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The impact of big data-artificial intelligence on sustainable performance considering the mediating role of green supply chain practices

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Abstract

The objective of this research is to explore the influence of big data artificial intelligence (AI) on sustainable performance, taking into account the mediating effect of green supply chain management (GSCM) practices. This research is quantitative and descriptive in nature, as it delineates the characteristics of the variables involved. Additionally, this study is correlational since it investigates the interrelations among the variables. A sample of 80 employees was examined through a standard questionnaire. The data gathered were analyzed employing the structural equation modeling (SEM) technique along with its associated software, partial least squares (PLS). The findings of this research revealed that GSCM practices serve as a mediator in the relationship between big data-AI and sustainable performance. Furthermore, the results demonstrated that big data-AI significantly influences GSCM practices, and they also corroborated our hypothesis that both big data-AI and GSCM practices exert a significant effect on sustainable performance.

Keywords: big data, artificial intelligence, sustainable performance, green supply chain management

1. Introduction

The subjects of sustainable organizational growth and performance are currently at the forefront of academic discourse. Recent research suggests that the capabilities of big data analytics and artificial intelligence (AI) represent two crucial emerging elements that contribute to the sustainability of organizational development (Litras and Visvizi, 2019). This is especially pertinent as organizations increasingly necessitate advanced technologies to proficiently manage and analyze large volumes of data and information. Big data analytics and AI possess the potential to promote sustainable development across various sectors, including the Internet of Things (IoT), social networks, sustainable development practices, and sustainable investments within the supply chain (SC). A multitude of organizations are directing investments towards the enhancement of big data analytics and AI to strengthen their market competitiveness and ensure their continued viability (Micallef et al., 2017). Considering that the capabilities of big data analytics allow organizations to extract valuable insights from extensive data sets, they can significantly improve operational efficiency and foster sustainable growth and performance. Nevertheless, scholars

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have warned that neglecting the analytical capabilities associated with big data may result in a transient social impact regarding sustainability (Litras and Visvizi, 2019). Additionally, SCs are encountering obstacles in achieving sustainable production in light of rising demand. Such disruptions can lead to financial difficulties, production setbacks, and weakened customer relationships. The integration of sustainability into supply chain management (SCM) presents unique challenges, as existing knowledge is insufficient to establish a truly sustainable SC (Beg et al., 2021). Sustainable SCM, which encompasses the oversight of material, knowledge, and capital flows, along with inter-company collaboration, addresses all critical dimensions of sustainability, including environmental, economic, social factors, and stakeholder expectations (Rashid et al., 2024). Modern SCs, which comprise numerous businesses located in different geographical areas and competing for consumer services, are inherently intricate. Within this complex framework, the evaluation of information and the management of risks become nearly unfeasible due to factors such as globalization, varying regulatory environments, and diverse cultural and human behaviors present in the SC network (Sabri et al., 2019). Practices aimed at sustainable development within SCs are likely to be spearheaded by innovative organizations (not exclusively centralized firms) and subsequently disseminated throughout the remaining segments of the SC. The implementation of sustainable development practices within the SC is driven by both threats and opportunities. These two elements are critical in the evolution of sustainable SCM (Coate, 2018).

In recent years, due to escalating pressure from both internal and external stakeholder groups, organizational leaders have become accountable for establishing cleaner operational practices (Chen and Kitsis, 2017). This shift underscores the fact that environmental issues have unequivocally emerged as primary concerns for businesses. Additionally, the significance of big data analytics and AI capabilities in green SC practices has not been extensively explored (Kitsis and Chen, 2021). Concerning sustainable SCM, the degree to which big data analytics and AI capabilities contribute to performance sustainability has not been thoroughly examined through empirical research. Consequently, this study aims to investigate this matter.

Given the ever-changing landscape of the business environment, it requires high-quality decision-making from strategic, operational, and tactical perspectives to sustain competitiveness in the market. Recently, the application of big data for decision-making in uncertain contexts has attracted considerable attention from industry experts. However, dependence on data-driven production necessitates the arrangement of physical resources and the improvement of workforce capabilities for sustainability, thereby requiring further exploration. External pressures from governmental entities, such as the Ministry of Trade and Industry, act as significant influences in this digital era. They compel organizations to align their operations with the national digital strategy (Grikagoitia et al., 2019). Companies do not always manage to utilize big data effectively, which is why big data analytics and AI have become essential for ensuring sustainable performance. Big data and AI not only enhance organizational efficiency but also foster environmental sustainability and carry substantial environmental and social implications for innovation. As a result, they can play a crucial role at the beginning of the green process. Big data can help prevent erroneous decision-making while enabling seamless operations through cloud computing and other vital technological resources, thus promoting green innovation. Therefore, it is critical to investigate the influence of big data and AI on sustainable performance, particularly concerning the mediating role of green supply chain practices within the company. Considering that the manufacturing sector is a key component of the nation's economic development, it serves as a catalyst for modernization and generates multiplier effects. Nonetheless, various studies indicate that the manufacturing industry contributes to greenhouse gas emissions, leading to environmental degradation. Consequently, the manufacturing sector must explore strategies to optimize material usage and enhance operational processes. In the pursuit of green practices, organizations ought to embrace a SC perspective, particularly in the manufacturing field. Thus, this study aims to address the question of whether big data and AI influence sustainable performance concerning the mediating role of green SC practices in Company.

The objective of this research is to develop a comprehensive framework that links big data analysis and AI as primary catalysts for green SC practices to attain favorable sustainable performance. The findings of this study are vital for comprehending how big data analysis and AI can facilitate the achievement of competitive advantages, surmount technological obstacles, and enhance sustainable performance. This research is structured into several sections, with the initial section offering an overview and articulation of the research problem, followed by sections that delve into theoretical concepts and the background of previous studies. Subsequently, the formulation of hypotheses is proposed. The next section elucidates the research methodology, and the fifth section evaluates the research hypotheses. Ultimately, the research findings are scrutinized, and recommendations for future research are provided.

2. Research background

Gallo et al. (2023) examined the connection between big data analytics and artificial intelligence (AI) in relation to environmental performance, utilizing a moderated mediation model that incorporates green supply chain (SC) collaboration and the commitment of top management. The results revealed that the use of big data analytics and AI has a beneficial effect on both green SC collaboration and environmental performance. Additionally, the results revealed that green SC collaboration positively impacts environmental performance. Our study revealed that green SC collaboration acts as a mediator in the connection between big data analytics, AI, and environmental performance. Moreover, the results showed that the commitment of top management influences the positive correlation between big data analytics, AI, and green SC collaboration, with this positive correlation being more pronounced at higher levels of top management commitment. Additionally, the findings indicate that top management commitment also moderates the positive link between big data analytics, AI, and environmental performance, where the strength of this positive link weakens at lower levels of top management commitment. No significant findings were discovered in the current literature. This research seeks to support SC and logistics managers, along with senior management, in the adoption of big data analytics and AI technologies to improve green SC collaboration and enhance environmental performance.

Rashid et al. (2025) demonstrated that AI-driven big data analytics exerts a considerable and beneficial effect on green SC collaboration, sustainable manufacturing, and the integration of environmental processes. Similarly, the findings suggested that green SC collaboration significantly and positively affects sustainable performance. In contrast, sustainable manufacturing and environmental process integration were observed to have a negligible impact on sustainable performance. It was concluded that green SC collaboration acts as a mediator in the significant relationship between big data analytics-AI and sustainable performance. Nevertheless, sustainable manufacturing and environmental process integration did not mediate the relationship between big data analytics-AI and sustainable performance. Bikli et al. (2025) carried out a study titled AI and big data in sustainable entrepreneurship. This research concluded that big data enhances AI's capacity to inform decision-making and to outline strategies for achieving desired outcomes. Farrokh Shahzad et al. (2025) studied industry 4.0 technologies and sustainable performance: do green SC collaboration, circular economy practices, technology readiness, and environmental dynamics matter? The findings of this research indicate that the adoption of Industry 4.0 technologies has a substantial impact on sustainable performance via green SC collaboration, circular economy practices, and technology readiness in the food industry of Pakistan. Furthermore, the interplay between Industry 4.0 technologies, green SC collaboration, circular economy practices, and technology readiness is positively influenced by environmental dynamics.

2.1. Literature review

AI pertains to the influence generated by comprehending the human psyche via computational means. Its presence is becoming increasingly ubiquitous in our everyday existence. In this contemporary age characterized by intelligence and cognitive advancements, AI, along with machine learning—which is a branch of AI that facilitates autonomous systems—has been employed to fundamentally transform and enhance business performance, thereby fostering sustainable development. AI possesses the capability to autonomously learn and assimilate knowledge from extensive datasets, utilizing this information to assist individuals in achieving their practical and technical objectives (Zhao et al., 2018). AI is a double-edged sword. The implementation of AI offers numerous advantages, including the value derived from big data and innovation, which can augment and automate business processes. Conversely, organizations and individuals may encounter the dilemma of "excessive data and uncertainty regarding its utilization." Within a corporate context, AI can be harnessed to improve the efficacy and efficiency of corporate social responsibility practices. Both companies and their stakeholders stand to gain from AI, as it promises substantial economic value and enhanced decision-making capabilities, thereby bolstering corporate resilience in the face of sustainability challenges and social issues. Nonetheless, it is equally crucial to scrutinize the potential hazards associated with AI and the concerns that arise from this formidable technology, ensuring that its application aligns with human values and ethical principles (Naqvi, 2021). Although the use of AI for sustainability is still in its nascent stages, this trend is already beginning to influence corporate sustainability efforts, particularly in applying AI to meet sustainable development objectives, such as minimizing CO2 emissions or utilizing machine learning to enhance horticultural yields. The deployment of AI for social and environmental advantages encompasses both formal and informal strategies aimed at raising awareness of performance, as well as standardizing and executing corporate social responsibility practices. The performance of AI must be supported in a responsible and ethical manner through regulatory insights to facilitate its sustainable development. Neglecting this responsibility may result in discrepancies in the application of AI concerning accountable and ethical standards (Vinosa et al., 2020).

Big data constitutes a collection of subject-oriented information that encompasses data from a specific timeframe, aiding decision-makers. In the contemporary landscape, the digital transformation of businesses necessitates the implementation of big data analytics (Papadopoulos and Balta, 2022). Big data analytics pertains to the examination of extensive volumes of data and datasets that traditional data management methods cannot access, analyze, or utilize promptly. This has generated opportunities within the current knowledge-driven economy, including ideas associated with sustainable development and environmental innovation. Furthermore, big data analytics is a crucial element in technology as it bolsters business efficiency and significantly contributes to sustainability. Additionally, it can mitigate the risk of uninformed decision-making by offering supplementary support, which ensures precise operations that promote sustainable practices. Big data analytics enhances and integrates the examination and utilization of data concerning green issues (e.g., green digital learning) and enables effective decision-making to tackle challenges related to resource depletion and environmental pollution (Lee et al., 2022).

In particular, the analysis of big data has emerged as a crucial element in today's corporate landscape, continuously transforming the competitive market. It encompasses various data management processes, such as the adoption, utilization, and assimilation of big data. Consequently, the extent to which stakeholders comprehend the significance of these technologies serves as an indicator of big data adoption. Big data routines provide a framework that businesses utilize to facilitate technology integration. The concept of big data assimilation mainly relates to the degree of technological application within an organization to attain optimal outcomes. The importance of big data can certainly be assessed from a resource-oriented perspective. A significant amount of data is essential for validating enhanced insights in the face of swift technological progress. Consequently, the function of big data analytics goes beyond simply applying novel analytical techniques (Chen et al., 2020). When data is collected, compiled, and examined within a company for multiple objectives, it can improve the organization's value regarding sustainable performance. Thus, the integration of big data presents the opportunity for a transformative shift in business operations. Nevertheless, the challenges posed by competitive and digital innovation have complicated the processes of storing, collecting, and analyzing big data, despite the fact that the dynamic capabilities of big data can produce tangible value outcomes regarding long-term performance advantages. Considering that the function of big data facilitates the amalgamation and evaluation of both quantitative and qualitative information, it has the potential to enhance forecasting and decision-making processes, which may result in improved performance (Raut et al., 2019).

The principle of sustainability has drawn significant interest in the business realm in recent years. Growing awareness of climate change, resource depletion, and social inequality has elevated sustainability to a primary concern on corporate agendas worldwide (Bangay, 2022).

The notion of sustainable performance pertains to an organization's capacity to fulfill its objectives while reducing its ecological footprint. This necessitates striking a balance among economic advancement, environmental stewardship, and social accountability. Various metrics can be employed to assess sustainable performance, encompassing both environmental and organizational performance. Environmental performance pertains to a company's effects on the environment, which includes its carbon emissions, energy usage, waste management practices, and the consumption of natural resources. Conversely, organizational performance emphasizes the company's societal impact, which encompasses its interactions with shareholders and financial metrics that indicate the organization's ability to generate profits and meet economic objectives (Chuang and Huang, 2018).

In light of the growing global consciousness regarding environmental issues, organizations are increasingly emphasizing sustainability to maintain their competitive edge and satisfy stakeholder expectations. This transition necessitates the adoption of a comprehensive strategy that integrates environmental, social, and economic factors. To enhance operational efficiency and mitigate environmental impacts, organizations are implementing sustainable green management systems. These systems not only foster environmental stewardship and social responsibility but also align business goals with sustainable practices. The manufacturing industry is acknowledged as one of the primary sources of carbon emissions, industrial waste, and energy usage. Consequently, shifting towards a more sustainable business model is not merely a strategic option but an essential requirement for survival in a competitive and heavily regulated environment. Companies are concentrating on lowering carbon emissions, enhancing corporate social responsibility, and ensuring ethical SCs, which together strengthen their market position. A supportive organizational culture is crucial for the success of sustainability practices.

Organizations must cultivate a green culture and enhance communication regarding sustainability objectives to effectively execute these practices. Although this approach presents considerable opportunities for innovation and competitive advantage, challenges such as substantial initial costs and intricate stakeholder relationships continue to pose significant obstacles (Coate, 2018).

GSCM represents a revolutionary methodology that incorporates eco-friendly practices across the entire SC, starting from the sourcing of raw materials to the management of products after consumer use. This approach not only tackles sustainability challenges but also enhances operational efficiency and corporate accountability. It merges green design, sustainable procurement, and waste reduction techniques with the objective of minimizing environmental repercussions throughout the SC. Furthermore, GSCM encompasses effective waste management strategies, which include the reuse and recycling of products after consumer use. The adoption of GSCM yields not only ecological advantages but also boosts operational efficiency, lowers long-term expenses, and improves the organization’s standing among environmentally aware consumers and investors. For successful implementation, collaboration among SC partners is essential, as is the ability to navigate obstacles such as financial limitations and regulatory complexities. The integration of green technologies and automation can greatly enhance efficiency and decrease costs, thereby fostering a more sustainable SC (Sarin and Srivastava, 2024).

2.2. Hypothesis development

The findings from the existing literature indicate that managers who leverage advanced digital technologies, such as AI and big data analytics, can enhance organizational performance under dynamic conditions. In the context of Industry 4.0, AI has re-emerged in the corporate landscape with increased potential. The adoption of AI and machine learning presents a variety of advantages, such as reduced costs, enhanced quality, and faster response times. Big data is generated in various formats—like text, images, audio, and video clips—emanating from a wide range of sources, including the internet, social media, enterprise resource planning systems, and cloud services. The combination of AI with big data analytics has triggered a digital transformation in the manufacturing industry. At the operational level, the capacity of machines to make autonomous decisions, coupled with collaborative efforts among agents, fosters a high degree of adaptability and has a significant positive impact on sustainable performance.

2.2.1. Mediation of green SC practices in the relationship between Big Data-AI and sustainable performance

The utilization of big data analytics capabilities through AI represents the sole viable method for substantially enhancing the productivity of manufacturing sectors to a markedly elevated level (Ali et al., 2023). Enhanced decision-making can be facilitated by data technologies aimed at refining industrial processes (Neo et al., 2023), optimizing SCs (Al-Khatib, 2022), and elevating product quality (Saini et al., 2023), among other domains, thereby contributing significantly to the advancement of sustainable resource management. The current body of research suggests that the implementation of sustainable practices in various industries results in greater resource efficiency and lower emissions (Ashley, 2016), alongside an improved sustainability of the value chain (Asha et al., 2023). The integration of Big Data and AI technologies represents the unique method by which manufacturing companies can successfully address environmental sustainability (Jen et al., 2023) and health-related challenges (Ashraf et al., 2023). This is achieved through the creation of green logistics and product offerings, along with the development of green SC practices. Therefore, it can be inferred that:

H1: GSCM practices serve as a mediator in the relationship between Big Data-AI and sustainable performance.

2.2.2. Big Data-AI and green SC practices

Previous research has recognized that the extensive adoption of information and communication technology has rendered big data strategically significant for organizations in formulating sustainable policies (Maheswari et al., 2021). Big data is defined by its significant diversity, considerable volume, and a swift increase in variety, velocity, and precision (Aghabhaji et al., 2020). This data accumulation enables organizations to create big data analytics and AI, which transform data into actionable insights, thus supporting decision-making and potentially improving the SC (Dubai et al., 2020). To promote GSCM, developing nations such as India and China are utilizing digital technologies, including smart detection devices, to tackle environmental issues both internally and externally. For example, in Jiangsu Province, China, a smart device was utilized to collect real-time environmental data, leading to millions of unique flows and streams in an unstructured format. In such scenarios, Big Data-AI proves beneficial for processing unstructured data to uncover valuable insights. For example, Big Data-AI can assess real-time data on dynamic energy consumption and carbon emissions, thereby supporting the optimization of production processes aimed at conserving energy and minimizing emissions (Loghman et al., 2017). By utilizing Big Data-AI, organizations can generate valuable information to enhance their environmental practices. Moreover, Big Data-AI allows organizations to decrease carbon emissions, minimize the waste of natural resources, and implement green product innovations (Benzidia et al., 2021). Consequently, we posit that Big Data-AI could serve as an effective tool for better implementing green SC practices and enhancing SC efficiency within an organization. Therefore, the following hypothesis proposed:

H2: Big Data-AI has a significant impact on green SC practices.

2.2.3. Big Data-AI on sustainable performance

Sustainable growth and performance within organizations are currently prominent subjects in academic literature. Previous studies have shed light on the factors that lead to sustainable growth and performance (Hao et al., 2019). Recent findings indicate that big data analytics and AI capabilities are two emerging competencies that enhance the sustainability of organizational development (Litras and Visvizi, 2019). Earlier research has demonstrated that big data serves as a crucial sustainable resource for businesses, necessitating the adoption of new technologies for the management and analysis of extensive data and information. The rise of big data analytics and AI capabilities has transformed the operational and production methodologies of companies. These capabilities can foster sustainable development across various domains, such as the IoT, social networks, sustainable development practices, and sustainable investments within the SC (Hao et al., 2019). Numerous organizations are channeling investments into the enhancement of big data analytics and AI capabilities to bolster their market competitiveness and ensure survival (Micallef et al., 2017). Given that big data analytics and AI capabilities enable organizations to derive valuable insights from large datasets, they can significantly enhance operational efficiency and facilitate sustainable growth and performance (Zhang et al., 2020). Nonetheless, scholars have cautioned that neglecting the sustainability aspect of big data analytics may result in only temporary social impacts. Consequently, we assert:

H3: Big data-AI has a significant impact on sustainable performance.

2.2.4. Green SC practices on sustainable performance

It is expected that when organizations embed environmentally sustainable practices into their SCM operations, their performance can achieve long-term sustainability. The establishment of strategic supply partnerships, the utilization of reverse logistics, the management of internal environmental factors, and the adoption of innovative environmental practices by organizations are anticipated to positively impact their sustainable performance (Antoy et al., 2022). In the research conducted by Ferjana et al. (2019), it was indicated that innovative environmental practices impact the sustainable performance of organizations that adopt them. An analysis of these results reveals that when organizations participate in practices recognized as green, it yields specific outcomes. Moreover, the research suggests that participation in activities deemed environmentally friendly is likely to yield positive results in social, economic, and environmental aspects. In light of these findings, we propose:

H4: Green SC practices significantly influence sustainable performance.

Subsequently, by reflecting on the meaning of each factor, these identifiers were defined within a cohesive concept; similar concepts were then categorized into explanatory groups to delineate the explanatory axes of sustainable performance as the primary components of the research. The resulting indicators are illustrated in a conceptual model in Figure 1 (Rashid et al., 2025).

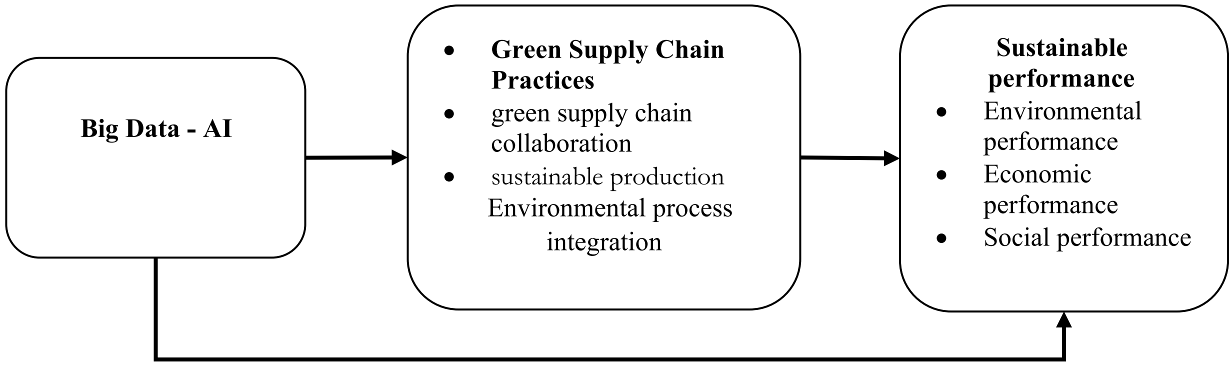

Fig. 1. Conceptual model of research.
Source: designed by the authors.

3. Methods

Applied research aims to enhance behaviors, methodologies, tools, devices, products, structures, and patterns utilized within human societies. This type of research leverages findings from basic research to cultivate applied knowledge within a specific domain. Consequently, it is classified as applied research. Furthermore, regarding the method of data collection, it falls under the category of correlational research, which employs SEM to be executed in the relevant field. The statistical population for this study comprises the employees of Company X in Urmia, totaling 100 individuals. According to the Morgan table, for a population of 100, the sample size is determined to be 80 employees from Company X in Urmia.

In this investigation, primary data concerning the variables of big data-AI, sustainable performance, and green SC practices were obtained through a survey utilizing a 25-question questionnaire following Rashid et al. (2025). Questions 1-6 dealt with the big data – AI. Questions 7-16 dealt with green SC practices (Questions 7-10 for green SC collaboration, Questions 11-12 for environmental process integration, Questions 13-16 for sustainable production). Finally, Questions 17-25 related to sustainable performance (Questions 17-19 for environmental performance, Questions 20-22 for economic performance, Questions 23-25 for social performance). The questionnaire was structured using a five-point Likert scale (5 = strongly agree; 4 = agree; 3 = neither agree nor disagree; 2 = disagree; 1 = strongly disagree) and was distributed online among the employees. Data collection was conducted in May 2024.

4. Results and discussion

In this research, the analysis of data will be conducted in two phases: descriptive and inferential statistics. Initially, we will outline the results derived from the characteristics of the statistical population through descriptive statistics, followed by an analysis and hypothesis testing utilizing inferential statistics. The analysis will employ SMART-PLS (Partial Least Squares Method) and SPSS software. This software adopts a component-based approach suitable for assessing reliability, validity, and the relationships among variables (Cheng and Yang, 2014). The partial least squares method is frequently regarded as an alternative to SEM (Hong et al., 2012). In the present study, SPSS software will be utilized for the descriptive statistics segment, while SEM and relevant software for SEM, including PLS software, will be employed for evaluating the research model.

The analytical approach was executed in two phases. The initial phase entails evaluating reliability, along with the convergent and divergent validity of both the model and the questionnaire. The subsequent phase requires the validation of all study assumptions through tests performed using software. The discourse surrounding validity and reliability indicates that the instrument employed for data collection is deemed reliable when it possesses two critical attributes: reliability and validity. Generally, reliability pertains to the consistency of the instrument in measuring data; specifically, to what degree will the measurement tool yield identical results under consistent conditions? Furthermore, validity in measurement refers to the extent to which the instrument can accurately measure the characteristics it is intended to assess. Ultimately, it is essential to ascertain whether the appropriate measurement method or tool has been utilized to achieve the desired objective and to what degree this method has proven effective for the intended purpose. In this research, data was gathered through the use of standardized questionnaires. These questionnaires have been utilized in esteemed studies within the domain of research variables, thus affirming their validity. Furthermore, the questionnaire was formally endorsed by 20 professors who are experts in this area; after the collection of general data, all information will be analyzed using PLS software to assess validity and reliability through Cronbach's alpha indices, composite reliability (CR), reliability coefficients, and factor loading values, in addition to convergent and divergent validity. According to the accompanying table, the alpha value for all constructs exceeds 0.70, signifying the validity of the questionnaire and the consistent intellectual understanding of the respondents regarding the content of the variables associated with each construct. The findings indicated that the alpha value for each construct does not exhibit a notable enhancement when certain variables are excluded. Nevertheless, all selected indicators for evaluating the constructs under study possess the requisite reliability, and the reliability of the instrument can be deemed acceptable. The overall Cronbach's alpha value for the research instrument, calculated for 25 questions, was found to be 0.835, a substantial figure that suggests a high level of reliability and, consequently, internal consistency for measuring this indicator. Regarding descriptive statistics, the results have indicated that, taking into account the samples chosen for this study, which include both male and female participants, the frequency percentages, along with education and age, are detailed in Table 1.

Table 1
General information of the questionnaire

Variable	Value	Frequency	Percent
Sex	Female	18	22.5
	Male	62	77.5
Education	Diploma	19	16.3
	Bachelor	39	48.8
	Master	26	32.5
	Ph.D	2	2.5
Age	Below 30	12	15
	35-30	24	30
	45-35	19	23.8
	Upper 45	25	31.3
	Total	80	100

Source: designed by the authors.

The measurement model, commonly known as the external model, serves as the part of the model that examines the connection between latent variables and their associated indicators. The Cronbach's alpha index, utilized to assess the reliability of the items, has a designated threshold of 0.7. The values recorded for this index in the context of big data-AI is 0.853, for green SC practices is 0.841, and for sustainable performance is 0.811, all of which exceed the stipulated threshold of 0.7. The PLS method employs a more contemporary metric than Cronbach's alpha, known as CR. This measure offers an advantage over Cronbach's alpha in that it evaluates the reliability of variables not in absolute terms but based on the inter-correlation of their respective variables. Consequently, both measures have been applied in this study to enhance the assessment of reliability. A CR score exceeding 0.7 signifies adequate internal consistency for the model, whereas a score below 0.6 indicates a lack of reliability (Nunally, 1987). Table 2 provides a summary of the findings related to alpha, the reliability coefficient, and CR. According to the data presented in Table 2, all indicators for every variable have been achieved at an acceptable standard. The findings indicate that Cronbach's alpha reflects strong reliability, given that it surpasses the 0.7 threshold. Furthermore, the reliability and reliability coefficient for all variables are consistently above 0.7.

A factor loading represents a numerical value that quantifies the strength of the association between a latent variable and its corresponding manifest variable during the path analysis procedure. A higher factor loading for an indicator in relation to a particular construct signifies a more substantial contribution of that indicator in elucidating the construct. Conversely, a negative factor loading for an indicator suggests a detrimental impact on the explanation of the associated construct. This implies that the question pertaining to that indicator is framed in a reverse manner.

The threshold for an acceptable numerical value for this indicator is set at 0.4. Should the value of this indicator fall below this established threshold, the corresponding question must be excluded from the analyses. As illustrated in Table 3, all these values exceed 0.4, which is deemed acceptable.

Table 2
Validity and reliability for the measurement model

Variable	Alfa	Reliability	CR
Green SC Practices	927.0	0.939	0.609
Sustainable Performance	924.0	0.937	0.627
Big Data - AI	858.0	0.895	0.587

Source: designed by the authors.

Table 3
Reliability with factor loadings for the measurement model

Variable	Question	Factor Loading
Big Data - AI	DBA-AI1	0.724
	DBA-AI2	0.810
	DBA-AI3	0.778
	DBA-AI4	0.835
	DBA-AI5	0.766
	DBA-AI6	0.673
Green SC Practices	GSCC1	0.846
	GSCC2	0.826
	GSCC3	0.766
	GSCC4	0.797
	EPI1	0.790
	EPI2	0.844
	SM1	0.732
	SM2	0.580
	SM3	0.726
	SM4	0.854
Sustainable Performance	ENP1	0.656
	ENP2	0.725
	ENP3	0.670
	EP1	0.804
	EP2	0.803
	EP3	0.767
	SP1	0.892
	SP2	0.864
	SP3	0.901

Source: designed by the authors.

Convergent validity serves as one of the essential criteria for assessing the validity of a measurement model. This index quantifies the extent to which a variable is elucidated by its corresponding questions; it is a metric employed to evaluate the internal validity of the measurement model. For this index to be deemed acceptable, its value must exceed 0.5 to affirm the validity of the variable in question. The findings presented in Table 4 indicate that the convergent validity for all variables examined in this study surpasses 0.5, thereby suggesting that the level of convergent validity is satisfactory.

Divergent validity (Fornell-Larker method) evaluates the robustness of the connection between a variable and its indicators in comparison to the relationship between that variable and other variables. Acceptable divergent validity within a study indicates that a variable in the model demonstrates stronger associations with its indicators than with other variables. Additionally, divergent validity is deemed acceptable when the convergent validity for each variable surpasses the shared variance between that variable and the other variables in the model. As a result, this divergent validity is considered acceptable when the values on the primary diagonal are greater than those beneath. As illustrated in Table 4, the Fornell-Larker criterion is deemed acceptable for this study.

Table 4
Divergent validity for the measurement model

Measure	Convergent validity	Divergent validity	
		Green SC Practices	Sustainable Performance
Green SC Practices	0.780		
Sustainable Performance	0.540	0.792	
Big Data - AI	0.522	0.686	0.766

Source: designed by the authors.

A structural model refers to a framework that investigates the interrelations among research variables. To determine whether the hypotheses are validated and to assess the overall adequacy of the model, it is essential to select appropriate tests, analyze the data in accordance with these tests, and utilize the designated software. In this research, the evaluation will be conducted using the R2 criterion and the collinearity index, which will be elaborated upon subsequently. Collinearity is assessed based on the VIF criterion, which should yield a value of less than 5. Should the VIF value exceed this threshold, it becomes imperative to eliminate certain structures, merge others, and establish second-order or higher-order structures. As indicated by the findings in Table 5, the collinearity among the constructs remains below 5, thus rendering this level of collinearity reasonable and acceptable, negating the need for any modifications to the model.

Table 5
Collinearity criterion

Indicators	Green SC Practices	Sustainable Performance	Big Data - AI
Green SC Practices		3.087	
Sustainable Performance			
Big Data - AI	1.000	3.087	

Source: designed by the authors.

The main standard for evaluating the endogenous latent variables in the path model is the coefficient of determination. This measure reflects the proportion of variation in the endogenous variable that can be ascribed to the exogenous variable. The R2 criterion serves as a link between the measurement component and the structural component of SEM. Chin (1998) identifies three thresholds of 0.19, 0.33, and 0.67, which correspond to weak, medium, and strong R2 values, respectively. The R2 criterion is utilized to assess the model's effectiveness. In this particular model, the R2 value for the dependent variable concerning green SC practices is 0.676, exceeding the threshold of 0.67; thus, it is classified as strong. Similarly, the R2 value of 0.803 for the dependent variable related to sustainable performance also surpasses the 0.67 threshold, confirming the structural model's strength.

The subsequent criterion pertains to effect size, with Cohen (1992) categorizing values of 0.02, 0.15, and 0.35 as weak, moderate, and strong, respectively. The effect size outcomes for all independent constructs in relation to the dependent constructs will be presented. Based on the findings in Table 6, it is evident that the values exceed the specified threshold, thereby rendering them acceptable.

Table 6
F criterion

Indicators	Green SC Practices	Sustainable Performance	Big Data - AI
Green SC Practices		0.249	
Sustainable Performance			
Big Data – AI	2.087	0.494	

Source: designed by the authors.

Path coefficients denote the standardized beta in linear regression. It is crucial to evaluate path coefficients in terms of their magnitude, sign, and significance. Positive path coefficients (positive beta) indicate direct relationships between endogenous and exogenous latent variables. Conversely, negative path coefficients (negative beta) denote an inverse relationship between these latent variables. The magnitude of this value reflects the strength of the relationship, which diminishes as indirect relationships are formed; thus, some researchers highlight the importance of total effects, which encompass both direct (path coefficient or beta) and indirect effects. The significance of path coefficients complements the magnitude and sign of the model's beta coefficient (Hayer and Ringel, 2011). Based on the results derived from the analyses conducted for the path coefficients and the R2 criterion, we can affirm the significance and validation of the hypotheses, as well as the substantial impact of each independent variable on the dependent variable. To evaluate the proposed hypotheses, the T- statistic coefficients were analyzed. The outcomes of the T-test are illustrated in Figure 3.

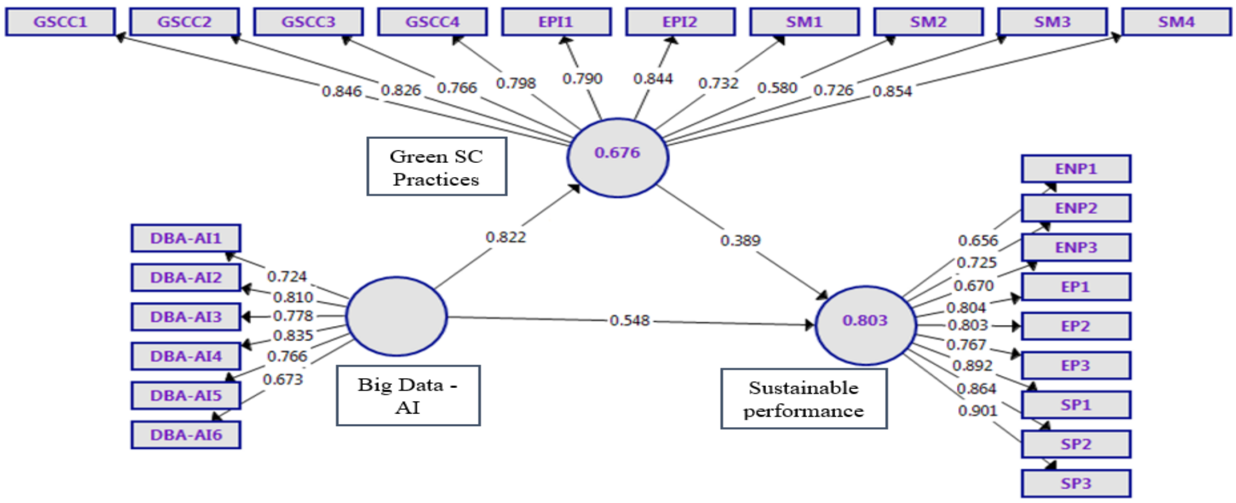

Fig. 2. Path coefficient test.
Source: designed by the authors.

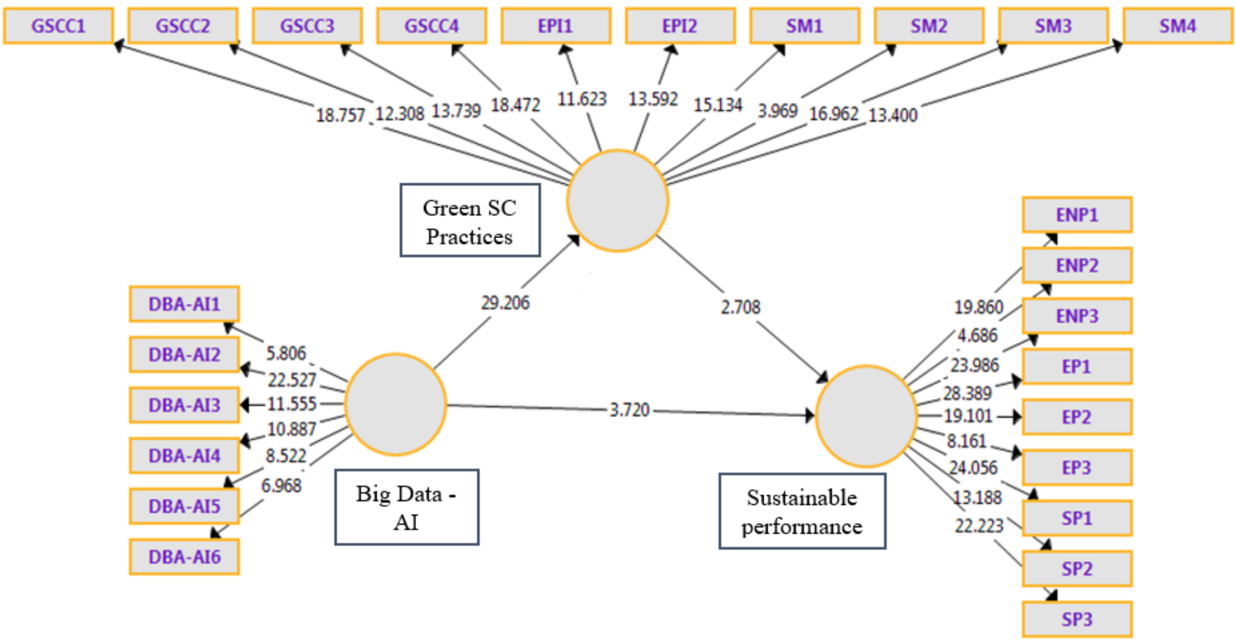

Fig. 3. T-test.
Source: designed by the authors.

Wetzels et al. (2009) have defined three thresholds of 0.01, 0.25, and 0.36, categorizing them as weak, moderate, and strong values for GOF, respectively. This implies that if a GOF value of 0.01 or something close to it is computed for a model, it indicates that the model's overall fit is weak, necessitating adjustments to the relationships among the model constructs. Likewise, the same guideline applies to the other two GOF thresholds (0.25 indicating moderate overall fit and 0.36 indicating strong overall fit). Using the test conducted for the overall fit of the model, a value of 0.670 was obtained, which, compared to the above baseline values defined for GOF, indicates that the model structure is appropriate. Table 8 presents the resulting estimates.

Table 8
Test of the main hypotheses

Hypothesis	Original Sample	Sample Mean	Standard Deviation	T Statistics	P Values
Big Data- AI -> Green SC Practices -> Sustainable Performance	0.320	0.476	0.121	2.635	0.078
Big Data-AI -> Green SC Practices	0.822	0.849	0.028	29.206	0.000
Big Data-AI-> Sustainable Performance	0.548	0.389	0.147	3.270	0.001
Green SC practices -> Sustainable performance	0.389	0.561	0.144	2.708	0.073

Source: designed by the authors.

The findings indicate that big data-AI significantly influences green SC practices (at a 1% significance level). Furthermore, the positive path coefficient of 0.822 suggests a direct relationship between these two variables. The findings pertaining to this hypothesis reveal that big data-AI has a notable impact on sustainable performance at a 1% significance level. Additionally, the statistical analysis indicates that the path coefficient of 0.548 confirms a direct relationship between big data-AI and sustainable performance. The results associated with this hypothesis demonstrate that green SC practices significantly affect sustainable performance at a 10% significance level. Moreover, the statistical analysis shows that the path coefficient of 0.389 establishes a direct relationship between green SC practices and sustainable performance.

The findings suggest that green SC practices serve as a mediator in the relationship between big data-AI and sustainable performance at a 10% significance level. Based on these results, it can be concluded that the knowledge generated through information technologies such as big data or AI can facilitate the development of dynamic capabilities. The insights derived from the analysis may assist in broadening strategic planning and provide the company with access to previously unattainable options. Big data fundamentally transforms the manner in which businesses engage with and manage their customers. Processes driven by sustainability-oriented dynamic capabilities influence both integrated green capabilities and sustainable environmental design capabilities. Consequently, a production line that collaborates with its suppliers to offer eco-friendly products can align itself with market demands or the strategies of competitors. The findings on this hypothesis are consistent with the research conducted by Chadori and Kawados (2021), Rashid et al. (2024), and Farrokh Shahzad et al. (2024).

The findings indicate that big data and AI significantly influence green SC practices. Previous research suggests that collaboration within the green SC, as an organizational element, bolsters the circular economy. The adoption of big data and AI in green SC collaboration is increasingly prevalent, enhancing visibility and integration within green SCs while providing access to valuable information. When suppliers adopt practices that are environmentally sustainable and responsive to customer demands, it fosters the development of green SC collaboration. By integrating large-scale data, artificial intelligence, cloud computing technologies, and operational research methodologies, organizations can create an innovative decision support system that enables the evaluation of gas emissions and carbon footprints throughout the supplier selection process. Moreover, artificial intelligence and machine learning provide a multitude of advantages, including reduced production expenses, improved quality, and faster response times in manufacturing. The application of big data in diverse formats enhances the autonomous decision-making abilities of machines and promotes collaborative efforts among production agents, leading to a significant level of adaptability. Conversely, the integration of environmental processes is associated with cross-functional integration, which implies that various functions must collaborate as part of a unified process. Literature indicates that a robust technical infrastructure is crucial for the integration of internal SC processes. Empirical research indicates that utilizing information technology improves coordination, standardization, and collaboration within internal functions. Supervisors can leverage big data and AI to augment their processing capabilities through modeling and simulation, while data analytics can assist in optimizing internal SC processes—such as logistics, warehousing, planning, and sourcing—making them more operationally efficient and environmentally sustainable. The results regarding this hypothesis are in line with the results of studies by Liu et al. (2018), Gallo et al. (2023), Kumar et al. (2021), and Abu Afifa et al. (2022).

The results demonstrate that big data-AI has a significant impact on sustainable performance. Additionally, the path coefficient of (0.868) denotes a direct correlation between big data-AI and sustainable performance. In light of these results, it can be inferred that, given the environmental crisis and the necessity to meet the decarbonization agenda, emerging smart sustainable enterprises are increasingly utilizing collective expertise in AI, IoT, and big data to develop innovative, urgent, and effective solutions aimed at achieving environmental sustainability. There is indeed an urgent requirement for more advanced AI models and methodologies to enhance current technological solutions with new capabilities in this area. Generally, AI includes computational abilities that draw inspiration from human cognitive functions (such as sensation, perception, language processing, learning, inference, reasoning, and advocacy) to solve problems and achieve goals. Consequently, as more focus is directed towards the integration of data-driven technologies and intelligent solutions to address the immediate challenges of environmental sustainability and the significant threats posed by climate change, an improvement in sustainable performance is anticipated. The results related to this hypothesis also align with the findings of research conducted by Bibury et al. (2023), Mahmoud et al. (2023), and Bikli et al. (2024).

The findings suggest that green SC practices significantly influence sustainable performance. The data indicates that business operations can represent a considerable risk to the environment, particularly concerning carbon monoxide emissions, discarded packaging, hazardous waste, traffic congestion, and various forms of industrial pollution. Incorporating environmental considerations into SCM is recognized as a form of environmental innovation. Environmental collaboration entails working alongside suppliers to meet environmental objectives and enhance waste reduction efforts, providing suppliers with design specifications that incorporate environmental criteria for procured items, motivating suppliers to devise new strategies for source reduction, and partnering with suppliers for cleanup practices. This collaborative approach aids companies in developing and nurturing the environmental competencies of their supply partners, ultimately enabling them to achieve sustainable performance. In the absence of effective environmental practices, manufacturing processes generate substantial waste, deplete natural resources, and lead to excessive energy use. This situation necessitates the formulation and execution of environmental practices within the manufacturing sector. Pollution prevention strategies are linked to lower production costs. Any proactive environmental measure can yield competitive advantages, aligning with the conclusions of Ramaiah et al. (2013), who asserted that a competitive market position can be established through the adoption of sustainable and green technologies and business practices. The integration of diverse business processes with SC partners also promotes enhanced sustainable performance. Insufficient quality at any stage of the SC adversely affects customer satisfaction and profitability, ultimately resulting in increased costs for downstream businesses and the end consumer. Furthermore, the absence of integrated approaches within the SC hinders organizations from sharing the costs and benefits associated with environmental practices. The findings surrounding this hypothesis align with the conclusions drawn from studies conducted by Persdotter et al. (2019), Hergilizius et al. (2019), and Han and Hu (2020).

Based on these findings, it is recommended that the government and other stakeholders intensify their pressure on manufacturing firms to respond to external demands and implement GSCM practices aimed at enhancing environmental conditions. In order to effectively respond to and adapt to these external pressures, focal companies should collaborate with their customers and closely monitor their suppliers to further disseminate the pressure throughout the SC, thereby achieving advantageous outcomes. Supplier monitoring, recognized as an effective strategy within the manufacturing sector, has a synergistic effect on environmental performance. Consequently, it is advisable for managers of manufacturing firms to prioritize supplier monitoring as a central strategy.

5. Conclusion

Data has emerged as one of the most crucial assets for modern enterprises. Additionally, organizations have adopted digitalization. Consequently, their SCs produce extensive volumes of data. Nevertheless, unlike traditional investments, big data lacks value without the appropriate tools to extract meaningful insights (Aydiner et al., 2019). Managers with the most extensive understanding and insight into their data are able to utilize it to develop corporate metrics. The combination of big data and predictive analytics enables businesses and organizations to reduce costs, enhance production speed, and innovate services and products to adapt to evolving customer demands. Furthermore, big data, when paired with artificial intelligence, significantly contributes to sustainable SCM by minimizing asynchronous information and handling intricate environmental data. Big data-AI analytics offers valuable insights for decision-makers aiming to enhance sustainable SCM and environmental performance. It also plays a role in external SC activities, such as selecting SC partners and designing for environmental considerations. Moreover, big data-AI analytics supports green SC practices and collaboration with SC partners, which ultimately aids in reducing waste and carbon emissions (Singh et al., 2018). Therefore, this research seeks to explore the influence of big data-AI on sustainable performance, particularly regarding the mediating effect of green SC practices.

This research presents several limitations that subsequent studies could potentially address. The primary focus of this research was on the direct impacts of Big Data-AI on sustainable performance. A lack of understanding regarding the factors that affect the implementation of Big Data-AI by domestic companies, as well as the mechanisms through which Big Data-AI influences green SC practices, further complicates our comprehension of the subject. Additionally, a limitation of this study is that the sample was restricted to Company, which constrained the ability to test the hypotheses and diminished the generalizability of the findings. This research is cross-sectional in nature. As data was not gathered over various time periods, the potential effects and causal relationships among the variables may differ. Future studies could utilize longitudinal data to overcome this limitation. Drawing from the conclusions and insights derived from this study, it is recommended that subsequent researchers utilize a larger sample size encompassing a wider array of businesses to improve the model's precision and the applicability of its results. Moreover, future researchers may wish to implement this framework in a developed country and conduct a comparative analysis with the results of the present study regarding developing economies to uncover new research avenues. It is prudent for upcoming studies to investigate the historical context of the adoption and integration of Big Data-AI methodologies within various green supply chain practices, as well as the internal mechanisms that support the connection between Big Data-AI and sustainable performance, to produce fresh insights. Furthermore, it is advisable for future research to assess the enhancement of organizational sustainability through more efficient resource management, diminished environmental impacts, and an elevated corporate reputation. Examining the role of management support for Big Data-AI and the implementation of sustainability practices on organizational sustainability could also expand the current understanding in this field.

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