Available online at www.HighTechJournal.org

HighTech and Innovation Journal

ISSN: 2723-9535

Vol. 7, No. 1, March, 2026

AI and Digital Innovation as Catalysts for Green Product Innovation and Sustainable Performance

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Received 29 August 2025; Revised 19 February 2026; Accepted 23 February 2026; Published 01 March 2026

Abstract

This study investigates the influence of AI and digital innovation on green product innovation, low-carbon behavior, and sustainable performance within small and medium-sized enterprise. Drawing on a mediation framework, it examines the mediating role of digital innovation between AI and green product innovation, and the mediating effect of green product innovation linking AI with low-carbon behavior and sustainable performance. The study further explores the sequential mediation of digital innovation and green product innovation. Using partial least squares structural equation modeling (PLS-SEM), data were collected from 1,336 respondents representing SMEs in developing economies. The results indicate that AI significantly and positively affects digital innovation and green product innovation. Digital innovation acts as a key mechanism through which AI strengthens green product innovation, while green product innovation mediates the effects of AI on low-carbon behavior and sustainable performance. These findings highlight the strategic value of AI-enabled digital innovation in advancing environmental sustainability. The study offers theoretical and practical implications for managers and policymakers, showing how SMEs can leverage AI and digital innovation to foster innovation and sustainable performance.

Keywords: Green Product Innovation; Artificial Intelligence; Digital Innovation; Low-Carbon Behaviour; Sustainable Performance.

1. Introduction

Minimizing pollution, protecting the environment, and achieving sustainable development are critical global strategic priorities [1, 2]. AI enhances green economic efficiency by optimizing energy use, reducing CO_2emissions, and facilitating clean production, which is particularly vital in rapidly industrializing emerging economies such as China, India, and countries in the Middle East. In the context of climate change, AI accelerates green technology innovation in lower-middle-income countries, where environmental challenges are substantial but resources remain limited [3-5]. Similarly, Pakistan, which is confronting severe industrial pollution and increasingly stringent environmental regulations, requires AI to optimize green processes and develop eco-friendly products. Firms in this region must address environmental crises, deficiencies in product regulation, and the need to strengthen global competitiveness within the manufacturing sector [6].

Green product innovation (GPI) refers to the use of non-toxic and renewable materials to modify products throughout their production and operational stages. GPI emphasizes reducing resource use and energy consumption to lower overall costs, decrease reliance on hazardous substances, and create new market opportunities, thereby generating both environmental and economic benefits [7]. GPI enables organizations to enhance their organizational, environmental, and social sustainability [8], as well as their sustainable business performance. Numerous studies indicate that firms'

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https://doi.org/10.28991/HIJ-2026-07-01-07

GPI initiatives generate enhanced environmental and economic value while promoting low-carbon behavior (LCB) [9]. The adoption of low-carbon behavior has become a critical concern for governments, organizations, and individuals worldwide due to the increasing urgency of climate change [10, 11]. LCB serves as an important strategy for mitigating climate change by reducing CO_2 and other greenhouse gas emissions [2]. The strategic alignment between organizational values and environmental initiatives optimizes sustainable outcomes and strengthens long-term viability [12]. Consequently, promoting GPI and LCB to improve firms' sustainable performance (SP) has become increasingly important and necessary.

To begin with, the advancement of digital innovation (DI) assists businesses in developing creative solutions. The widespread adoption of AI has emerged as a significant catalyst for organizational transformation and growth. In addition, AI supports firms in achieving enhanced economic and environmental benefits [13]. Kanellopoulou et al. [14] propose the "APSS" methodology, which emphasizes fostering organizational awareness, experimenting with AI applications to drive DI in response to specific business needs, scaling successful projects, and embedding AI into long-term strategies to generate sustainable impacts in major technology firms in Greece. The study also underscores the need for applications that can be continuously improved across diverse industries and contexts. Seraj et al. [15], drawing on dynamic capability theory, examine the influence of AI on DI. Using a convenience sample of 346 employees from five-star hotels and A-class travel agencies in Egypt, their PLS-SEM results indicate that organizational resources must be mobilized to facilitate AI adoption and strengthen DI, thereby achieving transformational resilience. However, this study does not account for variations in organizational size and maturity, particularly among SMEs. Although SMEs may benefit from greater flexibility and faster decision-making, they often face significant resource constraints. In a similar vein, Xu et al. [16] argue that GPI is a critical pathway to sustainable development. Using panel data from publicly listed Chinese firms, they empirically examine the effects and mechanisms of DI on GPI. The results show that DI has a positive effect on GPI, with stronger impacts observed in larger firms and in regions with higher levels of urbanization. AI serves as an organizational asset to address environmental challenges [17]. AI empowers individuals to analyze, design, and implement comprehensive solutions that foster GPI [18]. While some studies suggest that AI and digitalization positively influence GPI [19], others report contradictory findings, arguing that digitalization may hinder GPI [1, 20]. Consequently, empirical research on the effect of AI on DI, as well as on the mediating role of DI in the relationship between AI and GPI, remains limited. To address this gap, the present study employs primary data and quantitative methods to examine these relationships.

Second, AI is recognized as a transformative solution for enhancing GPI, encouraging LCB, and promoting SP [21]. Ying & Jin [21] examined the influence of AI on firms' GPI in China and found that AI positively affects GPI in business contexts. Their study extends the application of the resource-based view and dynamic capability theory to business practice by illustrating how AI supports the digital advancement of enterprise-level GPI. However, the authors note the need for more diverse samples across countries to validate these findings. Cheng et al. [22] developed a theoretical framework incorporating AI capacity, green information systems, green absorptive capacity, and GPI, grounded in dynamic capability theory, and conducted an empirical analysis using survey data from 288 manufacturing firms in Malaysia. The results indicate that AI capability significantly influences green absorptive capacity; however, AI does not exhibit a direct relationship with GPI, even when green absorptive capacity is considered as a mediating variable. Similarly, Dinh et al. [23] investigated the role of AI in facilitating LCB using data from 1,256 hotel managers. The findings show that AI promotes green practices aligned with environmental technology trends and enhances energy resource optimization, enabling hotels to collect real-time data on energy consumption and low-carbon behavior and to make timely operational adjustments to achieve sustainable development objectives. As this study is limited to the hotel sector, further research across diverse industries is required to clarify the role of AI in promoting LCB. The influence of AI on LCB and SP is contingent upon businesses effectively harnessing its potential through innovative processes and practices related to GPI [21, 24]. There is a scarcity of empirical studies exploring the relationship between the impact of AI on LCB and the mediating role of GPI, highlighting the necessity for further empirical investigations into this relationship

Third, AI is capable of identifying inefficiencies and improving decision-making through accurate predictions and recommendations, thereby promoting LCB [25, 26] and fosters a competitive edge. AI influences SP, encouraging environmentally responsible practices across various sectors [27]. Khan [28] investigated the effect of AI on SP by analyzing organizational performance data gathered from 325 respondents within Chinese enterprises. The results show that AI significantly affects sustainable performance, whereas environmental dynamics exhibit an insignificant relationship with organizational, environmental, and social performance. Although this study provides valuable theoretical and practical insights, it does not consider mediating variables such as GPI in the relationship between AI and SP. In a similar vein, Rashid et al. [29] gathered data from 249 supply chain professionals employed at various manufacturing firms in Pakistan. The findings revealed that big data analysis, augmented by AI, enhanced sustainable performance. However, production efficiency was found to have an insignificant effect on sustainable performance, and environmental performance did not mediate the relationship between AI and sustainable performance. As a result, the mediating roles of GPI and LCB in the relationship between AI and sustainable performance remain underexplored. Further research is therefore required to examine the interplay among these variables, particularly within manufacturing SMEs in Vietnam, to validate the significance and benefits of AI for firms' GPI, LCB, and sustainable performance capabilities.

Thus, the innovative contribution of this study lies in the examination of the mediating role of DI in the relationship between AI and GPI. The beneficial influence of AI on GPI and LCB is noteworthy. Specifically, the multi-faceted role of AI positively affects SP, with GPI and LCB functioning as intermediaries.

The objective of this research is to examine the effects of AI and DI on GPI, LCB, and SP among manufacturing SMEs in Vietnam. Drawing on the resource-based view (RBV) and social cognitive theory (SCT), the study investigates the relationships among AI, DI, GPI, LCB, and SP within the Vietnamese manufacturing context. Accordingly, the study addresses the following research questions:

RQ1: Is there a positive effect of AI on GPI with DI serving as a mediator?

RQ2: Is there a positive effect of AI on LCB with GPI serving as a mediator?

RQ3: Is there a positive effect of AI on SP with GPI and LCB serving as mediators?

This research is structured into six primary sections. Section 1 discusses the context, objectives, and the study's contribution to ecological sustainability. Section 2 explores the theoretical framework and formulates hypotheses. Section 3 outlines the research methodology employed. Section 4 showcases the results derived from PLS-SEM analysis. Section 5 offers a discussion, while Section 6 concludes with findings and suggestions for future research.

2. Theory and Hypotheses Development

2.1. Theory

This study incorporates two primary theoretical frameworks: the resource-based view (RBV) and social cognitive theory (SCT). According to the RBV, organizations can achieve sustainable competitive advantage by leveraging unique capabilities or resources that are valuable, rare, difficult to imitate, non-substitutable, and non-transferable, as originally proposed by Barney [30] and expanded by Sirmon et al. [31]. The resources that an organization controls or oversees have a significant impact on its long-term performance. This theoretical framework suggests that firms can establish a competitive advantage by effectively optimizing their resource utilization. When resources possess characteristics such as rarity, value, inimitability, and non-substitutability, they can substantially enhance organizational performance [32]. Furthermore, investments in AI and DI are expected to foster GPI, LCB, and contribute to organizational sustainability, as suggested by RBV theory [26].

SCT asserts that an individual's engagement in and acquisition of knowledge related to a specific task or behavior are shaped by the interaction among personal factors, behavioral patterns, and environmental influences [33, 34]. This theory emphasizes that the dynamic interplay between individuals' cognitive and emotional characteristics, their behavioral tendencies, and the surrounding social environment plays a critical role in shaping actions. SCT highlights two key components: outcome expectations associated with individuals' actions and beliefs regarding their ability to perform specific tasks, commonly referred to as self-efficacy [35]. According to SCT theory, the paper suggests that the level of employee commitment in LCB will be affected by the interplay of the social environment, individual behavioral inclinations, and cognitive elements [9]. This theoretical framework has been widely utilized in research examining the connection between environmental factors and behavior, in addition to the exploration of employee and management behaviors across multiple fields [36, 37].

2.2. Hypotheses Development

DI involves the creation and reconfiguration of digital elements to develop new products, services, or business models by leveraging the layered and modular characteristics of digital technologies [38]. In contrast, AI is defined as the imitation of human intelligence in machines, enabling them to think and learn in ways similar to humans [26]. AI encompasses a wide range of methods, technologies, and application systems across numerous fields and functions as both a simulation and an enhancement of human intelligence [39]. Moreover, AI is transforming various sectors by improving knowledge management, products, services, and customer support through its ability to streamline information layers and extract insights from large-scale data sets [40, 41]. It is essential for organizations to employ both incremental and radical innovations through the integration of AI within DI processes [42]. This approach supports the development of sustainable transformation capabilities and enables organizations to effectively deploy specific technologies to foster green innovation [40]. Emphasis should be placed on aligning AI-enabled DI initiatives with market dynamics and operational challenges that drive green product innovation (GPI), thereby ensuring that AI integration generates substantial business value in terms of environmental sustainability. Consequently, the development of transformation capabilities and the application of AI through micro-platforms within enterprises are imperative [43]. By strengthening AI capabilities, DI contributes to the extension of RBV theory within organizational contexts. It identifies digital resources-such as big data, AI algorithms, and dynamic adaptability-as sources of sustainable and non-imitable competitive advantage that enable firms to respond effectively to changing environments [44]. In light of these findings, the study puts forth the following hypotheses:

H1: AI positively influences DI within the enterprise.

H2: DI positively influences GPI within the enterprise.

AI enhances the efficiency of resource and energy utilization through advanced analytics and predictive modeling [45]. By processing large-scale data sets, AI algorithms can identify operational inefficiencies and recommend strategies to reduce energy consumption and waste, thereby improving the sustainability of processes and products [46]. Research conducted by Wang et al. [47] indicates that AI has substantial direct, indirect, and overall effects on green innovation. Insights derived from AI facilitate the development of sustainable materials and technologies [48]. Furthermore, AI promotes the sharing of information and collaboration, which are crucial elements in the creation of GPI [49]. A growing body of research shows that AI can effectively integrate diverse data sources to optimize resource management and enhance the coordination of both physical and non-physical assets. These capabilities extend to the development of environmentally friendly products and services, thereby strengthening GPI within organizations. As a transformative technological advancement, AI also plays a pivotal role in fostering green industries, accelerating the transition to clean energy, and contributing substantially to SP [50]. The promotion of the relationship between AI and GPI enhances RBV theory within organizations by considering AI as a unique strategic asset. This is integrated with green capabilities and GPI to establish a sustainable competitive edge through the reorganization of internal resources and ongoing innovation [21]. AI-driven platforms enable teams to share ideas and best practices, cultivating an atmosphere where collaboration and the exchange of varied viewpoints result in more thorough and effective green innovations [51]. Research predominantly focuses on the direct influence of AI on GPI, neglecting the intermediary function of DI, which results in an insufficient comprehension of the resource restructuring process [3, 52]. Consequently, this study puts forth the following hypotheses:

H3: AI has a positive impact on GPI in enterprises.

H4: AI has a positive impact on GPI with the mediating role of DI in enterprises.

GPI refers to the development of products or services that have little to no negative impact on the environment. It encompasses an organization's capacity to produce goods and services while prioritizing energy efficiency and minimizing air pollution [53], thereby reducing carbon emissions. LCB is characterized as a series of actions aimed at minimizing carbon emissions [54]. Positioned at the cutting edge of technology, GPI plays a crucial role in promoting sustainability by enhancing resource efficiency and reducing environmental pollution. The influence of GPI on carbon emissions is particularly pronounced in highly polluting industries, where the adoption of low-carbon products and green technologies can significantly reduce emissions [55]. GPI successes can create sustainable organizational competitive advantage [56], thereby enhancing a firm's overall performance as well as its sustainability [57]. At the same time, according to Khatib et al. [58], a firm's performance can be improved significantly by investing in environmental management, especially the ability of the firm to manage its carbon emissions effectively. As an outcome of green innovation (GI), GPI involves the creation of products or services that exert minimal or no detrimental impact on the environment. It reflects organizations' ability to prioritize energy efficiency and reduce air pollution during the production process [53], thus contributing to lower carbon emissions. LCB is defined by a variety of actions aimed at lowering carbon emissions [54]. GPIs, situated at the cutting edge of technology, are essential in fostering sustainability by enhancing resource efficiency and curtailing environmental pollution. Strengthening the relationships among GPI, LCB, and SP facilitates the integration of the RBV and SCT. From an RBV perspective, GPI and LCB are regarded as valuable internal resources. SCT complements this view by emphasizing the role of employees', customers', and stakeholders' expectations in driving GPI, LCB, and SP within organizations. Accordingly, RBV provides a resource-based foundation, while SCT explains behavioral mechanisms underlying the interactions among these variables [21, 59]. In light of these insights and evaluations, the research puts forward the following hypotheses:

H5: GPI has a positive impact on LCB in the enterprise.

H6: GPI has a positive impact on SP in the enterprise.

H7: LCB has a positive impact on SP in the enterprise.

AI has substantial potential to enhance GI, particularly GPI, while simultaneously fostering sustainable business practices. By simulating material properties and performance across diverse scenarios, AI can accelerate research and development activities aimed at identifying more sustainable solutions [60]. GPI refers to an organization's capacity to manufacture goods and services with an emphasis on energy efficiency and the reduction of air pollution [53], thereby contributing to lower carbon emissions. As noted by [61], GI--especially GPI-has been recognized as a critical positive driver of enterprises' sustainable development. Moreover, AI facilitates the development of sustainable products and services. Through advanced simulation and predictive capabilities, AI can expedite the research and development of sustainable innovations [62]. AI also supports the creation of energy-efficient technologies, environmentally friendly production systems, and intelligent manufacturing solutions [24]. This contributes to the development of RBV and SCT in relation to AI, GPI, and LCB variables in the context of promoting sustainable development. Nevertheless, existing studies have primarily examined the direct effects of AI on GPI or the influence of AI on LCB, with limited attention paid to the mediating role of GPI in the relationship between AI and LCB [52, 63]. Consequently, this study puts forth the following hypothesis:

H8: AI positively impacts LCB with the intermediary role of GPI in the enterprise.

SP reflects a company's capacity to achieve economic, social, and environmental objectives [64]. This perspective suggests that firms should not focus solely on profit generation but must also consider the impacts of their operations on society and the natural environment [8]. SP not only supports long-term business growth but also plays a critical role in advancing sustainable social development. In this context, GPI refers to the development or enhancement of products and services that employ eco-friendly materials, conserve energy, minimize pollution, promote waste recycling, and avoid toxic substances, with the objective of reducing adverse environmental impacts throughout the product life cycle [61, 65]. Moreover, AI can assist organizations in optimizing energy consumption, enhancing waste management systems, and creating eco-friendly products [66]. Furthermore, digital platforms facilitate collaboration and knowledge sharing among stakeholders, thereby fostering GPI and broader sustainable practices [16]. AI is a catalyst for sustainable product and service innovation [62]. The use of simulations and predictions can expedite AI-driven sustainability research and development [67]. These capabilities enable firms to develop environmentally sustainable solutions while responding effectively to evolving customer expectations and regulatory requirements [68].

Beyond environmental outcomes, AI also enhances employee equity and community engagement, thereby strengthening social sustainability [21]. SMEs will reduce their environmental footprint through green production methods and product innovation, which can boost customer interest in eco-friendly products [69]. Consequently, corporate pollution prevention initiatives can improve employee equity. SMEs that successfully implement GPI are more likely to achieve higher levels of employee equity [61, 70]. From a theoretical perspective, the RBV identifies AI and GPI as valuable strategic resources, while SCT complements this framework by emphasizing the role of stakeholders' expectations and beliefs in shaping equity and product development, ultimately contributing to a sustainable competitive advantage. Integrating RBV and SCT addresses key limitations of RBV, particularly its static nature, by incorporating dynamic, exogenous behavioral factors-an approach that is especially relevant for SMEs [27, 71]. However, existing research primarily concentrates on the effects of AI on GPI and AI on SP, overlooking the mediating influence of GPI and LCB, which results in limitations regarding the practical application of AI and its role in fostering sustainable development within businesses [21, 72]. Therefore, this study puts forth the following hypotheses:

H9: AI influences SP with GPI serving as a mediating factor in businesses.

H10: AI has a positive effect on SP with GPI acting as a mediating factor.

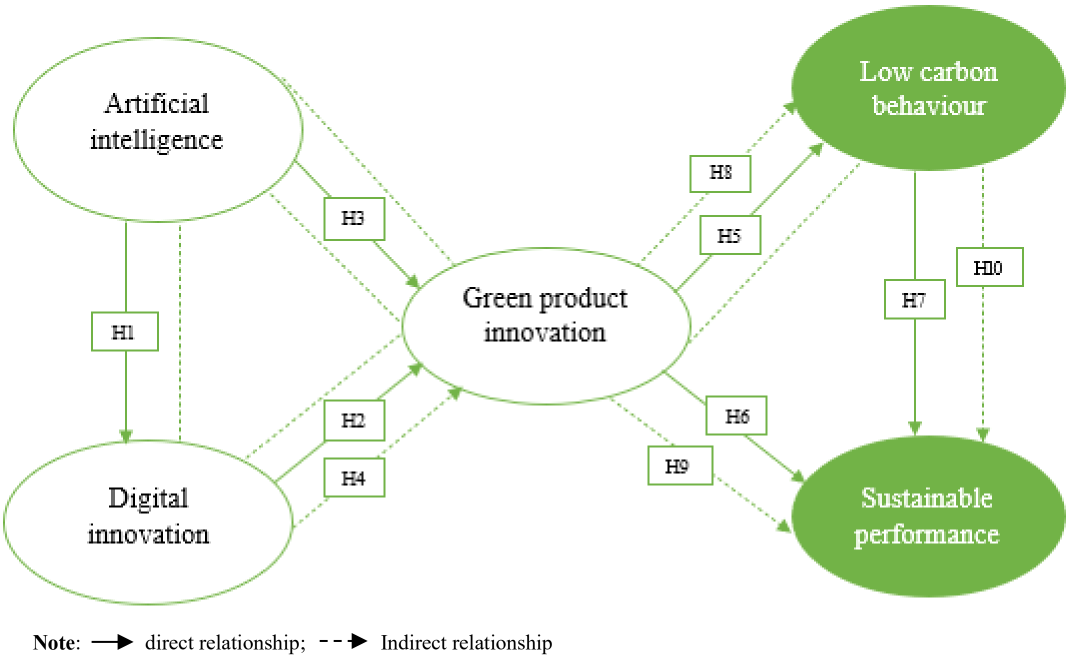

Figure 1. Research framework

From the ten research hypotheses, the suggested research model comprises five variables (refer to Figure 1). Among these, AI and DI function as independent variables. GPI and LCB serve as both dependent and mediating variables. SP is identified as the dependent variable.

3. Methodology

Figure 2, shows the flowchart of the research methodology through which the objectives of this study were achieved.

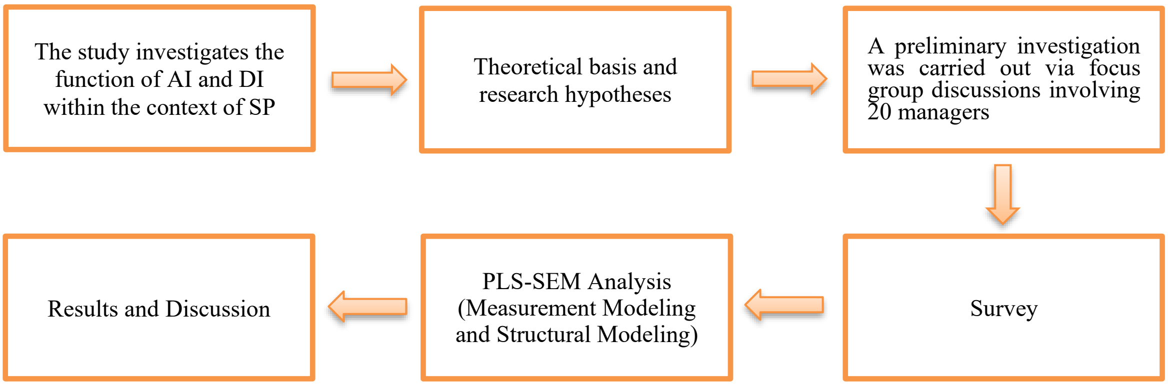

Figure 2. Research process

***Step 1*: Identification of the Research Problem: This study investigates the influence of AI and DI on product development. It examines the relationships among AI, DI, GPI, LCB, and product development, while identifying gaps in the existing literature. Based on these gaps, the study defines the research objectives and formulates the corresponding research questions.

Step 2: Theoretical Foundation and Hypothesis Development: Drawing on the RBV and SCT, this study develops a research model to examine the effects of AI and DI on product development, with particular emphasis on the roles of GPI and LCB. A total of ten hypotheses are proposed to explain the interactions among these variables, highlighting the mediating role of GPI in the relationship between AI and LCB, as well as the joint mediating roles of GPI and LCB in the relationship between AI and product development.

***Step 3*:** Initiate preliminary research through group discussions involving 20 business managers. The measurement scales for the variables in the research model were derived from earlier studies. In particular, the scale for the AI variable, which includes 5 observations, was taken from Khan et al. [25]. The scale for the DI variable, comprising 6 observations, was sourced from Al-Ayed [73]. The scale for the GPI variable was obtained from Chiou et al. [74]. The scale for the SP variable, which consists of 13 observations, was adapted from Asadi et al. [8]. Lastly, the scale for the LCB variable, featuring 7 observations, was derived from Sampene et al. [9].

The design of the questionnaire is divided into two sections. The initial section includes 35 questions that concentrate on five variables of the research model. The observed variables are evaluated using a five-point Likert scale, where 1 indicates strongly disagree, 2 signifies disagree, 3 represents somewhat disagree, 4 is neutral, 5 denotes partially agree, 6 stands for agree, and 7 indicates strongly agree. The subsequent section contains six questions pertaining to personal and business information, which encompasses gender, marital status, age, education level, income, and work experience. To validate the accuracy of the survey questions, the authors conducted a test of the questionnaire with 20 managers from Vietnamese manufacturing SMEs.

***Step 4*:** Survey Investigation. The participants of the survey were managers from Vietnamese manufacturing SMEs. Concerning sample size: As stated by Barclay et al. [75], the minimum sample size in PLS-SEM adheres to the rule of 10, which indicates that the sample size should be at least 10 times the highest number of observed variables associated with a concept in the model. In this research, the scale with the greatest number of questions contains 6; thus the minimum sample size required is 60. According to Hoyle [76], a sample size ranging from 100 to 200 serves as a suitable starting point for implementing the path model. Therefore, to facilitate the analyses, the authors aim to gather between 200 and 250 observations. The survey was executed in a convenient manner, utilizing the personal network of the research team; it was conducted online (through Google Docs links distributed via email, Zalo, and Messenger) and by directly sending questionnaires to participants from October 26 to November 28, 2024.

Following the survey, a total of 1412 responses were collected, of which 1336 were deemed valid, accounting for 94.62%. In terms of gender distribution, the majority of respondents were male (58.53%). Regarding marital status, most participants were married (89.37%). In terms of age demographics, the largest group of respondents fell within the 35-40 year age range (44.76%), which aligns with the characteristics typical of managerial positions. A significant portion of respondents held a graduate degree (67.22%). Their income primarily ranged between 30-40 million VND (48.80%). With respect to work experience, the majority of respondents reported having 10-15 years of professional experience (47.16%).

***Step 5*:** PLS-SEM Analysis. Data were gathered, processed, and examined utilizing SPSS 26 software for descriptive statistical analysis, along with Smart PLS4 software for the validation of scales (evaluating reliability, convergent validity, and discriminant validity of the scale). The authors additionally employed Smart PLS4 software to evaluate the model and research hypotheses through SEM and Bootstrap analysis techniques.

Step 6: Discussion and Conclusion. The findings of the research were deliberated upon and juxtaposed with contemporary research findings and earlier studies. Furthermore, the conclusion addressed the novel theoretical and practical contributions as well as the limitations of the study regarding the interplay between the variables AI, DI, GPI, LCB, and SP within manufacturing enterprises in Vietnam.

4. Results

4.1. Measurement Model

The study evaluates the quality of the observed variables by examining the outer loading factor, the reliability of the scales through Cronbach's Alpha and composite reliability (CR), as well as the convergent validity of the scales via the Average Variance Extracted (AVE). Bollen [77] suggests that Cronbach's Alpha for each scale should exceed 0.7, while the outer loading factor must be greater than 0.7 [78]. Additionally, CR should also be above 0.7, and the AVE should be at least 0.5 [79]. Following the initial analysis, the authors excluded the observed variables DI4, DI5, LCB4, LCB6, SP7, SP9, SP10, and SP13 due to their outer loading factors falling below the 0.7 threshold. Eliminating these observed variables contributes to enhancing the reliability and validity of the measurement model, which in turn yields more precise research outcomes. This elimination fortifies the assessment of the measurement model.

The measurement model results, after the removal of these ten observed variables, are presented in Table 1, revealing that the Cronbach's Alpha coefficients for all remaining variables range from 0.707 to 0.930, with CR values exceeding 0.7 and AVE values all greater than 0.5. This outcome confirms that each latent variable in the model accounts for more than 50% of the variance of the scales. Consequently, the reliability and consistency of the scales and variables within the research model are validated [80].

Table 1. Measurement model evaluation results through indicators

Code	Items	Outer loading factor	Cronbach' Alpha	CR(rho_a)	CR(rho_c)	AVE
AI1	"We possess the infrastructure and skilled resources to apply AI information processing system"	0.865	0.886	0.891	0.917	0.687
AI2	"We use AI techniques to forecast and predict environmental behavior".	0.865				
AI3	"We develop statistical, self-learning, and prediction using AI techniques"	0.797				
AI4	"We use AI techniques at all levels of the operations"	0.800				
AI5	""We use AI outcomes in a shared way to inform decision-making"	0.816				
DI1	"The quality of our digital solutions is superior compared to our competitors"	0.790	0.847	0.881	0.895	0.682
DI2	"The features of our digital solutions are superior compared to our competitors"	0.737				
DI3	"The applications of our digital solutions are totally different from our competitors"	0.885				
DI6	"Some of our digital solutions are new to the market at the time of launching"	0.883				
GPI1	"The company chooses the materials of the product that produce the least amount of pollution for conducting the product development or design"	0.872	0.883	0.884	0.919	0.739
GPI2	"The company uses the fewest amount of materials to comprise the product for conducting the product development or design"	0.858				
GPI3	"The company would circumspectly deliberate whether the product is easy to recycle, reuse decompose for conducting the product development "	0.854				
GPI4	"The company would circumspectly deliberate whether the product is easy to recycle, reuse decompose for conducting the product design"	0.855				
LCB1	"I take part in eco-initiatives at the workplace"	0.765	0.871	0.878	0.907	0.661
LCB2	"I educate and share knowledge about environmental issues with my co-workers"	0.784				
LCB3	"I generate various proposals for procedures to help my company operate better regarding environmental sustainability"	0.813				
LCB5	"I use ecologically friendly methods to complete jobs that are required of me"	0.828				
LCB7	"I appreciate recycling and practising energy efficiency"	0.870				
SP1	"Company has achieved important environment-related certifications"	0.753	0.938	0.953	0.947	0.645
SP2	"On average, overall environmental performance of our company has improved over the past five years"	0.751				
SP3	"The resource consumption e.g. water, electricity, and gas has decreased"	0.727				
SP4	"Improvement of environmental compliance".	0.707				
SP5	"Complying with environmental regulations (i.e., emissions, waste disposal)"	0.710				
SP6	"Decrease of cost for energy consumption"	0.930				
SP8	"Decrease of fee for waste treatment"	0.927				
SP11	"Company provides more social or environmentally friendly services in the community"	0.882				
SP12	"Our industry serving more beneficiaries (disadvantaged people) or solving environmental issues"	0.867				

To assess the discriminant validity of the variables in the research model, the HTMT index was utilized [81]. According to Kline [82], discriminant validity is established between constructs when the HTMT index is less than 0.85. The results presented in Table 2 indicate that the HTMT values for each construct meet the required threshold, confirming that the criterion for discriminant validity has been satisfied [82].

Table 2. HTMT

	AI	DI	GPI	LCB	SP
AI					
DI	0.501				
GPI	0.704	0.660			
LCB	0.592	0.591	0.754		
SP	0.676	0.552	0.708	0.700	

4.2. Structure Model

The structural model was evaluated using multicollinearity testing (VIF), path coefficients, effect size (f^2), the coefficient of determination (R^2), and hypothesis testing [80]. According to Hair et al. [83], VIF value of less than 5 indicates the absence of multicollinearity in the research model. The results as shown in Table 4, confirm that all VIF values are within acceptable ranges, indicating no multicollinearity issues among the variables.

The structural model underwent evaluation through the examination of multicollinearity VIF, path coefficients, f2, coefficient of determination (R^2), and the testing of research hypotheses [80]. In assessing the model and testing the research hypotheses, various indicators were utilized, including the path coefficient value (β) for endogenous latent variables, T-value, P-value, variance inflation factor (VIF), effect size (f^2), and R^2 [80]. A summary of the research findings is presented in Table 3 and Figure 3.

Direct impact

Table 3 presents six accepted hypotheses, all demonstrating a P-value of less than 0.05, a T-Value exceeding 1.65, and a VIF below 5 [83]. DI positively influences the enterprise's GPI with a coefficient of β = 0.461 (H1). Additionally, DI positively affects the enterprise's GPI with a coefficient of β = 0.366 (H2). AI also shows a positive impact on the enterprise's GPI, with a coefficient of β = 0.465 (H3). Furthermore, GPI positively influences the enterprise's LCB with a coefficient of β = 0.667 (H5) and has a positive effect on the enterprise's SP with a coefficient of β = 0.433 (H6). Lastly, LCB positively impacts the enterprise's SP with a coefficient of β = 0.357 (H7).

The effect size (f^2) of the exogenous variable on the endogenous variable is categorized according to Cohen [84], where f^2 values of 0.02, 0.15, and 0.35 are interpreted as weak, medium, and strong effect sizes, respectively. The findings presented in Table 3 further reveal that the GPI factor exerts a substantial effect on the LCB variable, while the AI factor significantly influences the GPI variable. Additionally, the AI factor demonstrates a moderate effect on the DI variable, and conversely, the DI factor also has a medium effect on the GPI variable. Furthermore, the GPI factor shows a medium effect on the SP variable, whereas the LCB factor has a minor effect on the SP variable.

Table 3. Confidence Interval for direct effects

Hypothesis	Path coefficient (β)	Standard deviation	T-value	P-value	VIF	f^2	Results
H1: AI → DI	0.461	0.036	12.936	0.000	1.000	0.270	Yes
H2: DI → GPI	0.366	0.049	7.511	0.000	1.270	0.214	Yes
H3: AI → GPI	0.465	0.025	25.408	0.000	1.270	0.345	Yes
H5: GPI → LCB	0.667	0.030	22.221	0.000	1.000	0.801	Yes
H6: GPI → SP	0.433	0.025	26.893	0.000	1.801	0.218	Yes
H7: LCB → SP	0.357	0.043	8.386	0.000	1.801	0.148	Yes

Indirect effects

Table 4 indicates that all four hypotheses were confirmed. In particular, the AI factor positively influences GPI, with DI serving as a mediator, yielding β = 0.169 (H4). Furthermore, the AI factor positively affects LCB, with GPI functioning as a mediator, resulting in β = 0.310 (H8). Additionally, the AI factor has a positive effect on SP, with GPI acting as a mediator, which is represented by β = 0.201 (H9). Lastly, the AI factor influences SP with GPI as a mediator, with β = 0.111 (H10).

Table 4. Confidence Interval for indirect effects

Hypothesis	Path coefficient (β)	Standard deviation	T-value	P-value	Results
H4: AI → DI → GPI	0.169	0.028	6.061	0.000	Yes
H8: AI → GPI → LCB	0.310	0.034	9.116	0.000	Yes
H9: AI → GPI → SP	0.201	0.028	7.314	0.000	Yes
H10: AI → GPI → LCB → SP	0.111	0.018	6.058	0.000	Yes

The adjusted R^2 coefficient quantifies the proportion of variance in the dependent variable that can be attributed to the independent variables [80, 81]. According to Cohen [84], an R^2 value exceeding 0.4 signifies a substantial effect, while a value ranging from 0.25 to 0.4 denotes a moderate effect, and a value falling below 0.1 reflects a minimal effect. Figure 3 report the adjusted R^2 values: the DI variable has an R^2 of 0.212, the GPI variable has an R^2 of 0.505, the LCB variable has an R^2 of 0.444, and the SP variable has an R^2 of 0.520. The AI variable explains 21.2% of the variance in DI. The AI and DI variables together explain 50.5% of the variance in GPI. The GPI variable explains 44.4% of LCB. The GPI and LCB variables together explain 52% of SP.

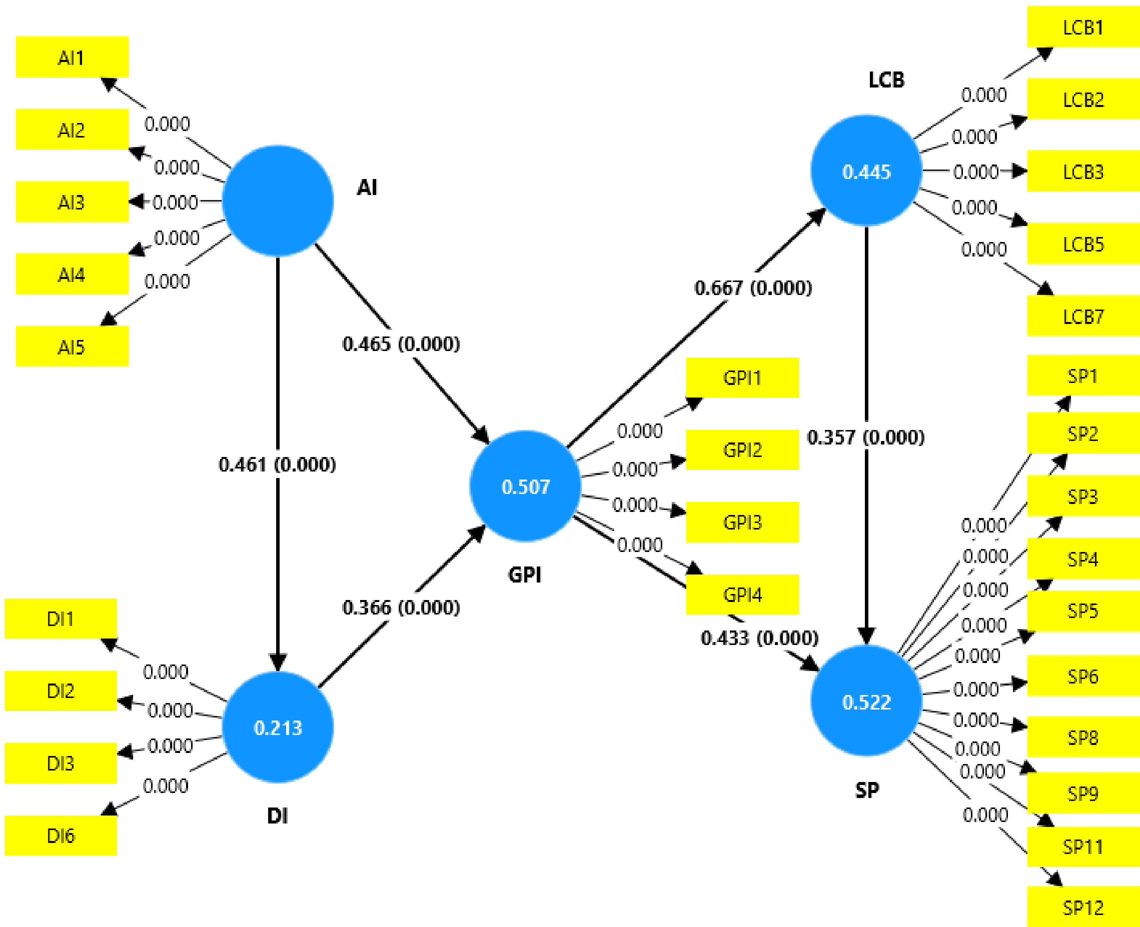

Figure 3. Structure model - SEM

5. Discussion

The research findings delve into the effects of AI and DI on GPI, LCB, and SP within Vietnamese manufacturing SMEs:

First, the results indicate that AI exerts a positive and significant influence on both DI and GPI, consistent with prior studies by Seraj et al. [15] and Luo & Zhang [20]. Notably, the effect of AI on GPI is stronger (β = 0.465) than its effect on DI (β = 0.461), suggesting that AI plays a more direct role in enhancing green product innovation. Specifically, AI improves GPI by optimizing production processes, reducing the use of hazardous materials, and lowering energy consumption. In contrast, DI technologies such as the Internet of Things (IoT) and cloud computing tend to support firms more indirectly by enabling data integration, connectivity, and process coordination [27, 63]. However, the effectiveness of AI is highly dependent on the availability and quality of data. Inaccurate or incomplete datasets may lead to biased DI outcomes, including flawed trend analyses and unreliable digital forecasts. Data collection remains a significant challenge for SMEs, particularly smaller firms with limited technological and financial resources [21, 63]. Moreover, AI systems may struggle to respond effectively to highly dynamic or complex environments, thereby requiring human intervention, which can slow down the DI process [85]. Importantly, the findings confirm the mediating role of DI in the relationship between AI and GPI. This result suggests that SMEs that successfully adopt AI can strengthen their digital innovation capabilities, which in turn enhances the efficiency and effectiveness of green product innovation. Consequently, DI serves as a critical mechanism through which AI contributes to improved environmental innovation outcomes in manufacturing SMEs.

Second, the findings demonstrate that GPI exerts a positive and significant effect on both LCB and SP. This finding aligns with the investigations conducted by Shan & Shao [55]; Sampene et al. [9] and Awwad et al. [86]. Notably, GPI has a stronger impact on LCB ($\beta = 0.667$) than on SP ($\beta = 0.201$), indicating a more robust direct influence at the individual behavioral level than at the organizational performance level. GPI directly shapes LCB by reducing resource waste and promoting energy efficiency [27]. Through GPI, individuals are more likely to adopt low-carbon practices and develop green habits more rapidly, whereas improvements in SP require broader and more complex organizational initiatives, such as the adoption of green certifications and sustainability management systems. Despite these benefits, the initial investment required for GPI and the longer payback periods pose substantial challenges for small enterprises [87]. The adoption of green technologies in the presence of outdated infrastructure often results in technological incompatibility, which hinders GPI implementation, creates operational instability, and increases compliance costs, ultimately undermining SP. Importantly, a key contribution of this study lies in identifying the positive indirect effect of AI on LCB through the mediating role of GPI. This finding is particularly relevant for firms pursuing global sustainability goals, as AI capabilities can support the achievement of such objectives [25] and, in turn, promote LCB [9]. Consequently, organizations that strengthen LCB through GPI can effectively reduce environmental impacts and enhance the efficiency of sustainable development.

Thirdly, the findings of the research indicate that LCB has a positive effect on SP ($\beta = 0.357$). This finding aligns with the studies conducted by Sharma et al. [88] and Sampene et al. [9]. Sustainable development requires the adoption of carbon-reducing behaviors, as such practices enhance resource-use efficiency and contribute to environmental protection, thereby supporting the integration of economic, social, and environmental objectives [11, 89]. However, SMEs often face substantial barriers to implementing LCB. These challenges include insufficient organizational processes, limited availability and quality of data, and a lack of employee knowledge and skills related to low-carbon practices. Moreover, internal resistance among employees can further hinder the effective adoption of LCB, thereby constraining improvements in SP [90]. Despite these obstacles, the findings reinforce the importance of LCB in enhancing sustainable performance within manufacturing firms operating in emerging economies. Moreover, this study examines the mediating roles of GPI and LCB in the relationship between AI and SP. AI can significantly accelerate research and development by simulating material properties and performance across diverse scenarios, thereby enabling firms to identify more sustainable solutions [13]. These capabilities reduce the time and costs associated with physical testing and experimentation, which in turn facilitates the development of green technologies [91]. Consequently, the findings underscore that AI, GPI, and LCB constitute critical strategic mechanisms for SMEs seeking to enhance sustainable performance and strengthen their green product offerings.

6. Conclusion

This research investigated the effects of AI and DI on GPI, LCB, and SP within Vietnamese manufacturing SMEs. In terms of its theoretical implications, the study examined the mediating function of DI in the connection between AI and GPI. These findings serve to enhance the RBV theory within the framework of sustainable development. Additionally, the research findings expand upon the mechanisms of expectations and beliefs in the theory regarding the positive influence of AI on LCB, with GPI serving as a mediator. Moreover, the study investigated the multifaceted role of AI in fostering a positive effect on SP, with GPI and LCB functioning as mediators. This represents a significant new contribution to the understanding of this relationship in the hotel sector, particularly in the context of advancing SP for sustainable development. It establishes a foundation for integrating RBV and SCT in the interplay between AI, GPI, LCB, and SP. These findings aid in elucidating the intricate interactions among the proposed variables and set the stage for future research.

From a practical standpoint, the research outcomes offer valuable insights for Vietnamese manufacturing SMEs to enhance GPI, LCB, and SP through the capabilities of AI and DI, enabling SMEs to reduce costs, improve product quality, and establish a green competitive edge in the marketplace. Despite the contributions made by this research in both theoretical and practical realms, certain limitations persist. Firstly, the study did not conduct a comparative analysis between SMEs and large corporations regarding the effects of AI and DI on GPI, LCB, and SP. Secondly, the focus was solely on small and medium-sized manufacturing enterprises in Vietnam, involving 1,336 participants, which may not accurately reflect the entire workforce within manufacturing SMEs. Furthermore, the use of a convenience sampling method through personal networks may introduce bias, thereby impacting the generalizability of the findings. Consequently, future research should aim to address these limitations, particularly in the context of SMEs in other emerging economies.

7. Declarations

7.1. Author Contributions

Conceptualization, A.N.N. and N.H.N.; methodology, H.T.D.; software, T.B.T.K.; validation, A.N.N. and T.B.T.K.; formal analysis, T.B.T.K.; investigation, N.H.N.; resources, N.H.N.; data curation, H.T.D.; writing—original draft preparation, A.N.N.; writing—review and editing, H.T.D. and N.H.N.; supervision, T.B.T.K.; project administration, H.T.D.; funding acquisition, H.T.D. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

The data presented in this study are available in the article.

7.3. Funding

This research is supported by Ministry of Education and Training of Vietnam (Grant number: B2025-TMA-01).

7.4. Institutional Review Board Statement

Not applicable.

7.5. Informed Consent Statement

Not applicable.

7.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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