmental performance. Investigating these moderating factors will provide a deeper understanding of how OC shapes the effectiveness of BDA-AI technologies in enhancing both operational and strategic outcomes within the SC context.

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