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Research article

Artificial intelligence and green product innovation: Moderating effect of organizational capital

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A R T I C L E I N F O

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A B S T R A C T

Green product innovation (GPDI) is crucial for addressing ecological issues and essential for enterprises' green operations and long-term growth. Digitization offers new possibilities for enhancing corporate green practices. Nevertheless, previous studies have predominantly addressed the association between overall digitalization and corporate green innovation, and research on the outcome of specific digital technology categories on green innovation is lacking. Within this framework, this study broadens the investigation into the connection between distinct categories of digital technologies and corporate green innovation. The period 2013–2022 was selected as the sample observation period, with companies listed on China's A-share market as the study objects. The fixed-effects model was applied to investigate the impact of artificial intelligence (AI) on firms' GPDI while exploring the interaction effect of firms' organizational capital. The findings indicate that AI is beneficial to GPDI in businesses. This effect is enhanced by employee and board human capital but diminished by board social capital. These results remained valid after two-stage least squares regression. This study broadens the utilization of the resource-based view and dynamic capacity theory in business implementation. Furthermore, it extends the resulting study of AI and provides a digital enhancement pathway for corporate GPDI. This study has significant theoretical and practical implications.

1. Introduction

Reducing pollution, protecting the environment, and achieving sustainable development are global strategic concerns [1,2]. In recent decades, economic development has been severely constrained by environmental pressures [3]. The United Nations has proposed sustainable development goals, and numerous countries have begun to work on greenhouse gas reduction and environmental protection [4,5]. These factors prompt companies to redesign their operational systems and strategize on how to attain holistic green environmental and health objectives at the micro level.

Green product innovation (GPDI) is the utilization of harmless and renewable resources to modify goods during manufacturing and operational stages. GPDI prioritizes the use of fewer resources or a decreased amount of energy to diminish consumption and achieve cost savings, reduce the use of toxic substances, and open up new markets to achieve environmental and economic benefits [6]. Specifically, organizations may utilize GPDI to attain an advantage over others in the market, strengthen customer trust, enhance the corporation's reputation, and reduce the volatility of its cash flows [7]. Several studies have documented that organizations find it relatively easier to implement GPDI as opposed to green process innovation (GPcI). GPDI does not require large investments or long

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payback periods, as opposed to GPcI [8]. Some studies indicate that firms' GPDI can contribute to the creation of superior environmental and economic value [9–11]. Therefore, enhancing enterprise GPDI capabilities is considerably significant. While green innovation research has been developing over time, earlier studies focus more on green innovation in the production process, such as energy conservation, pollution reduction, and increased energy efficiency, than on the product itself, and research on the antecedents of GPDI is not comprehensive [12]. To address the gaps in the literature, this study explores the driving factors of corporate GPDI from a completely new perspective.

Consumer preferences, governments, competitors, and the media will push companies to produce more environmentally friendly products [13–15]. Moreover, the implementation of environmental decentralization, digital finance, and financial inclusion has considerably influenced firms' shift toward the creation of eco-friendly goods, facilitating green transition [16]. Internal governance, corporate governance, investor attention, and management literacy help facilitate environmentally sustainable operations within organizations [17,18], which motivates them to participate in GPDI to a certain degree. In addition to the above factors, the advancement of digital technology (DT) offers fresh prospects for corporate GPDI [19]. Simultaneously, it plays an important role in enterprise green decision-making and business operation. However, the relationship between the two is not clear, and how DT affects enterprise GPDI remains unaddressed [20–22].

Artificial intelligence (AI) is a highly promising DT with vast applications across numerous domains [23]. AI can simultaneously analyze IoT data and make scientific decisions autonomously [24] and presents significant opportunities for businesses to streamline their manufacturing processes and achieve environmentally friendly production [18,25]. Nevertheless, DT has primarily concentrated on determining the effect of digital transformation (DX) on businesses' green innovation [26–28]. To address the gap in understanding the connection between AI and GPDI, this study breaks down DT and analyzes the act of AI in promoting GPDI within organizations.

Further investigation is necessary to comprehend the varying effects of AI on enterprise GPDI in diverse situations. Organizational capital is an extremely valuable intangible asset; however, it has not gained broad attention, mainly because it usually involves complex information, which makes it difficult to measure [29]. Research has utilized organizations' selling, general, and administrative (SG&A) expenses as proxy variables for organizational capital [30–32]. Nevertheless, the composition of SG&A expenses varies according to industry and includes components unrelated to organizational capital. This study follows Xing and Yan (2023) and focuses on an important component of such capital—human resource management—such as employee human capital (EHC) [33]. Moreover, organizational capital is believed to be embedded in the key personnel of the firm, such as managers and board capital, and more efficient processes and stronger management capabilities can achieve effective interaction between humans and assets [34]. Furthermore, board directors hold the highest authority in the process of making decisions and are typically viewed as the embodiment of an organization's social capital [35]. Therefore, this study divides board capital into board human capital (BHC) and board social capital (BSC) [36]. Several studies agree that board capital is beneficial to the strategic selection of innovation activities and, thus, affects the environmental innovation of enterprises [37]. At this stage, relevant research on board capital mainly focuses on developed countries. As the impact of such capital on enterprises varies under different national cultures and legal traditions, this study verifies whether the above findings are equally applicable in emerging markets [38]. From the corporate organizational capital perspective, this study establishes the logical correlation between AI and enterprise GPDI within this specific framework, using EHC, BHC, and BSC as moderating variables.

The linear research method was adopted, the bidirectional fixed effect model was used for large sample estimation analysis, and the results were verified by the two-stage least squares (2SLS) method. The key contributions of this study are as follows. First, to expand the research into the complex facets of green innovation in corporations, this study determines the inherent connection between AI and GPDI, which is an important component of environmentally friendly practices in businesses [39]. Further, it proves that the resource-based view (RBV) and the dynamic capability theory (DCT) can be used in green business practices. This study adds to the literature on how DT and green business practices work together. Second, this study enhances the precision of AI outcome research by focusing on the micro level. Moreover, our research complements existing studies that examine the factors influencing enterprises' GPDI at the micro level and reveals the conditional differences in this relational research from an organizational capital perspective. Third, this study contributes to the development of variable-measurement methods. Existing research mainly measures GPDI using financial indicators or questionnaire survey methods [40], whereas this study relies on text analysis to measure data, improving research on measurement methods for corporate green products. Additionally, while existing studies mainly use financial indicators to measure organizational capital, this study uses non-financial indicators to represent organizational capital, which improves the multi-dimensional study of organizational capital measurement. Finally, this study provides a digital pathway for companies to enhance GPDI and greening lessons for policies and norms.

2. Theoretical background and hypotheses

2.1. Theoretical background

The RBV has been widely employed in the domain of corporate green innovation [41–43]. The RBV posits that companies can possess a competitive advantage by leveraging scarce and distinctive resources, increasing their propensity to engage in innovative activities [44]. With the arrival of Industry 4.0, DT has become a key resource for sustainability [45]. Determining whether enterprises can effectively employ DT to address the problems posed by the evolving external environment is important. Dynamic capabilities are a precondition for achieving sustainable competitiveness. Teece et al. (1997) introduced the notion of dynamic capabilities, which builds on the RBV and pertains to a firm's ability to adapt and update resources in response to environmental unpredictability and ongoing shifts in market competition [46]. According to the DCT, firms need specific technological competencies to benefit fully from green innovation [47]. Following Wu et al. (2020), companies with advanced technology are more prone to face diverse and intricate challenges in the realm of green innovation [48]. AI technology, as an embodiment of an enterprise's technological capabilities [49], can support firms to modify their current products and services and facilitate their GPDI process.

A combination of resources and capabilities can provide enterprises with a strategic edge in the market. AI technology, which combines rare resources and technological capabilities, assists firms in identifying novel opportunities, reallocating resources, and creating environmentally friendly products. This study used a combination of the RBV and DCT to examine the influence of AI on enterprise GPDI.

2.2. AI and GPDI

DT helps enterprises optimize internal governance, promote the flow of information and resources, and increase information transparency, enhancing enterprises' green innovation capability [50–52]. Big data and cloud computing in DTs improve the level of information sharing among enterprises, promoting the improvement of enterprise innovation performance. However, the impact of AI on enterprise green innovation is not clear [53]. Existing literature has not yet provided a unified definition for AI, and some scholars have interpreted it from a process perspective, arguing that AI can replace humans through programming and algorithms by utilizing machine learning [54]. This study argues that AI can learn, reason, and help humans make decisions through data processing and technical analysis [55].

Some studies have demonstrated that AI technology can effectively acquire a variety of information to orchestrate resources rationally and enhance its ability to coordinate tangible and intangible assets, all of which can penetrate green products and services and promote GPDI in corporations [56]. Moreover, as a technological innovation, AI can cultivate green industries, promote the use of clean energy, and significantly impact sustainable development [57]. GPDI can be facilitated by mining and analyzing data collected from external stakeholders [58,59], and AI can help firms process this information quickly, ensure that these products are environmentally friendly, and minimize their impact on the environment. Some researchers argue that the incorporation of transformer-based language models into AI offers valuable prospects for corporate innovation. These models can be used to facilitate the creation of new products by summarizing text and generating insights for novel ideas. Additionally, they can expedite the product development cycle and contribute to the creation of eco-friendly and energy-efficient products [60]. Therefore, we formulate the following hypothesis.

H1. AI is beneficial to GPDI in enterprises.

2.3. Moderating role of organizational capital

Organizational capital is a precious resource exclusive to a business, is usually embodied in the key talent of the corporation, such as managers, executives, and key employees, and is one of the enterprise's most valuable intangible assets [61]. Organizational capital typically encompasses various facets, including the knowledge and competence of a business, which reflect the degree of matching between the enterprise's human and physical capital to some extent [62]. Numerous studies have investigated the outcome of organizational capital on enterprises' ability to innovate and determined that companies with a high level of organizational capital exhibit superior managerial quality, higher investment in information technology, and stronger innovation capability [63]. Conversely, some studies adopt the perspective of corporate risk, arguing that higher organizational capital results in a higher risk of losing key talent. This also represents the loss of specific skills and resources [64], which is not conducive to firms' sustainability. This study focuses on several important components of organizational capital—EHC, BHC, and BSC.

2.3.1. Moderating role of BHC

According to the RBV, knowledge is the primary competitive advantage that enterprises own and is a component of human capital, particularly in top management [65]. BHC is a general term for a board's professionalism, experience, knowledge, and abilities. It is a special resource within the enterprise and largely influences strategic decision-making and management operations [66], which can provide prerequisites for the application of AI to a certain extent. Further, professional and knowledgeable boards of directors can use their expertise and skills for effective collaboration, scientific assessment of risks, and rational strategic decision-making [67]. This will help companies create timely green operational strategies and increase the importance of GPDI. Directors with higher education levels can accept new knowledge faster to solve complex problems in decision-making [68]. Board directors possess a certain amount of human capital that can also help enterprises provide flexible and effective responses in the face of emergencies [69], which is conducive to sharing technological risks in the application of AI. Moreover, enterprises require considerable financial support to conduct GPDI. Researchers and academics have discovered that a significant amount of human capital on the board of directors can stimulate enterprises' investment in R&D [70], which provides material protection for enterprises' GPDI. Accordingly, we hypothesize the following.

H2. BHC promotes the beneficial effect of AI on enterprises' GPDI.

2.3.2. Moderating role of BSC

BSC refers to directors' capacity to obtain resources by leveraging their social connections; boards acquire more social capital by building strong social networks [71]. However, BSC may negatively impact corporate sustainability. From the perspective of attention, board members pose a greater risk to the enterprise when they serve as directors in multiple enterprises, and their service efficiency and work quality are significantly worse. Directors with more connections are more likely to exhibit more speculative behaviors for their interests [72], which can harm rather than benefit the enterprise [73]. Therefore, when companies apply AI, technological risks may be shielded by the negative impact of BSC, which reduces the likelihood that they will improve their corporate green practices using DT. Some scholars document that when board members resign from part-time positions in other firms, their role in monitoring and advising the firm increases significantly [74]. This can reduce the risk of AI applications and guarantee the implementation of GPDI in enterprises to a certain extent. Therefore, we formulate the following hypothesis.

H3. BSC inhibits the beneficial effect of AI on enterprises' GPDI.

2.3.3. Moderating role of EHC

According to the RBV, employees are among the most important resources of an enterprise, and the survival and development of an enterprise depend largely on whether it has qualified employees. Although employees are not involved in making decisions for the company, they play a crucial role in generating new ideas and implementing decisions [75]. An elevated degree of EHC can enhance firm productivity and exert a favorable and influential effect on enterprise productivity [76,77]; this impact is also apparent in the application of AI. Further, personnel with elevated levels of skill and competence are more inclined to earn the confidence of bosses. This will also inspire employees to improve products and engage in more innovative behaviors [78], which will help companies adopt DT to enhance their GPDI capacity. Moreover, personnel with advanced knowledge and technology can compensate for a lack of investment in R&D, which is more likely to enhance the enterprise's innovation performance [79]. Similarly, the initial application of enterprise AI may face problems such as insufficient capital, and a high level of employee capital can compensate for this deficiency, promoting enterprise GPDI. Accordingly, we hypothesize the following.

H4. EHC promotes the beneficial effect of AI on enterprises' GPDI.

The framework of this study is illustrated in Fig. 1. Based on resource-based and dynamic capabilities theories, we propose four hypotheses to investigate the impact of AI on GPDI and the moderating role of organizational capital.

3. Methodology

3.1. Sample data and steps

The sample comprises data from Chinese A-share-listed businesses spanning from 2013 to 2022. In 2013, the Chinese government began to view AI as a key area and enforced a range of strategies to encourage its adoption, which resulted in its subsequent thriving [80]. Considering the nature of this study, the year 2013 represented the beginning of research on the influence of AI on GPDI within the framework of publicly traded Chinese companies. Regarding the current body of knowledge [53,81,82], the data underwent the following processing steps to ensure quality. Initially, the data pertaining to companies operating in the financial industry were eliminated. This was due to the adoption of distinct accounting standards in China's financial and non-financial sectors, and the inclusion of the financial industry in the statistical sample would increase the data error. Further, data from organizations exhibiting aberrant observations were deleted to prevent any potential interference caused by data errors. Next, the data on ST, ST*, and PT companies were excluded. ST category firms represent the existence of two consecutive fiscal years with net profits in the red, ST* category firms represent the existence of three consecutive fiscal years with net profits in the red, and PT category firms represent those that have ceased trading and are waiting to be delisted. All three types of companies would affect the quality of the sample data. Finally, all continuous variables were applied to a 1% shrinkage, and the final sample contained 5751 observations. AI data were acquired from the annual reports of corporations, whereas corporate GPDI data were sourced from reports on corporate social responsibility (CSR). Other data were taken from databases such as CSMAR and WIND. Stata 17.0 and Python 3.8 were used to process and analyze the data.

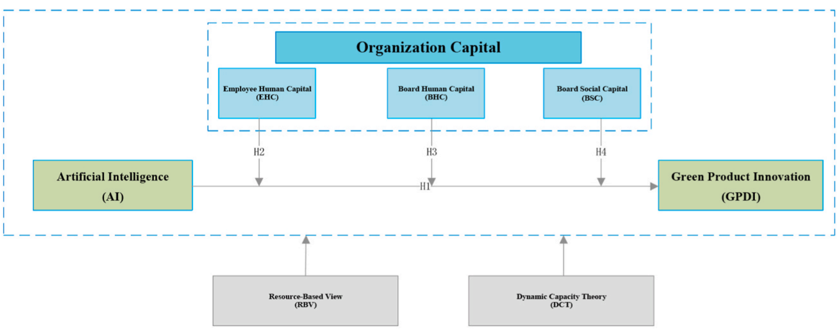

Fig. 1. Research framework.

3.2. Conception and quantification of variables

3.2.1. Green product innovation

GDPI refers to green product design, utilization of non-toxic primary substances, and mitigation of ecological contamination [83]. Some scholars have used corporate financial indicators to measure corporate GPDI [39,84], whereas others have used questionnaires [85–87]. Recent research employs textual analysis to measure green innovation more comprehensively [88]. As CSR reports provide details on organizations' environmental governance policies, including their green initiatives, readability, and tone [89], this method was considered appropriate for this study.

The core concept of this approach is examining the content of CSR reports and evaluating the degree of enterprise green innovation based on established inquiries and matching standards [88]. Drawing on existing literature [90–92], three question items were selected to assess corporate GPDI, as shown in Table 1. First, Python was used to capture and organize the listed CSR reports during the sample period [93]. Second, natural language processing (NLP) was used to train the model for each of the three questions to form a useable text analysis model. Third, we apply the model to the CSR reports for text analysis to obtain the similarity analysis results for the project questions and CSR reports. The scores were based on the criteria available in the literature [91], and if the question item was not disclosed in the CSR report, it was assigned a value of 0. If a simple textual description was provided, it was assigned a value of 1. If a quantitative description of the question was provided, it was assigned a value of 2. Finally, the mean value of the three questions was used as the basis for measuring the enterprise's GPDI.

3.2.2. Independent variable

Most measurements of AI in the existing literature rely on quantifying the industrial robots [94,95], AI dummy variables [55,96], and AI patents [97], whereas researchers use questionnaires for measurement [56,98]. Text analytics and machine-learning techniques have revealed new paths for the measurement of DTs. Corporate AI was measured according to the following steps: (1) refer to existing studies to construct a thesaurus of keywords for AI, as shown in Table 2; (2) utilize Python to gather the yearly reports of Chinese enterprises listed on the A-share market and extract the textual content of all the reports to form a complete library of texts available for retrieval; (3) use Python to retrieve textual content from the retrieved corporate annual reports, match them with AI keywords, and calculate the word frequency, which is used as the measurement basis for AI [57].

3.2.3. Moderating variables

First, the BHC was calculated using a combination of two variables: board members' education level and professional experience [66,99]. Education level was determined by computing the mean of the educational qualifications of board members, with 1, 2, 3, and 4 assigned for a bachelor's degree and below, bachelor's degree, master's degree, and doctoral degree, respectively. The proportion of board members with experience in accounting, economics, engineering, research, law, R&D, marketing, and design to the number of board members served as the basis for calculating the professional level. The board education and professional level indicators were standardized and aggregated to obtain the BHC indicator. Second, the BSC was quantified as the logarithm of the count of directors in outside businesses [68]. Finally, the level of schooling serves as a significant measure of human capital [100]. The EHC was calculated by determining the proportion of employees with a postgraduate degree or higher [101].

3.2.4. Control variables

To mitigate the impact of extraneous variables on the results, considering the relevant scholarly sources [47,102–104], this study controlled for the following variables: enterprise size (Size), period of the enterprise's listing on the stock market (ListAge), return on assets (ROA), nature of the enterprise's property rights (SOE), corporate environmental management certification (ISO 14001), percentage of female directors (Gender), and percentage of fixed assets (FIXED). Additionally, considering the effects of industry and year, we established industry and year dummy variables as controls.

All variables were defined and measured as outlined in Table 3.

3.3. Models

Referring to the existing literature [105], this study used ordinary least squares (OLS) regression to set the following model based on panel data:

$$GPDI_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \Sigma Control_{i,t} + \varphi_Y + \gamma_I + \varepsilon_{i,t}. \tag{1}$$

where $GPDI_{i,t}$ indicates the level of GPDI for enterprise i in year t. Similarly, $AI_{i,t}$ reflects the level of AI for firm i in year t. Larger values

Table 1
Questions relating to GPDI.

Variable	Question
GPDI	Q1: Make changes to product designs to avoid pollution or toxic compounds within production processes. Q2: Improve and design environmentally friendly packaging for existing and new products. Q3: Make product design modifications aimed at improving energy efficiency during usage.

Table 2
Keywords for AI.

Artificial intelligence	Business intelligence	Image understanding
Investment decision support system	Intelligent data analysis	Intelligent robot
Machine learning	Deep learning	Semantic search
Biometric identification technology	Face recognition	Speech recognition
Authentication of identity	Autonomous driving	Natural language processing

Table 3
Definitions and measurements of the variables.

	Variable	Symbol	Definition
Dependent variable	Green product innovation	*GPDI*	Text analysis of CSR report, score evaluation
Independent variable	Artificial intelligence	*AI*	Take logarithm of frequency of AI keywords in annual report
Moderating variables	Board human capital	*BHC*	Comprehensive indicator combining educational level and professional experience of board directors
	Board social capital	*BSC*	Logarithm of number of concurrent directorships in other companies
	Employee human capital	*EHC*	Employee education level (master's degree or above)
Control variables	Size of enterprise	*Size*	Logarithm of total assets
	Year of listing	*ListAge*	Logarithm of year of listing plus 1
	Net profit rate on total assets	*ROA*	Net profit/average balance of total assets
	Nature of enterprise property rights	*SOE*	I 1 for state-owned enterprises and 0 otherwise
	Enterprise environmental management system certification	*ISO14001*	1 for ISO14001 certified and 0 otherwise
	Proportion of females on board	*Gender*	Number of female directors/Number of directors
	Proportion of fixed assets	*FIXED*	Fixed assets/total assets
	Dummy variable of industry	*Industry*	1 for belonging to industry and 0 otherwise
	Dummy variable of year	*Year*	1 for belonging to year and 0 otherwise

of $GPDI_{i,t}$ and $AI_{i,t}$ indicate a higher level of GPDI and AI in enterprises, respectively. Moreover, $\Sigma Control_{i,t}$ denotes the total value of controlled variables. Fixed effects are considered. φ_Y and γ_I denote year and industry fixed effects, respectively. $\varepsilon_{i,t}$ reflects the residual error. If β_1 is significantly positive, it indicates that AI positively affects the GPDI of enterprises and supports H1.

$$GTFP_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 AI_{i,t} \times BHC_{i,t} + \beta_3 BHC_{i,t} + \Sigma Control_{i,t} + \varphi_Y + \gamma_I + \varepsilon_{i,t} \tag{2}$$

$$GTFP_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 AI_{i,t} \times BSC_{i,t} + \beta_3 BSC_{i,t} + \Sigma Control_{i,t} + \varphi_Y + \gamma_I + \varepsilon_{i,t} \tag{3}$$

$$GTFP_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 AI_{i,t} \times EHC_{i,t} + \beta_3 EHC_{i,t} + \Sigma Control_{i,t} + \varphi_Y + \gamma_I + \varepsilon_{i,t} \tag{4}$$

To test the moderating effect, we refer to the existing literature and verify it by testing the significance of the interaction term [106]. Other models were employed to determine the moderating impacts of the BHC, BSC, and EHC, respectively. $AI_{i,t} \times BHC_{i,t}$, $AI_{i,t} \times BSC_{i,t}$, and $AI_{i,t} \times EHC_{i,t}$ indicate the interaction of the independent and moderating factors, respectively. In these three models, if β_2 is significantly positive while β_1 is significantly positive, the moderating variable promotes the positive effect of AI on enterprise GPDI, and if β_2 is significantly negative while β_1 is significantly positive, there is a negative moderating effect.

Table 4
Descriptive statistics.

Variable	N	Mean	SD	Min.	Median	Max.
GPDI	5751	1.11	0.575	0.0000	1.0000	2.0000
AI	5751	0.25	0.553	0.0000	0.0000	2.5649
EHC	5751	0.04	0.049	0.0000	0.0200	0.2151
BSC	5751	1.37	0.633	0.0000	1.6094	2.3979
BHC	5751	0.16	1.507	−4.4837	0.3740	3.5448
Size	5751	23.16	1.425	20.5180	23.0297	26.9940
ListAge	5751	2.42	0.773	0.0000	2.6391	3.3673
ISO14001	5751	0.39	0.488	0.0000	0.0000	1.0000
SOE	5751	0.50	0.500	0.0000	0.0000	1.0000
ROA	5751	0.04	0.058	−0.1897	0.0363	0.2198
Gender	5751	0.14	0.127	0.0000	0.1111	0.5000
FIXED	5751	0.22	0.165	0.0025	0.1872	0.6948

Table 5
Correlations.

	GPDI	AI	EHC	BSC	BHC	Size	ListAge	|ISO14001	SOE	ROA	Gender	FIXED
GPDI	1											
AI	0.193***	1										
EHC	0.024*	0.199***	1									
BSC	0.105***	0.124***	0.022*	1								
BHC	0.115***	0.105***	0.209***	0.125***	1							
Size	0.210***	0.060***	0.118***	0.089***	0.153***	1						
ListAge	−0.032**	−0.081***	0.003	−0.185***	0.049***	0.332***	1					
ISO14001	0.210***	0.067***	−0.036***	0.086***	−0.0130	−0.183***	−0.147***	1				
SOE	−0.047***	−0.084***	0.117***	−0.132***	0.115***	0.332***	0.363***	−0.169***	1			
ROA	0.064***	0.0160	0.027**	0.064***	−0.0210	−0.062***	−0.188***	0.046***	−0.162***	1		
Gender	−0.0100	−0.0100	−0.042***	0.0120	−0.030**	−0.163***	−0.067***	0.086***	−0.214***	0.083***	1	
FIXED	0.025*	−0.127***	−0.304***	−0.043***	−0.083***	0.044***	0.066***	0.033**	0.132***	−0.085***	−0.0170	1

***, **, and * = $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

3.4. Mathematical approaches

Based on the applicability of the research topic, we refer to statistical methods in the existing literature [107–109]. The statistical methodologies employed and the order in which they were used are as follows. First, White's test was applied to determine whether the sample had a problem of heteroskedasticity. Second, the Hausman test was utilized to assess the suitability of the study for the two types of random- and fixed-effects models. Third, the distribution properties of the sample data were observed to ensure that they did not violate the fundamental assumptions of regression. Fourth, we assessed the correlation between variables and computed the variance inflation factor (VIF) to mitigate the issue of multicollinearity. Finally, the 2SLS method was employed for robustness testing.

4. Results and further analysis

4.1. Descriptive statistics

First, a heteroskedasticity test revealed that the sample did not have a heteroskedasticity problem. To improve the applicability of the model to the sample, we performed a Hausman test, which indicated that the fixed-effects model is better.

The descriptive statistics for all variables are presented in Table 4. For GPDI, the SD was 0.57, the mean value was 1.11, the lowest value was 0.0, and the peak was 2.0, which suggests deficits in the level of GPDI among firms and huge discrepancies between businesses. For AI, the SD was 0.55, the mean value was 0.25, the lowest value was 0.00, and the peak was 2.56, indicating that the degree of AI application in Chinese enterprises was generally low, and there were large differences in AI levels among different firms. The lowest and median values of the EHC were 0.00 and 0.02, respectively, which signify a low overall level of EHC among listed companies in China. The lowest value of the BSC was 0.00, the median value was 1.60, and the SD was 0.63, suggesting that firms' boards of directors' human capital levels were generally higher; however, there were large gaps among firms. Additionally, the lowest value of BHC was negative because of the standardization of the variable with reference to the existing literature.

Table 6
Regression results.

Variable	(1)	(2)	(3)	
	GPDI	GPDI	GPDI	GPDI
AI	0.0677***	0.0590***	0.0749***	0.0579***
	(4.0316)	(3.6576)	(4.3292)	(3.3135)
BHC		0.0063		
		(0.8152)		
BSC			0.0064	
			(0.2904)	
EHC				0.4690
				(1.0546)
AI × BHC		0.0341***		
		(3.2053)		
AI × BSC			−0.0656***	
			(-2.6298)	
AI × EHC				0.7154**
				(2.5071)
Size	0.0829***	0.0807***	0.0827***	0.0805***
	(3.1433)	(3.0551)	(3.1161)	(3.0686)
ListAge	0.0966**	0.0961**	0.1013**	0.0993**
	(2.3458)	(2.3312)	(2.4486)	(2.4055)
ISO14001	0.0885***	0.0881***	0.0886***	0.0864***
	(4.3646)	(4.3670)	(4.3890)	(4.2569)
SOE	−0.0342	−0.0299	−0.0326	−0.0363
	(-0.4004)	(-0.3492)	(-0.3806)	(-0.4255)
ROA	−0.1350	−0.1334	−0.1405	−0.1172
	(-0.8586)	(-0.8488)	(-0.8927)	(-0.7414)
Gender	−0.2107**	−0.2058**	−0.2034**	−0.2101**
	(-2.2422)	(-2.1888)	(-2.1759)	(-2.2394)
FIXED	0.0482	0.0479	0.0405	0.0516
	(0.3711)	(0.3700)	(0.3112)	(0.3980)
Constant	−1.0864*	−1.0350*	−1.1016*	−1.0575*
	(-1.7749)	(-1.6870)	(-1.7992)	(-1.7367)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	5751	5751	5751	5751
R-squared	0.0949	0.0903	0.102	0.0997

Robust t-statistics are in parentheses. ***, **, and * = $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

4.2. Correlation

Pearson's correlation analysis was conducted for all variables. In Table 5, the correlation coefficient between AI and GPDI was 0.193, which passes the 1% significance level threshold. A substantial and strong connection exists between AI and enterprise GPDI. This finding initially supports H1, but further investigation is required. The correlations of the other variables were all below 0.4, which highlights a tenuous association among additional variables; this can aid the model in better discerning the impact of AI on GPDI. To avoid covariance interference, the VIF is employed to calculate multicollinearity. The results reveal that all VIF values are below 3, which indicates the absence of multicollinearity.

4.3. Regression results and analysis

The regression results for the model used to evaluate the hypotheses are reported in Table 6. The coefficient of AI was 0.0677 and significant at the 1% level, which verifies H1—AI has a beneficial impact on GPDI. Regarding the moderating impact of BHC, the coefficient of the interaction term between AI and BHC was 0.0341 and demonstrated statistical significance at the 1% level. Moreover, the coefficient of AI was positive and significant, which suggests that BHC enhances the favorable impact of AI on GPDI, which supports H2. The coefficient of the interaction term between AI and BSC was −0.0656 and statistically significant at the 1% level. Additionally, the coefficient of AI was statistically significant and positive, which indicates that BSC suppresses the beneficial impact of AI on GPDI, supporting H3. Similarly, BHS enhances the favorable impact of AI on enterprise GPDI; thus, H4 is also supported.

4.4. Robustness test

To verify the robustness of the observational findings, we employ a one-period delayed corporate AI (AIt-1) as an instrumental variable (IV) and use the 2SLS method [110]. In Table 7, the IV test yields a Cragg-Donald Wald F statistic value of 238.553, which surpasses the critical value of the instrumental variable at the 10% level. This indicates that the lagged one-period independent variable is strong IV. Meanwhile, the p-value for the non-identifiable test is 0.000, which suggests that the IV is legitimate. As the number of IVs equals that of independent variables, an over-identification test was not required. In the first stage of the robustness regression, IV is employed to perform a regression analysis on AI and obtain the estimated values of the endogenous variables. Second, after successfully addressing the issue of endogeneity, the coefficient of AI is 0.1424, which passes the significance test, confirming the beneficial outcome of AI on GPDI in firms. Consequently, the original conclusion remains valid.

Table 7
Robustness test results.

Variable	(1)	(2)
	AI	GPDI
AI_{t-1}	0.2844***	
	(15.4452)	
AI		0.1424**
		(2.0027)
Size	0.0684***	0.0398
	(2.6013)	(1.3460)
ListAge	0.1344**	0.0224
	(2.3398)	(0.3494)
ISO14001	−0.0238	0.0694***
	(-1.2203)	(3.2363)
SOE	0.0325	−0.1457*
	(0.4161)	(-1.6994)
ROA	−0.0905	−0.0722
	(-0.5646)	(-0.4091)
Gender	−0.0866	−0.2215**
	(-0.9658)	(-2.2465)
FIXED	0.1163	0.0080
	(0.9957)	(0.0623)
Constant	−1.7705***	0.1379
	(-2.7390)	(0.1894)
N	3660	3660
Industry FE	YES	YES
Year FE	YES	YES
R-squared	0.153	0.028
Under-identification test p-value	0.000	
Cragg-Donald Wald F statistic	238.553	
10% maximal instrument variable size	16.38	

Robust t-statistics are in parentheses. ***, **, and * = $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

5. Discussion and conclusions

5.1. Discussion

Considered one of the most promising DTs, AI is likely to become a generalized technology and be incorporated into business innovation processes, contrary to other DTs [111,112]. However, much of the literature ignores this trend and focuses on the broad topic of digitization [113–115]. AI can improve internal operational procedures within an organization [116], operational effectiveness [117], scientific decision-making [118], and commercial frameworks [119]. Nevertheless, how AI affects businesses that innovate green products remains unclear.

This study finds that AI can promote GPDI in enterprises. Previous studies have emphasized the influence of stakeholders [120], leadership [13], organizational climate [121], and institutional pressure [122] on GPDI in enterprises. However, these studies were incomplete and neglected AI within businesses and its ability to drive green operations. This study determines the outcome of AI on enterprise GPDI using the RBV and DCT. AI can mine and analyze large-scale data through machine learning, which provides the possibility of quickly processing complex information and determining the direction of product development. Moreover, AI technology can intelligently analyze the environmental friendliness of products and their degree of impact, minimize the utilization of hazardous raw materials, and encourage the advancement of environmentally friendly items, which is significant for environmentally sustainable development. The empirical research further supports the proposed hypothesis that AI promotes GPDI in enterprises.

Furthermore, this study reveals differences in the relationship between AI and corporate GPDI in a heterogeneous setting. The utilization of AI and GPDI is intricately linked to the involvement of essential company individuals. Board members and corporate employees, as leaders and followers, are important resources in the organization. This study focuses on the impacts of BHC, BSC, and EHC on organizational capital regarding the utilization of DTs and corporate green operations. BHC represents the educational and professional backgrounds of board members. Professional directors with deep educational backgrounds are more likely to make scientific and effective decisions, which promotes the effective execution of company strategies [67]. This study also confirmed this finding. A high level of BHC aids in the application of AI to corporate GPDI. The secondary influence of EHC on the development of environmentally friendly practices within corporations is typically ignored. Employees usually do not participate in corporate decision-making. However, the implementation of any innovative decision cannot be separated from employees, and their competence is related to the output of corporate innovations, which is a key part of corporate GPDI. This study highlights that EHC is beneficial to the association between AI and GPDI, which further confirms the significance of high-quality employees in promoting environmentally sustainable practices inside corporations. Nevertheless, the effect of BSC on firms remains controversial. Some studies have documented that when a board has more social capital, its behavior is more speculative, and directors who are more occupied with other responsibilities harm the overall quality of board decisions. Theoretically, higher BSC leads to more external resources; nonetheless, in practice, the costs associated with higher BSC often outweigh the benefits. This study further validates that BSC has a markedly adverse effect on the GPDI process of AI-enabled enterprises.

5.2. Conclusions

This study utilized a two-way fixed-effects model and specifically focused on Chinese A-share-listed companies to determine the direct outcome of AI on GPDI as well as the indirect results of BSC, BHC, and EHC. The study was conducted within the theoretical framework of the RBV and dynamic capability.

First, AI positively affects enterprises' GPDI, and this conclusion remained valid after the robustness test. According to the RBV and DCT, businesses should have the corresponding dynamic capabilities to deal with digital development trends. As a scarce resource for businesses, AI offers strong technical support for innovative behavior [123]. Businesses should also conform to the prevailing trajectory of DT to promote the amalgamation of AI and corporate innovation alongside environmentally friendly and sustainable growth [124]. This finding confirms the benefits of AI for GPDI and solves the problem of the unclear relationship between the two in existing research. Moreover, we examined the correlation between AI and GPDI in relation to BHC, BSC, and EHC. The results indicate that BHC and EHC support the beneficial influence of AI on green innovation within businesses. A board of directors with a deep educational background, professional experience, and employees with a higher level of education can encourage managers to make scientific decisions and ensure the effective implementation of these, which is more conducive to promoting the strong effect of AI on enterprise GPDI. BSC inhibits the beneficial effect of AI on enterprises' GPDI, which is mainly explained from the perspective of attention. When the board of directors works part-time in other enterprises more, the board is busier, which reduces the quality and efficiency of their work, and they are more likely to engage in speculative behaviors, which is detrimental to the impact of AI on enterprises' GPDI, as empirically proven in this study. This finding confirms that the impact of board capital on enterprises varies under different national cultures and legal traditions and further expands the literature on the moderating effect of organizational capital.

5.3. Implications

This study has significant theoretical and practical implications. First, most studies have broadly defined enterprises' green innovation activities, such as green technological innovation. However, corporate green innovation encompasses various innovations, which include those related to production methods and goods. Therefore, a general understanding may not be sufficient to comprehend its underlying principles fully. This study expands the research on green innovation by specifically examining enterprise GPDI. Second, this study enhances existing knowledge on the connection between DT and green enterprise practices. This confirms the practical implementation of the RBV and DCT. Third, while research on AI outcomes currently focuses on the macro level, the inclusion of the corporate perspective completes the multifaceted study of AI outcomes and enhances the research on the micro perspective-based antecedents of corporate GPDI. Fourth, while most research measuring corporate GPDI uses financial indicators or questionnaire surveys, this study uses text analysis and CSR reports to collect data. This enhances the use of machine-learning techniques in empirical research and advances the field of corporate green product measurement. Fifth, this study examines how organizational capital interacts with AI, highlighting the circumstances that apply to AI and the development of green products. While most previous studies used financial indicators to measure organizational capital, this study improves the multi-dimensional research on organizational capital measurement because it uses non-financial indicators to represent organizational capital. Sixth, as China presently ranks among the major AI marketplaces globally, our research demonstrates a favorable influence of AI on GPDI. The conclusion drawn from the data is typical and based on listed enterprises in the Chinese context. Further, it offers digital enhancement channels for environmentally friendly product innovation and serves as a guide for policymakers to create environmentally friendly laws. Moreover, this study establishes an effective connection between AI and GPDI, which promotes the green and low-carbon development of enterprise products, improves resource utilization, and enhances enterprise economic value. This research is conducive to the adjustment and optimization of public policy on DT, especially under the guidance of digital policy. Additionally, this study contributes to the body of knowledge on green development and improves the research on the dimensions of AI under a wave of DT.

5.4. Limitations and forthcoming research

Future research should address the following limitations. First, the data utilized in this study were acquired from Chinese firms, and the conclusions may not apply to other countries or regions. The diversity of samples should be expanded in the future to verify these conclusions. Second, owing to the limitations of research methodology and space, this study did not thoroughly investigate the mechanism of the influence of AI on enterprise GPDI, which remains unclear. Therefore, future studies should include more intermediary variables. Finally, this work was only a thematic study of enterprises with a listed background; the conclusions may not be generalizable to enterprises with other property rights and should be verified for enterprises in the private sector in the future. Simultaneously, more methods, such as questionnaires, can be introduced in the future to enrich and improve research on this topic. Additionally, the role of DT in industrial structures is gradually becoming increasingly important [125], and topic extension research in this context can be considered in the future.

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Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Ying Ying: Writing – original draft, Investigation, Data curation. **Shanyue Jin:** Writing – review & editing, Methodology, Investigation.

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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