

# Beyond CSR Commitments: The Mediating Role of AI-Enabled Big Data Analytics in Unlocking Green Innovation

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## Article

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# Abstract

Corporate social responsibility (CSR) has become an important strategic approach for firms seeking to address environmental challenges and promote sustainable innovation. However, the organizational mechanisms through which CSR contributes to green innovation remain insufficiently understood, particularly in the context of artificial intelligence (AI)-enabled digital capabilities. This study investigates the relationship between CSR and green innovation and examines the mediating role of big data analytics (BDA) powered by artificial intelligence. Drawing on stakeholder theory and the resource-based view, the study develops and empirically tests a model using partial least squares structural equation modeling (PLS-SEM), mediation analysis, and multi-group analysis. The findings demonstrate that CSR has a strong and positive relationship with BDAI, while BDAI is positively associated with green innovation. In contrast, the direct relationship between CSR and green innovation is statistically insignificant, indicating that CSR contributes to green innovation primarily through BDAI. The mediation analysis confirms a significant indirect relationship between CSR and green innovation through BDAI, with approximately 96% of the total effect transmitted through this mechanism, supporting full mediation. The multi-group analysis further reveals meaningful heterogeneity across firm characteristics. Firm size significantly differentiates the CSR–BDAI and BDAI–green innovation relationships, while profitability significantly differentiates the CSR–BDAI relationship. R&D expenditure significantly differentiates the direct CSR–green innovation relationship. However, the overall indirect CSR–BDAI–green innovation pathway does not significantly differ across the examined groups. These findings indicate that CSR commitments alone may not be sufficient to generate green innovation and that firms need to develop AI-enabled analytical capabilities to convert socially responsible practices into tangible innovation outcomes. The study contributes to the sustainability and digital transformation literature by identifying BDAI as a key organizational mechanism linking CSR to green innovation and by demonstrating that this mechanism remains broadly consistent across different firm characteristics.

## 1. Introduction

SMEs in Egypt constitutes greater than 90 percent of all business types. Also, it contributes to 60 percent of employment and about 75 percent of domestic value added. To achieve more rapid growth, digital technologies introduce up to date opportunities with respect to business efficiency, innovation and approach to markets and finance. Therefore, Egypt vision 2030 fosters advanced technologies as a strategic goal to execute progression goals and improve position of Egypt in the international economy. In this sense, the Egyptian government introduces the SMEs digital adjustment initiative for supporting SMEs with an innovation thought. Among them is “Digital future” initiative targeting SMEs by providing support in various digital transformation technologies among them is big data analytics. Hence, SMEs are more inclined to achieve competitive advantage through big data analytics (Metawa et al., 2022).

Bag et al., (2021) argued that BDA enhances the enterprise’s cost and operational performance. The main advantage of BDA is that it helps entrepreneurs to improve the quality of their decision making and to adjust strategies based upon the dynamic surrounding business environment. During dynamic times,

SMEs success in future will be accomplished by BDA through AI-based metrics utilization while preserving human resources. In this respect, BDA and AI improve the overall health and performance of enterprises. Particularly, BDA-AI provides opportunities for sustainability domain.

The manufacturing industry is perceived as an essential aspect to national economies Wu et al., (2024). However, the manufacturing sector initiates emissions that lead to pollution Hence, manufacturing enterprises should determine the appropriate ways for material usage and production process enhancement (Gallo et al. 2023). To increase their value added, manufacturing firms should be more sustainable (Wu et al., 2024).

Mukhtar et al., (2024) noted that an indispensable element for sustainable environment is green innovations which should be incorporated into manufacturing enterprises strategies. However, the market is featured by aggressive competition, and the implementation of green innovation solely will not meet stakeholders' needs. The environmental crisis calls for long term sustainable solutions that foster environmental and social concerns (Mukhtar et al., 2024). Therefore, SMEs can take advantage of adopting CSR capabilities to sustain strategic fit between resources available and stakeholder expectations with respect to green innovation implementation which raise their legitimization from various stakeholders (Achi et al., 2022). In this respect, not only green innovation should be incorporated but also enterprises should consider corporate social responsibility (CSR) issues to address socioeconomic and environmental shareholder interest and thus ensure enterprise sustainability and survivability (Mukhtar et al., 2024).

Further research is required with respect to digital transformation technologies such as big data analytics which provide firms with competitive advantage and thus perceived as a hot research issue (Metawa et al., 2022). Additionally, Padilla-Lozano & Collazzo, (2022) noted that most previous research on green innovation is theoretical focusing on the development and conceptualization of the construct, which indicates the importance of empirical research on green innovation. A call for research by Mariani et al., (2023) to examine the extent to which CSR generates investments in AI to support green innovation. There is a gap in investigating the relationship between CSR and innovation that grasps extensive attention (Wang et al., 2025). Furthermore, there is limited research that examines the relationship between AI implementation and key performance metrics (Al Halbusi et al., 2025). Moreover, studies investigating the role of BDA-AI on green performance in manufacturing industry is relatively scarce (Gallo et al., 2023; Makhoulfi et al., 2023).

In this respect, more research is needed to examine the association between BDA-AI and green innovation taking environmental pressures and customer environmental awareness into consideration (Makhoulfi et al., 2023). This is consistent with Chotia et al., (2024) who noted the scarcity of research investigating AI technologies value creation activities. In particular, Makhoulfi et al., (2023) mentioned that future research should incorporate SMEs in investigating BDA-AI from the viewpoint of entrepreneurs and top managers. Despite that, there is scant research on the forces that directly affect BDA, and also further research needs to examine the relationship between BDA powered by AI and

sustainability aspects (Bag et al., 2021). Also, there is still inconsistent research findings regarding CSR and SMEs performance in developing countries (Achi et al., 2022). Additionally, limited research examined sustainability in a comprehensive manner, further research should incorporate the three pillars of sustainability, not only its environmental aspects but also its economic and societal aspects (Calik, 2024).

Wang et al., (2025) examined the relationship between CSR and innovation performance moderated by BDA, also mentioned that further research should replicate their study in various organizations from diverse industries. Gallo et al., (2023) investigated the relationship between BDA and environmental performance mediated by green supply chain collaboration, and noted that further research should study manufacturing enterprises in other emerging countries and also they mentioned that other constructs as stakeholders pressure should be considered. Ma & Chang (2025) identified that further research should determine the type of information to be integrated into BDA-AI and its usage and sources to increase the value obtained from data. Drawing on the resource-based view, dynamic capability theory and stakeholder theory, the current research aims to examine the relationship between SMEs CSR and green innovation mediated by BDA –AI in SMEs Egyptian Context.

The present research contributes to the present research on CSR outcomes by examining the association between CSR and green innovation. Additionally, by examining BDA-AI mediating role, the current research contributes to the literature on dynamic capabilities theory. Practically, BDA-AI adoption can offer advantages for SMEs managers and policy makers to develop appropriate action plans to meet their sustainable development goals. The current research findings motivate policymakers to support SMEs in Egypt as an emerging market by strengthening digital transformation through BDA-AI to boost sustainable development.

## **2. Literature review and Hypothesis**

The present study focuses on three associated streams of literature, namely, CSR implementation, big data analytics, artificial intelligence (AI) and green innovation. The current research framework is built upon Dynamic capability view (DCV) and stakeholder theory (ST). The major controversy on whether Egyptian SMEs may improve green innovation value by CSR implementation activities and big data analytics powered by AI.

### **2.1. Corporate social responsibility (CSR)**

According to Gallo et al., (2023), enterprises faces diverse pressures from communities, media, non-governmental institutions and environmental legislation. CSR is defined as the “actions that appear to further some social good beyond the interests of the firm and that which is required by law” (McWilliams & Siegel, 2001). SMEs recognized the importance of CSR activities during the preliminary and post stages of COVID-19 pandemic. In this respect, socially responsible activities implementation enhances the satisfaction of the company’s stakeholders and sustainability concerns (Chotia et al., 2024; Mukhtar

et al., 2024). Also, (Chotia et al., 2024) noted that CSR improves environmental performance of business with respect to waste management, cost efficiency, reputational image and competitive advantage achievement. Recently, SMEs invested significantly in CSR activities and practices to enhance their performance (Achi et al., 2022)

According to Padilla-Lozano & Collazzo, (2022), CSR is categorized into five dimensions. The first dimension is environmental related CSR which reflects the goal to lessen the enterprise negative effect on the environment. The second dimension represented in workplace related CSR activities which foster superior work and family balance, equal opportunities and diversity. The third dimension reflects community-related CSR activities, which indicates how the enterprise production process influences society. The fourth dimension represents marketplace-related CSR, which reflects how enterprise interact with partners in the supply chain such as suppliers, distributors and customers. The fifth dimension which was added recently reflects formal CSR tools which indicate structural managerial practices. For instance, the usage of eco-friendly labels, environmentally friendly reporting and certification. In this sense, previous research findings indicated a positive relationship between CSR and business performance (Clarkson et al., 2011; Ioannidis et al., 2021). Hence, CSR has been recognized as an important construct to be researched in management and social fields among practitioners, policymakers and researchers (Mukhtar et al., 2024).

## **2.2. Green innovation**

In today's global environment, innovation has become essential for the company's survival. Particularly, sustainable innovation has received special attention in which societal awareness and natural resource efficient use become more popular. Sustainable innovation incorporates three dimensions; environmental, societal and economic aspects (Calik, 2024). Green innovation is used interchangeably with sustainable innovation, ecological innovation or eco-innovation and environmental innovation (Calik, 2024; Mukhtar et al., 2024).

Green innovation is defined by (Cleff & Rennings, 1999) as *"a change in production processes and technologies to formulate innovative products that enhance sustainable development by taking into account economic, environmental and social considerations"*. In this respect, (Padilla-Lozano & Collazzo, 2022) noted that green innovation reflects the importance of the firm to meet the ecological regulations and concerns.

Enterprises that implement green innovation are more likely to lessen waste, accomplish better energy efficiency which in turn leads to improve productivity, greater profitability, decrease environmental concerns and reinforce their environment friendly image (Mukhtar et al., 2024). Green innovation is classified mainly into two dimensions; sustainable product and process innovation as mentioned by (Mukhtar et al., 2024). Both dimensions are illustrated in the following sections.

### **2.2.1. Sustainable product innovation**

Calik & Bardudeen (2016) argued that sustainable product innovation (SPI) is defined as “a new or significantly improved product that provides positive environmental and societal benefits as well as economic benefits”. Sustainable product innovation calls for a new point of view regarding the life cycle of their product from the producer to disposition. Sustainable product innovation allows enterprises to select healthier components and raw materials in their product formulation which enhances the recyclability and durability of products (Mukhtar et al., 2024). In this respect, the environment friendly product design is different from the conventional innovation design (Padilla-Lozano & Collazzo, 2022). By developing new green products successfully, enterprises can prevent themselves from ecological disputes and maintain a good environment friendly image in emerging markets (Mukhtar et al., 2024). Also, there is a growing segment of customers who are more directed toward purchasing green products that are eco-friendly (Bag et al., 2021).

### **2.2.2. Green Process innovation**

Green Process innovation focuses on improving the methods of production by recycling, lessening emissions and raw materials usage which influence directly enterprises’ environmental performance as noted by (Chotia et al., 2024). Green Process innovation can be implemented by using materials that are environmentally friendly (Bag et al., 2021). Better application of sustainable process innovation lessens the unfavorable consequences of production process (Mukhtar et al., 2024). Previous research (Huang & Li, 2017; Xie et al., 2019) suggest that enterprises implement green process innovation to improve their overall performance.

## **2.3. Big data analytics powered by artificial intelligence AI (BDAI)**

BDAI has prompted a digital revolution in the context of manufacturing (Bag et al. 2021; Makhoulfi et al., 2023). Notably, there has been a societal transition from traditional to information-technology-driven systems, through the utilization of big data (Al Halbusi et al., 2025). Big data analytics is defined according to (Ma & Chang, 2025) as a recent generation of information technology intended to get value from extensive volume of data through exploration and analysis. It exceeds traditional data systems in terms of processing capacity (Al Halbusi et al., 2025). In this respect, big data analytics capability reflects the capability of prompting business insights through data analytics (Wang et al., 2025).

Bag et al., (2021) argued that big data is featured by seven Vs: variability, veracity, volume, velocity, variety, visualization and value. Enterprises encounter challenges in the management of big data which can be dealt with by BDAI methods application for instance; predictive, descriptive data analysis. The former allows firms to recognize the surrounding environment. While the latter enables enterprises to grasp business opportunities (Ma & Chang, 2025; Bag et al., 2021). Social media, ERP systems, cloud forms and web are sources from which big data can be generated in various layouts (Bag et al., 2021).

Big data analytics capability allow firms to acquire information, enhance the enterprise information acquisition capability and provide firms with the ability to predict opportunities and threats to respond

and adapt to external environment changes (Wang et al., 2025; Makhoulfi et al., 2023). Consequently, leading entrepreneurs to gain insights for more quality decision making (Bag et al., 2021) and thus enable firms to gain competitive advantage (Zong et al., 2025). Big data plays a significant role in introducing AI capabilities (Al Halbusi et al., 2025) in which BDA is better supported by AI (Ma & Chang, 2025) through opportunities provision which allows for real time responses and applications to big data (Narwane & Priyadarshinee, 2025). According to Al Halbusi et al., (2025), AI applications reflect an organized manufacturing system that provide insights or perform to implement specific objectives consistent with the enterprises goals. AI imitates the cognitive and intellectual skills of human with computers and machines help (Ma & Chang, 2025).

Big data combined with the AI high computing power are perceived to be vital for business to be successful in the current digital 4.0 era (Bag et al., 2021). Zong et al., (2025) defined big data powered by AI as systems and techniques that analyze enormous amounts of unstructured and structured data to reinforce the enterprise strategy. In this sense, BDA powered by AI provide valuable insights for effective decision making and can alter strategy correspondingly in the current dynamic business environment (Ma & Chang, 2025). BDA powered by AI is stronger and more sophisticated than conventional technology through its unique analysis (Ma & Chang, 2025). Consistent with this, Bag et al., (2021) noted that BDA powered by AI is positively associated with circular economy capabilities. Narwane & Priyadarshinee (2025) revealed that AI positively affects BDA implementation. Also, Ma & Chang (2025) concluded that BDA-AI has an indirect effect on digital supply chain transformation (DSCT), which is mediated by supply chain internal integration (SCII), supply chain external integration (SCEI) and supply chain agility (SCA). Despite the aforementioned benefits, Ma & Chang (2025) and Mariani et al., (2023) noted that BDAI implementation encounter challenges such as IT systems compatibility, Data privacy and security aspects. The trade-off between BDA-AI benefits and challenges generates an opportunity for studying BDA-AI role. BDAI is conceptualized in the current study as an analysis of information for large data sets directed toward sustainability goals.

## **2.4. Corporate Social responsibility and green innovation**

The present research is built upon stakeholder theory, which stresses that not only SMEs must consider economic interests, but also environmental and societal aspects must be considered (Mukhtar et al., 2024). According to Wang et al.,(2025), stakeholder theory suggests that CSR towards internal and external stakeholders is the cornerstone for improving performance. In this respect, it explains the relationship between CSR and green innovation. Based upon stakeholder theory, some studies have concentrated on the CSR impact on disruptive innovation (Wang et al., 2025), and green innovation (Yuan & Cao, 2022).

Kraus et al., (2020) postulated that CSR practices are more inclined to maximize green innovation and thus lessens costs. Also, firms that implement CSR activities are more likely to meet stakeholders' needs through green innovation. Enterprises that execute CSR activities are more likely to implement innovative performance through internal and external stakeholder satisfaction (Wang et al., 2025).

Chen & Peng (2023) study found that corporate social responsibility (CSR) negatively influences domestic firms' green innovation and has a destructive spillover effect on adjacent areas. On the other hand, Homayoun et al., (2023) findings revealed that green innovation acts as a mediator between CSR and corporate financial performance. Additionally, Padilla-Lozano & Collazzo (2022) research findings revealed a positive association between CSR and green innovation which affect manufacturing competitiveness in the emerging economy. Also, Mukhtar et al., (2024) findings revealed that CSR is positively significantly correlated with green innovation in the Malaysian manufacturing industry.

Chen & Jin (2023) indicated that corporate social responsibility (CSR) has a significant positive effect on green technology innovation (GTI) capabilities among Chinese companies. Novitasari & Agustia (2022) concluded that green innovation did not mediate the impact of CSR on firm performance. On the other hand, (Ruan et al., 2022 ; Mo et al., 2022 ; Chen & Jin, 2023) findings revealed that CSR positively enhances green innovation. In SMEs context, Achi et al., (2022) research findings indicated that CSR was indirectly associated with MSME performance via green process innovation. While Nsiah et al., (2023) study findings concluded that CSR has no effect on green process innovation. Thus, previous research findings indicated inconsistent results with respect to the relationship between CSR and green innovation. Also, previous research focuses solely on the association between CSR and general innovation. But whether CSR improves green innovation is still a research gap (Mukhtar et al., 2024). Hence, it is essential to examine the relationship between CSR and green innovation with respect to sustainable product and sustainable process innovation. In this respect, the current study postulates the following hypothesis:

H<sub>1</sub>. CSR implementation is positively associated with green innovation.

## **2.5. The relationship between CSR and BDAI**

Bag et al., (2021) argued that there are several external resources and forces. However, there is limited research on their direct relations with BDAI. Resource based view (RBV) theory illustrates the relationship between resources and sustainable competitive advantage in which such resources should be valuable and not easily imitated by others. In this respect, such resources promotes capability building in distinct business areas among them is technology (Bag et al., 2021). By responding to the three environmental aspects, enterprises maintain BDAI green dynamic capability which integrates environmental knowledge within business strategies (Makhloufi et al.,2023). Such view illustrates the relationship between CSR as a distinctive resource that enterprise maintains through its practices and BDAI as a dynamic capability. In this respect, Bag et al., (2021) noted that institutional pressures and resources affect the adoption of BDAI. Al Halbusi et al., (2025) identified that governance system and stakeholders understanding of the significance of technology facilitates integration of technology and the use of big data. Also, Makhloufi et al., (2023) mentioned that increasing institutional and environmental pressures leads to BDAI implementation to support green practices. In this respect, Bag et al., (2021) revealed that institutional pressures have significant role in the adoption of BDAI in South African automated and allied manufacturing firms. Based upon the aforementioned discussion, the present research postulates the following:

H<sub>2</sub>: CSR is positively associated with BDAI

## 2.6. The relationship between BDAI and green innovation

According to Zong et al., (2025), the dynamic capability view (DCV) motivates the firm to introduce new competencies to adapt to the dynamic environment. DCV promotes various dynamic capabilities in which such capabilities assist enterprises to be innovative. BDAI is viewed as a dynamic capability which improves performance in a turbulent business environment. Additionally, Wang et al., (2025) noted that big data analytics capability is viewed as a dynamic capability that assist enterprises in altering resources in an innovative way. Thus, DCV supports the relationship between BDAI and green innovation. As BDAI assists enterprises to make effective decisions with respect to green practices and aspects in their supply chain (Gallo et al., 2023). In this respect, Bag et al., (2021) revealed that BDAI adoption was found to have a positive association with sustainable manufacturing practices and circular economy capabilities. Wu et al., (2024) study applied in Chinese manufacturing context in which their findings indicated that BDAI indirectly influence radical innovation via business intelligence. Gallo et al., (2023) study concluded that BDA indirectly affects environmental performance mediated by green supply chain collaboration and moderated by top management support. Zong et al., (2025) study found that BDA indirectly affects value chain innovation via dynamic marketing capability. Makhoulfi et al., (2023) study applied in medium and large Algerian manufacturing enterprises showed that BDA positively impacts knowledge management and green innovation practices. Al Halbusi et al., (2025) study supported the moderating role of BDA between AI capability and green innovation. Also, the moderating role of BDA in the relationship between external CSR and innovation performance was supported. Despite that many studies examine the association between BDAI and innovation, limited studies examine the relationship between BDA and green innovation (Wu et al., (2024) and also most studies examine BDAI moderating role, and few studies examine BDA mediating role (see Fig. 1). As such, the present research postulates the following hypothesis.

H<sub>3</sub>: BDAI is positively associated with green innovation.

H<sub>4</sub>: BDAI mediates the relationship between CSR and green innovation.

Insert Figure [1]

## 3. Research Methodology

### 3.1 Measures

The measurement scales intended to represent the construct in the research framework were derived from previous validated scale in addition to some modifications to fit research context. Items underlying CSR construct are adopted from (Trumpp et al., 2015 ; Berman et al., 1999 ; Henriques & Sadosky, 1999 and Mukhtar et al., 2024). BDA powered by AI items measures were adapted from (Bag et al., (2021). Green innovation is classified into two dimensions green product innovation and green process innovation. Both dimensions items measures were adopted from (Chen et al., 2006; Yuan & Cao, 2022).

All research items are measured on a five-point Likert scale in addition to the questionnaire including demographic variables (see appendix 1). Table 1 provides the source of three constructs.

Table 1  
Scale and source of measurement.

| Construct                          | Abbreviation | Source                                                                                            | Items |
|------------------------------------|--------------|---------------------------------------------------------------------------------------------------|-------|
| Corporate Social Responsibility    | CSR          | (Trump et al., 2015);(Berman et al., 1999); (Henriques & Sadosky, 1999)and (Mukhtar et al., 2024) | 6     |
| Big data analytics supported by AI | BDAL         | (Bag et al., 2021)                                                                                | 10    |
| Green innovation                   | GI           | (Chen et al., 2006); (Yuan & Cao, 2022)                                                           | 8     |

Insert Table [1]

### 3.2 Sample and Data collection

The study focused on manufacturing SMEs in Egypt, considering the number of manufacturing SMEs in Egypt reached 30 firm in year 2026 and contribute to at least 43% of the total GDP (Elshennawy & Bouaddi, 2026). Hence, manufacturing SMEs are perceived as the cornerstone of Egyptian economy which accounts for 90% of the total number of projects operating in the private sector (Hajj et al., 2026). As there is no population frame existing for manufacturing SMEs, a quota nonprobability sample was drawn from Cairo and Giza governorate. A sampling frame was developed from SMEs list by the Social Fund for Development (SFD). We conducted pilot study across 30 respondents working in manufacturing SMEs to ensure the validity and reliability of the survey components before collecting the data in addition to the survey reviewed by six colleagues specializing in manufacturing SEMs to assess the study objectives. Based on the pilot results, some items were revised to enhance their relevance.

Data were collected from 350 respondents based on the rule of ten (Hair et al., 2017). 50 responses from respondents excluded and thus the study had 300 valid responses. The response rate of the study sample amounted to 86%, which is considered a very acceptable percentage in the field of social sciences. The high response rate may be due to the clarity of the questionnaire questions, which helped to decrease the excluded lists, as well as the long period of data collection, which took almost 3–4 months.

Table 2 indicates that there is no common method bias in the data because the explained percentage of variance is 12.26%, which is less than 50%.

Table 2  
Harman's single-factor Test

| <b>Total Variance Explained</b>              |                     |               |              |                                     |               |              |
|----------------------------------------------|---------------------|---------------|--------------|-------------------------------------|---------------|--------------|
| Factor                                       | Initial Eigenvalues |               |              | Extraction Sums of Squared Loadings |               |              |
|                                              | Total               | % of Variance | Cumulative % | Total                               | % of Variance | Cumulative % |
| 1                                            | 10.111              | 42.129        | 42.129       | 9.616                               | 40.067        | 40.067       |
| 2                                            | 2.794               | 11.642        | 53.771       |                                     |               |              |
| 3                                            | 1.407               | 5.864         | 59.635       |                                     |               |              |
| Extraction Method: Principal Axis Factoring. |                     |               |              |                                     |               |              |

Table 3  
Demographic information

| <b>Items</b>                | <b>Category</b>              | <b>Frequency</b> | <b>Percent</b> |
|-----------------------------|------------------------------|------------------|----------------|
| <b>Industry</b>             | Consumer Goods Industry      | 59               | 19.7           |
|                             | Basic Materials              | 43               | 14.3           |
|                             | Telecommunications           | 115              | 38.3           |
|                             | Health Care Industry         | 83               | 27.7           |
| <b>Firm Size</b>            | From 10w to 49 w             | 223              | 74.3           |
|                             | From 50 to 250w              | 77               | 25.7           |
| <b>AIE</b>                  | Less than one year           | 104              | 34.7           |
|                             | 1–2 years                    | 125              | 41.7           |
|                             | 4–5 years                    | 23               | 7.7            |
|                             | More than 4 years            | 48               | 16.0           |
| <b>Position</b>             | Executive Manager            | 43               | 14.3           |
|                             | Marketing Manager            | 62               | 20.7           |
|                             | HR Manager                   | 31               | 10.3           |
|                             | Financial Manager            | 79               | 26.3           |
|                             | Business Development Manager | 31               | 10.3           |
|                             | Chief of Financial Officer   | 28               | 9.3            |
|                             | IT Manager                   | 26               | 8.7            |
| <b>R &amp;D expenditure</b> | Under 10 million             | 163              | 54.3           |
|                             | 10–50 million                | 137              | 45.7           |
| <b>ROA</b>                  | Under 10%                    | 275              | 91.7           |
|                             | 10–20%                       | 25               | 8.3            |
| <b>Firm Age</b>             | Under 5 years                | 112              | 37.3           |
|                             | 5–10 years                   | 91               | 30.3           |
|                             | 11–20 years                  | 97               | 32.3           |
| <b>Total</b>                |                              | <b>300</b>       | <b>100</b>     |

Table 4  
Descriptive analysis

| Constructs/ Items                                                                                                                                                                                                        | Mean  | Std. Dev | CV    | Rank | VIF   |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|----------|-------|------|-------|
| CSR1                                                                                                                                                                                                                     | 4.077 | 1.078    | 26.43 | 3    | 1.645 |
| CSR2                                                                                                                                                                                                                     | 4.217 | 0.997    | 23.63 | 1    | 1.895 |
| CSR3                                                                                                                                                                                                                     | 3.790 | 1.224    | 32.29 | 6    | 1.485 |
| CSR4                                                                                                                                                                                                                     | 4.047 | 1.123    | 27.76 | 4    | 1.819 |
| CSR5                                                                                                                                                                                                                     | 3.767 | 1.210    | 32.12 | 5    | 1.474 |
| CSR6                                                                                                                                                                                                                     | 4.113 | 0.985    | 23.95 | 2    | 1.579 |
| CSR                                                                                                                                                                                                                      | 4.002 | 0.793    | 19.83 |      |       |
| BDA1                                                                                                                                                                                                                     | 3.737 | 1.088    | 29.13 | 5    | 1.760 |
| BDA2                                                                                                                                                                                                                     | 3.743 | 1.193    | 31.86 | 7    | 2.359 |
| BDA3                                                                                                                                                                                                                     | 3.750 | 1.116    | 29.75 | 6    | 2.135 |
| BDA4                                                                                                                                                                                                                     | 3.820 | 1.067    | 27.93 | 1    | 2.549 |
| BDA5                                                                                                                                                                                                                     | 3.770 | 1.074    | 28.50 | 4    | 2.710 |
| BDA6                                                                                                                                                                                                                     | 3.797 | 1.137    | 29.95 | 6    | 2.786 |
| BDA7                                                                                                                                                                                                                     | 3.773 | 1.061    | 28.12 | 2    | 2.084 |
| BDA8                                                                                                                                                                                                                     | 3.460 | 1.379    | 39.85 | 9    | 2.746 |
| BDA9                                                                                                                                                                                                                     | 3.417 | 1.348    | 39.44 | 8    | 2.703 |
| BDA10                                                                                                                                                                                                                    | 3.910 | 1.110    | 28.40 | 3    | 1.684 |
| BDA_AL                                                                                                                                                                                                                   | 3.718 | 0.897    | 24.13 |      |       |
| GI1                                                                                                                                                                                                                      | 3.527 | 1.252    | 35.50 | 2    | 2.380 |
| GI2                                                                                                                                                                                                                      | 3.600 | 1.303    | 36.21 | 3    | 2.405 |
| GI3                                                                                                                                                                                                                      | 3.690 | 1.194    | 32.35 | 1    | 2.106 |
| GI4                                                                                                                                                                                                                      | 3.470 | 1.391    | 40.09 | 4    | 2.178 |
| GI5                                                                                                                                                                                                                      | 3.063 | 1.324    | 43.21 | 7    | 1.857 |
| GI6                                                                                                                                                                                                                      | 2.973 | 1.329    | 44.68 | 8    | 2.004 |
| GI7                                                                                                                                                                                                                      | 3.003 | 1.292    | 43.01 | 6    | 1.941 |
| Notes: CSR1–CSR6 represent corporate social responsibility; BDA1–BDA10 represent big data analytics supported by AI; GI1–GI8 represent green innovation; CV = Coefficient of Variation; VIF = Variance Inflation Factor. |       |          |       |      |       |

| Constructs/ Items                                                                                                                                                                                                        | Mean  | Std. Dev | CV    | Rank | VIF   |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|----------|-------|------|-------|
| GI8                                                                                                                                                                                                                      | 3.050 | 1.270    | 41.64 | 5    | 1.714 |
| GI                                                                                                                                                                                                                       | 3.287 | 0.763    | 23.21 |      |       |
| Notes: CSR1–CSR6 represent corporate social responsibility; BDA1–BDA10 represent big data analytics supported by AI; GI1–GI8 represent green innovation; CV = Coefficient of Variation; VIF = Variance Inflation Factor. |       |          |       |      |       |

#### Insert Table [2]

Table (3) shows the sample characteristics of the 300 respondents involved in this study. Based on the industry, telecommunications firms represent the largest ratio, almost 38.3% of respondents then followed by firms operating in the health care industry (27.7%), consumer goods industry (19.7%), and basic materials industry (14.3%). The distribution refers to the sample covering several important industry sectors, with relatively greater representation from telecommunications and health care firms. Regarding the firm size, the sample is predominantly composed of relatively small and medium-sized firms, almost 74.3% of the respondents reported that their firms have between 10 and 49 employees, whereas 25.7% reported between 50 and 250 employees. In terms of artificial intelligence experience (AIE), 41.7% of respondents indicated that their firms had between one and two years of experience, while 34.7% had less than one year of experience. A further 16% reported more than four years of experience, whereas 7.7% had between four and five years of experience. These results suggest that a substantial proportion of the firms are at the early stages of developing or implementing AI-related capabilities. For the respondents' positions, financial managers constitute the largest group, representing 26.3% of the sample, followed by marketing managers (20.7%) and executive managers (14.3%). Human resource managers and business development managers each account for 10.3%, while chief financial officers and IT managers represent 9.3% and 8.7%, respectively. The participation of respondents occupying different managerial positions provides a relatively broad organizational perspective on the issues examined in the study. For research and development (R&D) expenditure, 54.3% of the firms reported spending less than 10 million, while the remaining 45.7% reported expenditure between 10 and 50 million. Concerning return on assets (ROA), the vast majority of firms (91.7%) reported ROA below 10%, whereas 8.3% reported an ROA between 10% and 20%. For firm age, 37.3% of the firms had been operating for less than five years, 30.3% had an operating history of between five and ten years, and 32.3% had been established for between 11 and 20 years.

#### Insert Table [3]

## 4. Results

### 4.1 Descriptive analysis

The results in table (4) show that CSR records the highest mean of 4.002, with a standard deviation of 0.793 and a coefficient of variation of 19.83%. This indicates a relatively high level of CSR practices among the sampled firms, with responses showing a reasonable degree of concentration around the mean. At the item level, the mean values range from 3.767 to 4.217. CSR2 records the highest mean (4.217), followed by CSR6 (4.113) and CSR1 (4.077), indicating comparatively stronger agreement with these CSR practices. In contrast, CSR5 has the lowest mean (3.767), although its value still indicates a relatively favorable assessment. The CV values range from 23.63% to 32.29%. CSR2 records the lowest CV (23.63%), suggesting the greatest consistency in responses, whereas CSR3 has the highest CV (32.29%), reflecting comparatively greater variation among respondents.

For BDAI, the mean is 3.718, accompanied by a standard deviation of 0.897 and a CV of 24.13%. These results indicate a moderately high level of adoption of big data analytics practices within the sampled firms. The item means range from 3.417 to 3.910. BDA10 has the highest mean (3.910), followed by BDA4 (3.820) and BDA5 (3.770), suggesting that these practices are relatively more prevalent among the participating firms. Conversely, BDA9 records the lowest mean (3.417), followed closely by BDA8 (3.460), indicating comparatively lower levels of agreement with these practices. The CV values vary from 27.93% to 39.85%, with BDA4 showing the lowest dispersion and BDA8 the highest. Although the variation is greater than that observed for CSR, the results still indicate a broadly consistent pattern of responses across the BDA items.

Regarding GI, the overall mean is 3.287, with a standard deviation of 0.763 and a CV of 23.21%. Compared with CSR and BDA, GI has the lowest overall mean, indicating that green innovation practices are comparatively less developed or less strongly perceived among the sampled firms. The item means range from 2.973 to 3.690. GI3 records the highest mean (3.690), followed by GI2 (3.600) and GI1 (3.527), indicating relatively stronger agreement with these green innovation practices. In contrast, GI6 has the lowest mean (2.973), followed by GI7 (3.003) and GI8 (3.050). These items may therefore represent areas in which firms have comparatively greater scope to strengthen their green innovation activities. The CV values range from 32.35% to 44.68%, with GI3 exhibiting the lowest dispersion and GI6 the highest, indicating greater differences among respondents regarding the latter practice. The VIF values remain well below the commonly applied thresholds of 5, indicating that there is no serious multicollinearity problem among the indicators. These findings provide an appropriate descriptive basis for proceeding with the subsequent assessment of the measurement and structural models.

**Insert Table [4]**

## 4.2 Reliability and validity tests

For both Table 5 and Fig. 2 present the results of the measurement model assessment based on prior studies (Hair et al., 2019) ; (Kline, 2016). Following (Hinton et al., 2014), a Cronbach's alpha value above 0.70 indicates a high level of internal reliability. In addition, (Hair et al.) suggest that factor loadings of 0.70 or above provide evidence of practical significance for the indicators. For composite reliability, both rho\_a & rho\_c should exceed 0.70, while an average variance extracted (AVE) above 0.50 indicates

satisfactory convergent validity (Hair et al., 2019). The measurement model demonstrates acceptable indicator reliability, strong internal consistency, and adequate convergent validity across CSR, BDAI, and GI. All constructs have factor loading, cronbach's alpha and composite reliability values above 0.70, while their AVE values exceed 0.50. Although CSR1 and BDA10 have loadings slightly below 0.70, their retention is supported by the satisfactory reliability and AVE values of their respective constructs. These findings provide sufficient evidence that the measurement model is reliable and suitable for proceeding to the assessment of the structural model.

Table 5  
Factor loadings, reliability, and convergent validity.

| Cons | Items | Factor Loading | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|------|-------|----------------|------------------|-------------------------------|-------------------------------|----------------------------------|
| CSR  | CSR1  | 0.645          | 0.815            | 0.823                         | 0.866                         | 0.519                            |
|      | CSR2  | 0.736          |                  |                               |                               |                                  |
|      | CSR3  | 0.713          |                  |                               |                               |                                  |
|      | CSR4  | 0.796          |                  |                               |                               |                                  |
|      | CSR5  | 0.687          |                  |                               |                               |                                  |
|      | CSR6  | 0.735          |                  |                               |                               |                                  |
| BDAL | BDA1  | 0.698          | 0.925            | 0.926                         | 0.937                         | 0.600                            |
|      | BDA10 | 0.699          |                  |                               |                               |                                  |
|      | BDA2  | 0.782          |                  |                               |                               |                                  |
|      | BDA3  | 0.755          |                  |                               |                               |                                  |
|      | BDA4  | 0.790          |                  |                               |                               |                                  |
|      | BDA5  | 0.815          |                  |                               |                               |                                  |
|      | BDA6  | 0.830          |                  |                               |                               |                                  |
|      | BDA7  | 0.762          |                  |                               |                               |                                  |
|      | BDA8  | 0.802          |                  |                               |                               |                                  |
|      | BDA9  | 0.803          |                  |                               |                               |                                  |
| GI   | GI1   | 0.869          | 0.878            | 0.882                         | 0.916                         | 0.732                            |
|      | GI2   | 0.873          |                  |                               |                               |                                  |
|      | GI3   | 0.835          |                  |                               |                               |                                  |
|      | GI4   | 0.845          |                  |                               |                               |                                  |
|      | GI5   | 0.837          | 0.845            | 0.847                         | 0.896                         | 0.682                            |
|      | GI6   | 0.834          |                  |                               |                               |                                  |
|      | GI7   | 0.832          |                  |                               |                               |                                  |
|      | GI8   | 0.801          |                  |                               |                               |                                  |

Table 6  
Discriminant validity using the Fornell-Larcker criterion.

| Construct | BDAL   | CSR    | GI    | Process | Product |
|-----------|--------|--------|-------|---------|---------|
| BDAL      | 0.775  |        |       |         |         |
| CSR       | 0.729  | 0.720  |       |         |         |
| GI        | 0.585  | 0.435  | 1.000 |         |         |
| Process   | -0.023 | -0.059 | 0.581 | 0.826   |         |
| Product   | 0.712  | 0.642  | 0.717 | 0.233   | 0.856   |

Table 7  
Discriminant validity using Heterotrait monotrait ratio (HTMT).

| Construct | BDAL  | CSR   | GI    | Process | Product |
|-----------|-------|-------|-------|---------|---------|
| BDAL      |       |       |       |         |         |
| CSR       | 0.826 |       |       |         |         |
| GI        | 0.607 | 0.463 |       |         |         |
| Process   | 0.054 | 0.110 | 0.630 |         |         |
| Product   | 0.895 | 0.748 | 0.763 | 0.069   |         |

**Insert Table [5]**

**Insert Figure [2]**

Discriminant validity is the extent to which the construct of the latent variable is distinct from other constructs of other latent variables in the model and does not measure other model variables according to experimental standards. Thus, proving the discriminant validity means that the construct is unique and includes items that are not represented by constructs of other latent variables in the model (Hair et al, 2017). Discriminant validity was measured through the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). Table (6) represents the square root of the average variance extracted for each variable. We find that they are greater than their association with other variables in the model, which indicates that the variables that make up the study model are characterized by discriminant validity.

**Insert Table [6]**

Table (7) shows that all HTMT values are less than 0.9, which indicates the discriminant validity of all the variables that make up the study model.

**Insert Table [7]**

Table 8 reports the variance explained ( $R^2$ ) and effect size ( $f^2$ ) of the endogenous constructs. The  $R^2$  values indicate that the model explains 53.1% of the variance in BDA, 33.8% in Process, 51.4% in Product, and 34.3% in GI. These results indicate moderate explanatory power for the endogenous constructs, with particularly strong explanatory capacity for BDA and Product (Chin, 1998). The  $f^2$  values range from 0.234 to 1.133. Based on the conventional thresholds of 0.02, 0.15, and 0.35 for small, medium, and large effects, respectively, the value of 0.234 represents a medium effect, whereas 0.510, 1.059, and 1.133 indicate large effects. Hence, the predictors make meaningful substantive contributions to the explained variance of the corresponding endogenous constructs, particularly for the relationships associated with the  $f^2$  values above 1.00 (Benitez et al., 2020). The  $R^2$  and  $f^2$  results provide evidence of satisfactory explanatory power and meaningful effect sizes within the structural model.

Table 8  
Variance explained ( $R^2$ ) and  $F^2$

|         | Variance explained ( $R^2$ ) |                   | F-square |
|---------|------------------------------|-------------------|----------|
|         | R-square                     | R-square adjusted |          |
| BDAL    | 0.531                        | 0.530             | 0.234    |
| Process | 0.338                        | 0.336             | 0.510    |
| Product | 0.514                        | 0.513             | 1.059    |
| GI      | 0.343                        | 0.338             | 1.133    |

#### Insert Table [8]

Table 9 presents the model fit statistics for the saturated and estimated models. Both models report an SRMR of 0.056, which is below the recommended threshold of 0.08 and indicates a satisfactory model fit. The  $d_{ULS}$  (0.877) and  $d_G$  (0.849) values are identical for both models, as are the Chi-square value (1,184.61) and NFI (0.921). The NFI exceeds the commonly accepted threshold of 0.90, providing further evidence of satisfactory comparative fit. Importantly, the identical fit statistics for the saturated and estimated models indicate that neither specification demonstrates superior fit. Overall, the results provide evidence that the proposed PLS-SEM model has an acceptable and satisfactory level of model fit.

Table 9  
Model Fit Summary.

| Fit summary | Saturated model | Estimated model |
|-------------|-----------------|-----------------|
| SRMR        | 0.056           | 0.056           |
| d_ULS       | 0.877           | 0.877           |
| d_G         | 0.849           | 0.849           |
| Chi-square  | 1184.61         | 1184.61         |
| NFI         | 0.921           | 0.921           |

Insert Table [9]

## 4.3 Structural model

### Hypotheses Testing

For both Table 10 and Fig. 3 present the structural path estimates and hypothesis-testing results. The direct effect of CSR on GI is positive but statistically insignificant ( $\beta = 0.018$ ,  $t = 0.262$ ,  $p = 0.794$ ); therefore, H1 is not supported. In contrast, CSR has a strong and positive effect on BDAI ( $\beta = 0.729$ ,  $t = 22.569$ ,  $p < 0.001$ ), supporting H2. Similarly, BDAI positively affects GI ( $\beta = 0.572$ ,  $t = 9.082$ ,  $p < 0.001$ ), providing support for H3.

Table 10  
Structural Path analysis

| Path                                                                                                                      | Coefficient | Standard error | T statistics | P values | H              | Decision      |
|---------------------------------------------------------------------------------------------------------------------------|-------------|----------------|--------------|----------|----------------|---------------|
| CSR -> GI                                                                                                                 | 0.018       | 0.068          | 0.262        | 0.794    | H <sub>1</sub> | Not Supported |
| CSR -> BDAI                                                                                                               | 0.729       | 0.032          | 22.569       | 0.000    | H <sub>2</sub> | Supported     |
| BDAI -> GI                                                                                                                | 0.572       | 0.063          | 9.082        | 0.000    | H <sub>3</sub> | Supported     |
| CSR -> BDAI -<br>> GI                                                                                                     | 0.417       | 0.050          | 8.329        | 0.000    | H <sub>4</sub> | Supported     |
| Notes: CSR represents corporate social responsibility; BDA represents big data analytics; GI represents green innovation. |             |                |              |          |                |               |

Table 11  
Mediation analysis

| Total Effect<br>(CSR → GI)                                                                                     |       | Direct Effect<br>(CSR → GI) |       | Indirect Effect<br>(CSR → BDAI → GI) |       | Effect Size             |
|----------------------------------------------------------------------------------------------------------------|-------|-----------------------------|-------|--------------------------------------|-------|-------------------------|
| Coefficient                                                                                                    | p-v   | Coefficient                 | p-v   | Coefficient                          | p-v   | (Indirect/Total effect) |
| 0.435                                                                                                          | 0.000 | 0.018                       | 0.794 | 0.417                                | 0.000 | 0.96                    |
| Notes: CSR= corporate social responsibility; BDAI = big data analytics supported by AI; GI = green innovation. |       |                             |       |                                      |       |                         |

Insert Table [10]

### Mediating Effect

Table (11) shows the indirect effect of CSR on GI through BDAI is positive and statistically significant ( $\beta = 0.417$ ,  $t = 8.329$ ,  $p < 0.001$ ), supporting H4. The total effect of CSR on GI is also significant ( $\beta = 0.435$ ,  $p < 0.001$ ), whereas the direct effect remains insignificant ( $\beta = 0.018$ ,  $p = 0.794$ ). The mediation effect accounts for approximately 96% of the total effect (indirect effect/total effect = 0.96). These results indicate that BDAI fully mediates the relationship between CSR and GI, suggesting that CSR contributes to green innovation primarily through the development and effective use of big data analytics capabilities. Thus, the findings highlight BDAI as an important mechanism through which CSR translates into green innovation.

Insert Table [11]

Insert Figure [3]

## 4.4 Multi-Group Analysis

Multi-group analysis (MGA) was conducted to examine whether the structural relationships differ across firm size, ROA, and R&D expenditure. The results are presented in Tables 12–14. Table 12 shows that the BDAI → GI relationship differs significantly between medium- and small-sized firms ( $\beta$  difference = 0.602,  $p = 0.046$ ), with a stronger positive effect among small firms ( $\beta = 0.506$ ,  $p < 0.001$ ) than medium firms ( $\beta = -0.096$ ,  $p = 0.742$ ). However, the differences in CSR → BDAI ( $\beta$  difference = - 0.292,  $p < 0.001$ ), CSR → GI ( $\beta$  difference = - 0.400,  $p = 0.228$ ), and the indirect effect CSR → BDAI → GI ( $\beta$  difference = 0.399,  $p = 0.148$ ) indicate that the mediation pathway itself does not significantly differ across firm-size groups. Table 13 indicates that ROA significantly moderates the CSR → BDAI relationship, with a significant difference between the lower- and medium-ROA groups ( $\beta$  difference = - 0.152,  $p = 0.008$ ). The relationship remains positive and significant in both groups, although it is stronger among medium-ROA firms ( $\beta = 0.866$ ) than lower-ROA firms ( $\beta = 0.714$ ). In contrast, the differences in BDAI → GI, CSR → GI, and the indirect CSR → BDAI → GI relationship are statistically insignificant ( $p > 0.05$ ). Thus, ROA does not significantly alter the overall mediation mechanism.

Table 12  
Multigroup analysis via Size

| Path              | Medium Size |        |       | Small Size |        |       | Difference |       |       |
|-------------------|-------------|--------|-------|------------|--------|-------|------------|-------|-------|
|                   | Beta        | T-v    | p v   | Beta       | T-v    | p v   | Beta       | T-v   | p v   |
| BDAI -> GI        | -0.096      | 0.329  | 0.742 | 0.506      | 7.727  | 0.000 | 0.602      | 2.029 | 0.046 |
| CSR -> BDAI       | 0.909       | 34.185 | 0.000 | 0.617      | 12.992 | 0.000 | -0.292     | 5.380 | 0.000 |
| CSR -> GI         | 0.391       | 1.210  | 0.226 | -0.009     | 0.129  | 0.897 | -0.400     | 1.216 | 0.228 |
| CSR -> BDAI -> GI | -0.087      | 0.322  | 0.748 | 0.312      | 6.385  | 0.000 | 0.399      | 1.461 | 0.148 |

Table 13  
Multigroup analysis via ROA

| Path              | Lower ROA |        |       | Medium ROA |        |       | Difference |       |       |
|-------------------|-----------|--------|-------|------------|--------|-------|------------|-------|-------|
|                   | Beta      | T-v    | p v   | Beta       | T-v    | p v   | Beta       | T-v   | p v   |
| BDAI -> GI        | 0.594     | 9.662  | 0.000 | -0.061     | 0.165  | 0.869 | 0.654      | 1.797 | 0.085 |
| CSR -> BDAI       | 0.714     | 20.539 | 0.000 | 0.866      | 20.357 | 0.000 | -0.152     | 2.794 | 0.008 |
| CSR -> GI         | 0.006     | 0.083  | 0.934 | 0.630      | 1.780  | 0.075 | -0.624     | 1.765 | 0.090 |
| CSR -> BDAI -> GI | 0.424     | 8.688  | 0.000 | -0.052     | 0.160  | 0.873 | 0.476      | 1.470 | 0.155 |

Table 14  
Multigroup analysis via R & D

|                   | Lower R & D |        |       | Higher R & D |        |       | Difference |       |       |
|-------------------|-------------|--------|-------|--------------|--------|-------|------------|-------|-------|
|                   | Beta        | T-v    | p v   | Beta         | T-v    | p v   | Beta       | T-v   | p v   |
| BDAI -> GI        | 0.684       | 9.172  | 0.000 | 0.453        | 4.222  | 0.000 | 0.230      | 1.769 | 0.079 |
| CSR -> BDAI       | 0.707       | 14.443 | 0.000 | 0.764        | 21.136 | 0.000 | -0.056     | 0.928 | 0.355 |
| CSR -> GI         | -0.132      | 1.533  | 0.125 | 0.178        | 1.613  | 0.107 | -0.310     | 2.222 | 0.028 |
| CSR -> BDAI -> GI | 0.484       | 7.040  | 0.000 | 0.346        | 4.196  | 0.000 | 0.137      | 1.285 | 0.201 |

Table 14 shows that R&D significantly differentiates the CSR → GI relationship ( $\beta$  difference = - 0.310,  $p = 0.028$ ). The direct effect is negative and insignificant for firms with lower R&D ( $\beta = -0.132$ ,  $p = 0.125$ ) and positive but insignificant for firms with higher R&D ( $\beta = 0.178$ ,  $p = 0.107$ ). However, the differences in CSR → BDAI, BDAI → GI, and the indirect CSR → BDAI → GI pathway are not statistically significant ( $p > 0.05$ ). The MGA results suggest that the core mediating role of BDAI in the CSR–GI relationship is

generally robust across the examined firm characteristics, although specific structural paths vary across groups.

Insert Table [12]

Insert Table [13]

Insert Table [14]

## 4.5 PLS-Predict

Table 15 reports the PLS-predict results for the endogenous constructs. All  $Q^2_{predict}$  values are positive, including BDAI (0.523), GI (0.182), Process (0.297), and Product (0.300), indicating that the model has out-of-sample predictive relevance for all four constructs. The highest predictive relevance is observed for BDAI, followed by Product, Process, and GI. The RMSE and MAE values further indicate the magnitude of prediction errors, with lower values reflecting greater predictive accuracy. The positive  $Q^2_{predict}$  values provide evidence that the proposed model possesses meaningful out-of-sample predictive capability across the endogenous constructs.

| Table 15<br>PLS predict |                 |       |       |
|-------------------------|-----------------|-------|-------|
| BDAI                    | $Q^2_{predict}$ | RMSE  | MAE   |
|                         | 0.523           | 0.694 | 0.546 |
| GI                      | 0.182           | 0.909 | 0.754 |
| Process                 | 0.297           | 0.954 | 0.843 |
| Product                 | 0.3             | 0.841 | 0.707 |

Insert Table [15]

## 5. Discussion

Our study findings affirm the significance of big data analytics powered by AI (BDAI) and expand the knowledge by asserting that BDAI significantly mediates the association between CSR and green innovation. BDAI importance lies in its ability as a dynamic capability mechanism to implement sustainable solutions represented by green products and process innovation. In this respect, we empirically investigated the mediating role of BDAI in the relationship between CSR and green innovation applied on manufacturing SMEs operating in Egypt. We found support for an indirect positive relationship of CSR on green innovation when channeled through BDAI. In light of the above discussion, our study offers theoretical and practical implications, which are illustrated below.

### Theoretical contribution

The present study contributes to stakeholder theory by examining the relationship between CSR and green innovation. First, there are still inconsistent research findings regarding CSR and SMEs performance in developing countries (Achi et al., 2022). Additionally, Wang et al., (2025) noted that limited attention has been paid to innovation performance role in CSR outcomes. In this respect, there is a gap in investigating the relationship between CSR and innovation that grasp extensive attention. Our findings reveal the indirect positive relationship of CSR on green innovation mediated by BDAI. Thus, extending the research of stakeholder theory. Second, the present research contributes to dynamic capability theory and digital transformation literature by examining the mediating role of BDAI in the relationship between CSR and green innovation. Prior studies investigating the role of BDAI on green performance in manufacturing industry is relatively scarce (Gallo et al., 2023), additionally, Makhoulfi et al., (2023) noted that BDAI factors combined with AI adoption have not been studied before. Also, Ma & Chang (2025) identified that further research should determine the type of information to be integrated into BDAI and its usage and sources to increase the value obtained from data. In this sense, our findings confirm BDAI full mediation between CSR and green innovation, extending the research of dynamic capabilities theory. Findings reveal that a well-designed and effective BDAI powered by AI that is built on accumulated CSR-based capabilities can help firms in ensuring that their CSR practices translate into green innovation.

Third, the present research contributes contextually and empirically to SMEs literature by examining the mechanism through which CSR is associated with green innovation from a developing economy's lens in manufacturing SMEs context. Chotia et al., (2024) noted that limited studies for environmental performance enhancement in the Egyptian manufacturing sector are conducted. Our study focuses on the Egyptian manufacturing SMEs, thus, contributing to this scarce literature on performance enhancement in the Egyptian manufacturing context. The manufacturing sector was primarily selected as it is more likely to initiate emissions that lead to pollution. Hence, manufacturing enterprises should find the appropriate ways for material usage and production process enhancement (Gallo et al., 2023). To increase their value added, manufacturing firms should be more sustainable (Wu et al., 2024).

In light of the above discussion, the present study provides a more accurate and comprehensive picture of the implementation of green innovation in manufacturing enterprises and clarifies the complex relationship between CSR and manufacturing SMEs enterprises green innovation. Additionally, Wang et al., (2025) noted that the technological adoption level and integration varies significantly among SMEs, which can result in diverse results. In this respect. Multigroup analysis was conducted to investigate such differences. Thus, our research advances knowledge by coming up with a green innovation model for the Egyptian SMEs manufacturing industry in which the results uncover new insights into how manufacturing SMEs in Egypt as one of the developing economies' can employ BDA powered by AI to attain better performance outcomes from their CSR practices. The research framework provides valuable insights to SMEs manufacturing enterprises that can significantly contribute to their desired sustainable development goals achievement.

## Practical Implications

This study has significant practical implications for both business managers and policymakers. For managers, they must emphasize enhancing their sustainable performance rather than focusing only on the financial aspects. If managers want their CSR practices to result in green innovation, they should pay attention to BDA powered by AI.

In this respect, managers should focus on enhancing big data analytics skills through training programs. To cope with the rapid pace of digital transformation and the rapidly changing external environment, SMEs managers should update their big data analysis capabilities continuously to remain competitive. For instance, integrating artificial intelligence and machine learning with big data analytics which can assist managers in reaching rapidly changing external information.

Such information shall be used for sustainable manufacturing practices. In this respect, developing products by utilizing special tools and clean production techniques. Also, the information developed would help managers in relying upon renewable energy sources such as wind or solar energy. As such, eco-friendly designs shall become more significant and environmental factors shall be concentrated when choosing business partners. Thus, more attention would be given to innovative approaches to find recycling solutions. Hence, the research framework offers guidance to managers regarding how to improve green innovation initiatives.

The proposed framework could serve also as a reference for policymakers in formulating policies and decisions related to the adoption of BDA powered by AI to improve green innovation. As part of the framework, incentives could be provided for the adoption of BDA powered by AI and the establishment of environmental standards in the SMEs manufacturing enterprises. Policymakers can cooperate with educational institutions to design programs on data analytics proficiency and AI literacy. Thus, the present study offers a distinctive pathway for Egyptian policymakers by advocating an integrative and collaborative approach to utilize big data analytics, AI and green innovation across SMEs manufacturing enterprises in Egypt.

## Limitations and further research

The present study limitations provide an avenue for further research investigations. First, data was collected using a survey method which may lead to participants' bias. Hence, it is proposed that future research should collect data from annual reports of firms. Second, we only tested BDA powered by AI as a mediator between CSR and green innovation. Other constructs that might mediate such relationships shall be investigated in future studies. Third, the sample of our study focus on manufacturing SMEs operating in Egypt which could lessen the ability to generalize our findings. Thus, we suggest that future research should investigate other different industries and countries. Also, further research should focus on specific industry to examine the relationship between CSR and green innovation in this specific industry by using measures suited for that industry executed by different enterprises within that industry.

Fourth, qualitative approaches should be explored in examining the relationship between CSR and green innovation in future studies to provide clear insights into such relationships when channeled through BDAI. Finally, the present research is a cross-sectional study; therefore, longitudinal study is suggested for future research. Additionally, future research may involve other control variables than those investigated in the present study, for instance, enterprise strategy.

## Declarations

**Disclosure statement:** No potential conflict of interest was reported by the author(s).

**Data Availability Statement:** All data and materials underpinning this study are provided as supplementary files with this submission.

**Ethical Approval:** Name of the approval body : General Scientific report development (GSRD), Cairo University, Cairo, Egypt. By ensuring informed consent from all participants and protecting participants' privacy and confidentiality. Date of Project: April 4, 2026. All procedures were performed in accordance with the ethical standards of the institutional research ethics guidelines of Cairo University. The study also adhered to relevant national regulations governing research in Egypt.

**Informed Consent:** Data were collected from employees of small and medium-sized enterprises (SMEs) operating in Egypt through a survey questionnaire administered on 30 April 2026. Participation was entirely voluntary. The introductory section of the questionnaire explicitly informed participants of the voluntary nature of their participation and their right to decide whether to participate. Participants' privacy and confidentiality were protected throughout the data-collection process.

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## Author Contribution

S.A. and D.M. developed the conceptual framework and research design. S.A. and A.R. conducted the data analysis and interpreted the results. A.R. and O.T. contributed to the theoretical development and methodology. S.A. prepared the main manuscript text and tables, while D.M., A.R., and O.T. contributed to the revision and refinement of the manuscript. All authors reviewed, commented on, and approved the final version of the manuscript.

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Figures

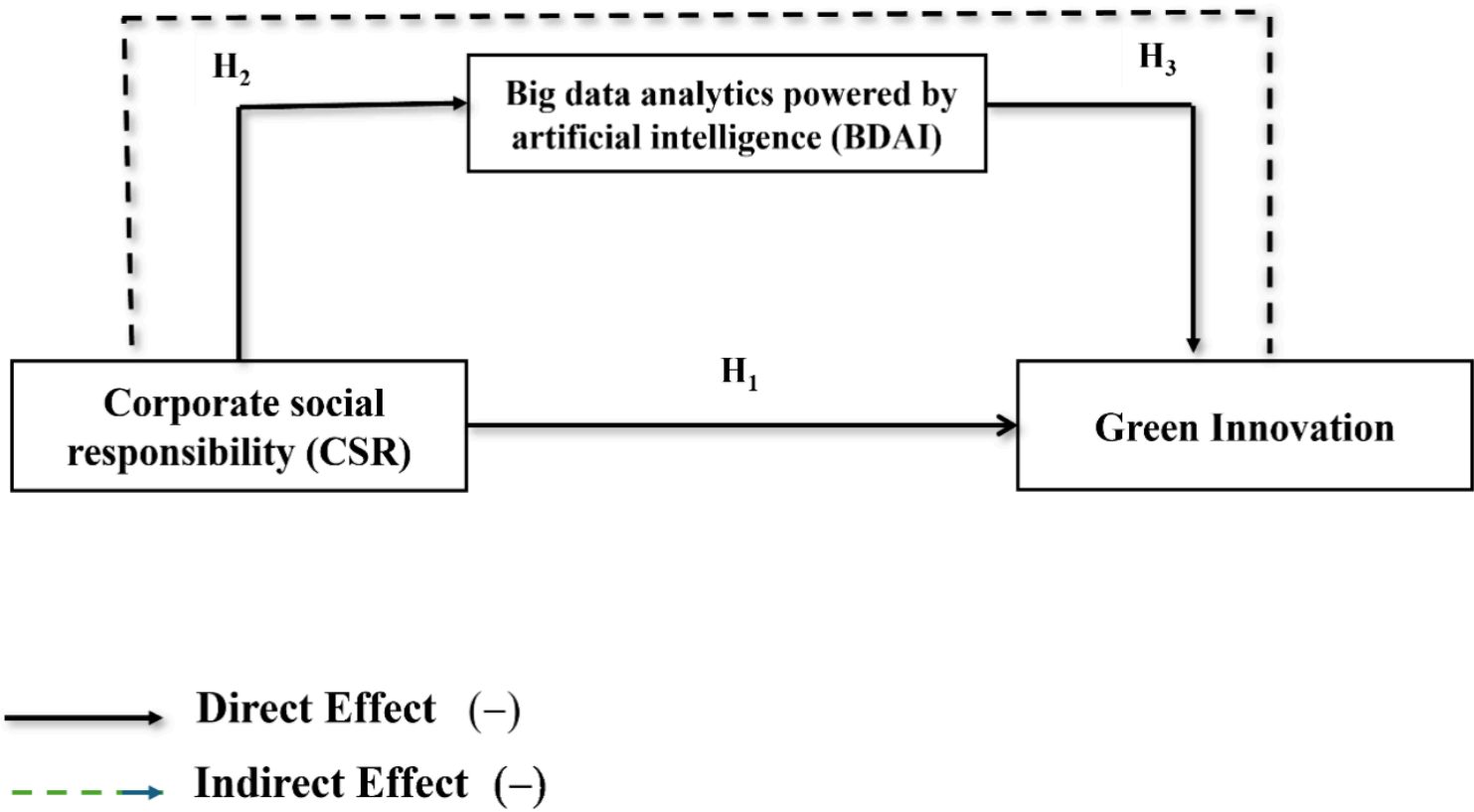


Figure 1

Research Model

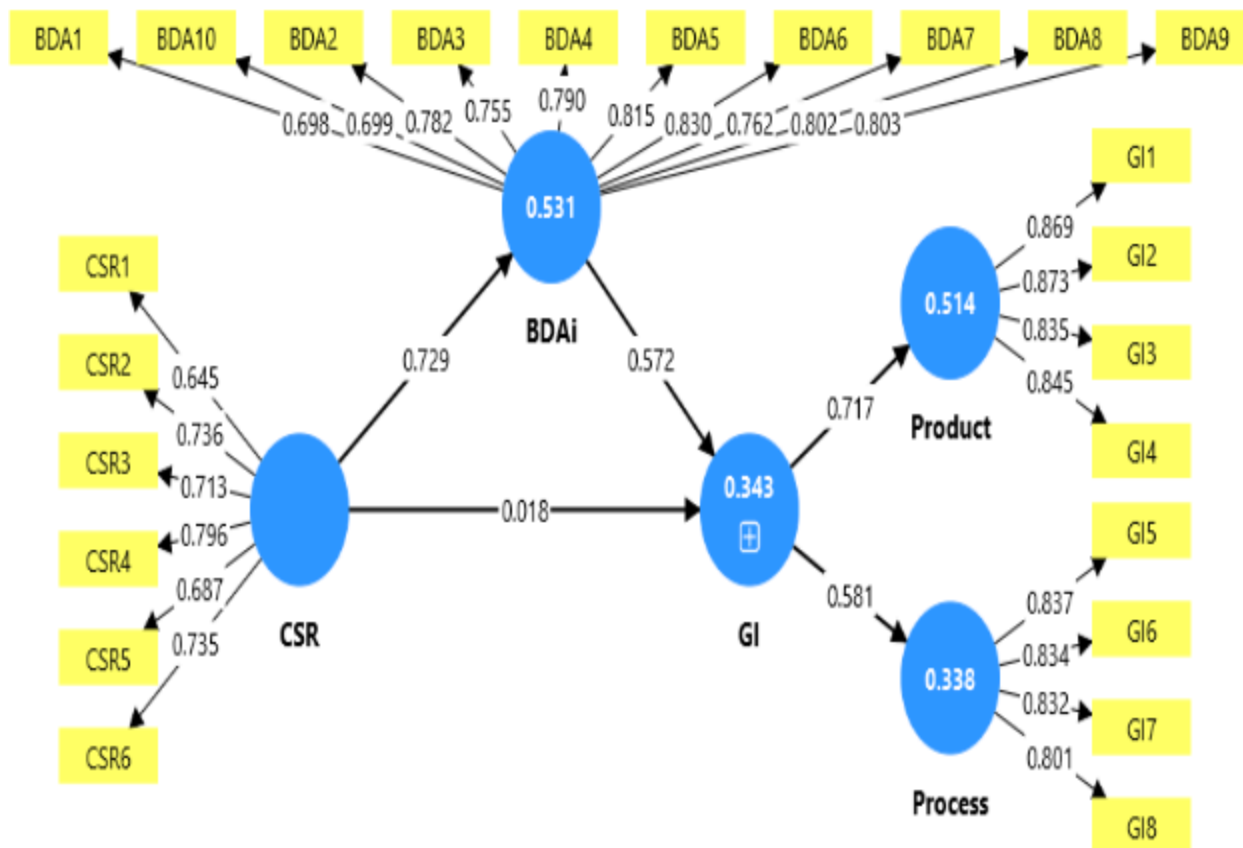


Figure 2

## Measurement Model

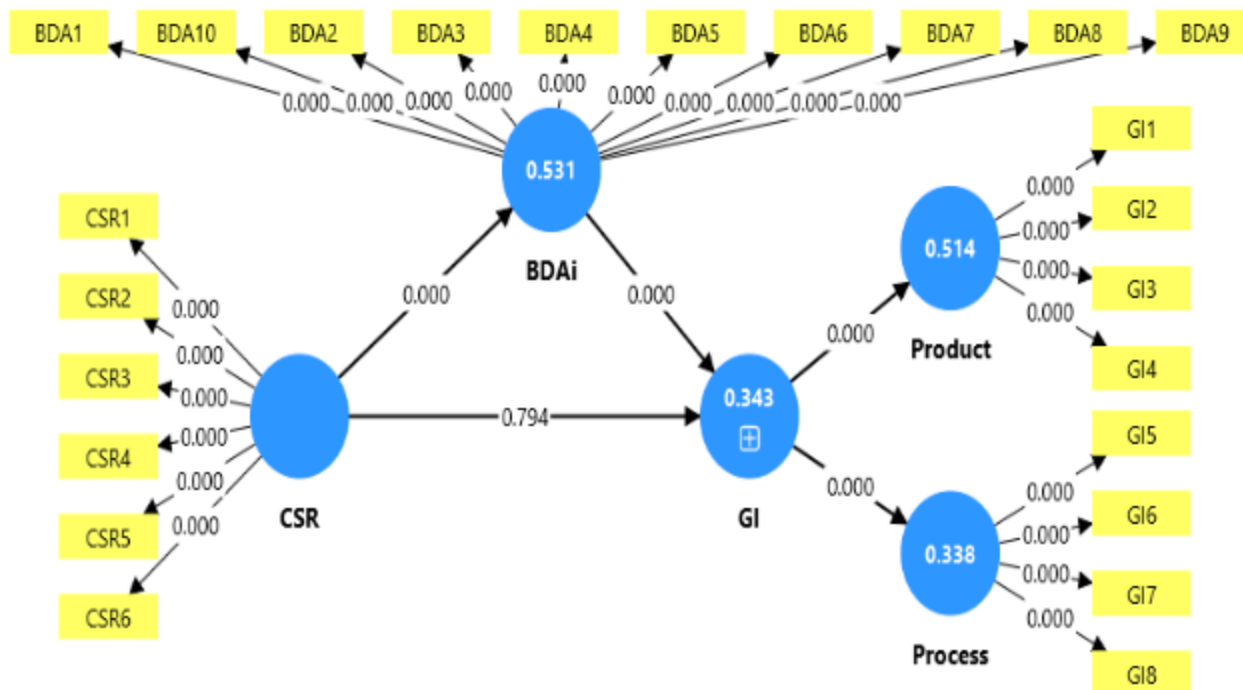


Figure 3

## Structural Model

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [data.sav](#)
- [Appendix1.questionnaire.docx](#)