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The Functional Mechanisms through Which Artificial Intelligence Influences the Innovation of Green Processes of Enterprises

Jue Wang [1], Xiao Wang [2], Feng Sun [3] and Xinyu Li [4,*]

[1] Department of Business Administration, Gachon University, Seongnam 13120, Republic of Korea
[2] Enterprise Compliance Research Center, Binzhou Polytechnic, Binzhou 256603, China
[3] School of Humanities, Binzhou Polytechnic, Binzhou 256603, China
[4] Department of Business Administration, Semyung University, Jecheon 27136, Republic of Korea
* Correspondence: 2023613806@semyung.ac.kr

Abstract: Green process innovation is an important strategy in the high-quality development of enterprises. Digital technology is becoming a key factor in helping businesses address environmental issues and contributes to their green process innovation and sustainable growth. Nevertheless, there is a lack of studies on how particular digital technology categories affect corporate green process innovation. Artificial intelligence (AI) is an important part of digitalization as it can provide new technical means and guidance for enterprise's innovation of green processes. This study aims to fills this research gap by revealing the logical relationship between digital technology and the green development of enterprises. Using China's A-share-listed companies as the research object from 2013 to 2022, this study employed a two-way fixed-effects model and investigated the impact of artificial intelligence (AI) on corporate green process innovation and the moderating effect of multidimensional intellectual capital. The results revealed that AI positively impacts corporate green process innovation. Human capital, structural capital, employed capital, and relational capital strengthen this positive effect. Robustness tests validated these conclusions. This study expands the literature on digital technology and corporate green innovation and provides a reference for enterprises to implement green practices using digital technology.

Keywords: artificial intelligence; green process innovation; resource-based theory; intellectual capital; sustainability

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1. Introduction

Environmental issues are currently a global concern [1]. Corporate green innovation plays a key role in solving these problems and achieving sustainable development goals [2,3]. Sustainable development means the relative limitation of the impact of human activities through technological means and social organizations to ensure the long-term survival and well-being of all people [4]. In China, socioeconomic development is the cornerstone of sustainable development [5]. Green innovation is the process of creating new production and technologies that contribute to the reduction in environmental hazards as part of achieving sustainable development [6]. As an important part of green innovation, green process innovation (GPI) has attracted the attention of academia [7] and is an important way for enterprises to improve their environmental performance [8]. Green process innovation is mainly reflected in clean technology and end-treatment innovation at the enterprise level [9]. Existing research has confirmed that green process innovation can improve enterprises' environmental performance [10] and contribute the sustainable development of enterprises [11]. Therefore, exploring ways to improve green process innovation effectively is particularly important.

Digital technology is gradually becoming important for enterprises to engage in green innovation [12,13]. Through research, some scholars have preliminarily confirmed the positive impact of digital technology on green enterprise innovation [14]. However, few scholars have explored the relationship between specific categories of digital technology and corporate green innovation [15], which is not conducive to comprehensively clarifying the internal logic of the effects digital technology on corporate green development. As one digital technology, artificial intelligence (AI) is advanced, dynamic, and application-oriented and has a profound and complex impact on the green development of enterprises [16]. Artificial intelligence technology can bring an organizational-level focus to green process innovation, facilitating data collection, detection, and calculation, to help companies improve their environmental performance [17]. With the advent of the technological revolution, the digital intelligence transformation is a means with which companies can drive green process innovation by improving efficiency and optimizing resource allocation [18,19]. Thus, AI is a means for enterprises to break away from the long-term traditional growth model and can open up new paths for innovation and development.

Although existing studies have found that artificial intelligence helps promote green innovation in the manufacturing industry, its impact on enterprises' green innovation remains unclear [20]. At the same time, there are other scholars who hold the opposite view. First, AI advances have led to lower energy costs, stimulating companies to expand resource extraction, production, and consumption, thus increasing energy consumption and possibly creating a "rebound effect" [21]. Second, when the process of smart transformation is not stable enough, more data management support will be needed [22], putting more pressure on the supply chain. Therefore, the purpose of this study was to clarify the relationship between AI applications and green process innovation at the enterprise level and to expand the research on this topic. At the same time, in the research on corporate green process innovation, most scholars have used a questionnaire survey to collect data [23,24], which may have led to a small sample size or subjective bias [25], thus reducing the accuracy of the research. This study used text analysis to collect data and attempted to compensate for these limitations by introducing large samples and a machine learning method. The current research on digital technology and green enterprise innovation is still in the preliminary stage [26]. This study explored the impact of AI on corporate green process innovation, which helps open the black box of digital technology and corporate green development from a more comprehensive perspective.

In addition, when studying the impact of artificial intelligence on enterprise green process innovation, it is important to explore the conditional differences in such impacts in different environments, which is helpful for comprehensively understanding the relationship between the two. With the development of the digital economy, the role of intellectual capital in enterprise development has gradually attracted attention [27]. As an important resource owned by enterprises, intellectual capital (IC) plays a positive role in enterprise innovation and sustainable development [28]. Existing studies have extensively explored the direct effects of intellectual capital on various aspects of enterprise performance [29–32], and few have paid attention to the possible indirect effects of intellectual capital in different situations, which also provided opportunities for this study. From a multidimensional intellectual capital perspective, this study attempted to determine the interactive effect of intellectual capital on the relationship between artificial intelligence and enterprise green process innovation.

In recent years, China has attached great importance to the green economy and environmental protection [33]. At the same time, artificial intelligence is developing rapidly in China and is being widely used in manufacturing, transportation, and environmental protection [34]. Chinese enterprises are typically used as research subjects in this context. This study selected 2013–2022 as a 10-year observation period, the data of listed Chinese enterprises as the research sample, used a two-way fixed-effects model to explore the impact of artificial intelligence on enterprise green process innovation, and explored the conditional differences in this impact considering multidimensional intellectual capital.

The contributions of this study are as follows: First, it focused on discovering the impact of artificial intelligence on enterprise green process innovation, which not only revealed an effective way to improve enterprise green process innovation but also expands the research literature on digital technology and enterprise green innovation according to resource-based theory. Second, the existing research on artificial intelligence has mostly focused on the macro level and has not been deeply expanded to the micro level [20]. Therefore, this study broadens the existing research by exploring the micro perspective of enterprises. Third, most previous studies have used questionnaire surveys to measure enterprises' green process innovation. This study uses textual analysis and assigns values. This approach provides new ideas and methods for the measurement of variables. Fourth, from the perspective of intellectual capital, this study not only expands the boundary conditions of artificial intelligence and green process innovation and explains the conditional differences in the relationship between the two under different intellectual capital levels but also clarifies the scope of application of intellectual capital in enterprises and expands the research literature on the indirect effect of intellectual capital. Fifth, this study provides a reference for enterprises to promote green innovation with the help of digital technology and for relevant departments in formulating green policy guidance.

2. Theoretical Background and Hypotheses

2.1. Artificial Intelligence and Green Process Innovation

Resource-based theory holds that enterprises can achieve strategic goals with the help of key resources and capabilities to obtain sustainable competitive advantages [35]. With the rise in digital technology, artificial intelligence has become an important resource for enterprise operations and development, which can help enterprises achieve established goals [36]. In fact, artificial intelligence technology has begun to fundamentally reshape enterprises' business and organizational processes [37] and has gradually become an important technical tool promoting enterprise environmental management [38,39]. Green process innovation is regarded as an important part of enterprises' responses to environmental problems to achieve sustainable development and is mainly reflected in clean technology and end treatment [9]. According to resource-based theory, AI can be a key resource helping companies implement green process innovation. In terms of clean technology, artificial intelligence can not only accurately predict supply and demand and reduce resource consumption but also carry out the real-time management of the enterprise production process and improve the utilization rate of enterprise resources and energy [40], providing technical support for traditional industries to create a green production process and transform and innovate, realizing green innovation. In terms of end treatment, as an emerging intelligent technology, machine learning, data processing, and other functions of AI can not only collect, distribute, classify, and recycle different pollutants [41] but also train and cultivate artificial intelligence models to analyze end pollutant indicators and formulate optimization schemes to reduce pollution emissions [42], which in turn lead to green innovations in the process. It can be seen that AI plays an important role in both aspects of enterprise green process innovation. Thus, Hypothesis 1 is proposed:

H1. *Artificial intelligence has a positive impact on corporate green process innovation.*

2.2. The Moderating Effect of Intellectual Capital

The firm-based view of intellectual capital is important in resource-based theory [43]. Intellectual capital has become one of the most discussed topics in the field of management [44,45] and is considered the aggregate of knowledge and resources within an organization that is critical to organizational capabilities and performance [46,47]. In transitioning from a material-resource-based economy to a knowledge-based economy, intellectual capital is a driver of corporate progress and helps companies build a competitive advantage [48]. It has been found that intellectual capital empowers firms to improve operational and financial performance [49,50], optimize business models [51], promote innovation [52], and help them gain sustainable competitive advantages [53]. Studies initially recognized the direct impact of intellectual capital on enterprises. However, few studies have focused on the indirect effects of intellectual capital on enterprises' business development, and even fewer have comprehensively grasped the interactive effects of intellectual capital on enterprises' green development. Meanwhile, the relationship between intellectual capital and dynamic markets has become an important branch in the research on intellectual capital, which focuses on the role of innovation- and knowledge-based intellectual capital in dynamic and technological markets [54]. This shows the direction of research in analyzing the indirect effects of intellectual capital on the green development of enterprises from the perspective of digital technology.

Scholars have classified the scope and measured intellectual capital in different ways [55,56]. Some scholars have classified intellectual capital as human, structural, or relational capital, the most common classifications [57,58]. Other scholars regarded human capital, structural capital, and capital as the whole of intellectual capital [59]. Other scholars combined the above two classifications and classified intellectual capital into four categories: human capital, structural capital, employed capital, and relational capital [60]. To comprehensively analyze the interaction effects of intellectual capital, this study followed the four classifications of intellectual capital.

2.2.1. The Moderating Effect of Human Capital

Human capital (HC) is the collection of employees' knowledge, skills, experience, and abilities that play a key role in a firm's production operations and added economic value [61]. Resource-based theory suggests that employee resources are the underlying organizational capabilities that enable firms to mobilize, rearrange, and deploy resources and are the key to a competitive advantage [62]. By investing in human capital, firms can improve the overall level of pre-existing technology and increase their application of new technology in, and thus improve innovation [63]. Artificial intelligence is essentially knowledge engineering that considers knowledge as an object; acquires, analyzes, and researches the expressions of knowledge; and applies them to achieve the effect of simulating human intellectual activities [64]. High-quality corporate human capital means that employees are more cognizant of technological development and innovation, leading to intelligent applications within the organization. This is conducive to supporting employees in managing and analyzing green data with the help of AI, which enables intelligent management of processes and green innovations, identifying opportunities for environmental improvement, and promoting green process innovation in the enterprise. Thus, Hypothesis 2 is proposed.

H2. *Human capital promotes the positive impact of AI on corporate green process innovation.*

2.2.2. The Moderating Effect of Structural Capital

Structural capital (SC) is the "repository of all non-human knowledge" within an organization, which includes practices, processes, systems, databases, culture, and philosophy [65]. The institutionalization of system structures can facilitate innovation in firms where new knowledge is applied to solve existing problems by combining experiences to produce new processes or services [66]. The ability to integrate, utilize, and innovate with structural capital provides a good foundation for companies to use AI technology to promote green innovation. This provides suitable environmental conditions for applying enterprise AI in green process innovation, lays a good foundation, and ensures the effective use of AI technology. Advanced corporate visions and philosophies are often accompanied by environmental goals that motivate organizations to internalize and practice sustainable behaviors and disseminate green practices and policies to achieve goals that benefit both the organization and the environment, and can promote smart transformation and green process innovation behaviors in companies [67]. This provides a clear direction for corporate AI applications and avoids the fragmentation of resources for technology and projects. Structural capital also helps increase the likelihood of green process innovation by increasing employee engagement and environmental behaviors and stimulating employee innovation potential [68]. As a result, Hypothesis 3 is proposed:

H3. *Structural capital promotes the positive impact of AI on corporate green process innovation.*

2.2.3. The Moderating Effect of Capital Employed

Capital employed (CE) refers to the material capital invested in a firm, which is a valuable resource for a firm [69] and is essentially capital for shareholder value creation [70]. CE is the bedrock on which companies make changes. Capital increases enhance an enterprise's ability to cope with external technological changes, thus promoting innovation and organizational performance [71]. The application and development of artificial intelligence technology reflect the potential for technological change in the digital era, which brings uncertainty while offering multiple possibilities for enterprises [72]. Capital employed can provide necessary and solid tangible support in the application of enterprise artificial intelligence technology, reduce the impact of technological change, and weaken the risk of new technologies; thus, the application of enterprise artificial intelligence technology is more pragmatic. Additionally, adequate access to capital employed is a fundamental safeguard for companies in their pursuit of technological change, sustainable development, and risk management. The capital employed guarantees that enterprises create a green environment, strengthening their green practices [73]. This implies that the capital employed can positively interact with AI, providing both material resource support for green enterprise innovation and digital technology guarantees for green process innovation. Thus, this paper argues that capital use can facilitate the application of AI by firms to realize green process innovation. Hypothesis 4 is proposed.

H4. *The capital employed promotes AI's positive impact on corporate green process innovation.*

2.2.4. The Moderating Effect of Relational Capital

Relational capital theory suggests that relational capital (RC) has two main dimensions: internal and external relationships [74]. The former refers to the interaction between the enterprise and stakeholders in the organization, and the latter is the communication link between the enterprise and external stakeholders [75]. Good relational capital promotes environmental cooperation in knowledge sharing, contributing to green innovation c. Within a firm, quality relational capital promotes active employee participation and cooperation and facilitates the application of AI technologies to increase productivity and reduce resource waste in production and business processes, realizing green development though, e.g., low-carbon and high-efficiency processes. In addition, relational capital helps companies maintain good relationships with external stakeholders, including customers, creditors, and suppliers [76]. Among these, a stable and favorable customer relationship is an important prerequisite for implementing technological reform and green innovation [71]. Positive relationships with customers contribute to green process innovation. At the same time, good interorganizational relationships facilitate mutual benefits and collaboration [77]. By leveraging such quality relationships, organizations can significantly increase their ability to integrate internal and external resources and capabilities for open innovation [78]. This facilitates enterprises' access to the latest AI technologies and green innovation practices, helps them share the risks of IT applications, and ensures the implementation of AI, thus helping them innovate green processes. As a result, Hypothesis 5 is proposed:

H5. *Relational capital promotes the positive impact of AI on corporate green process innovation.*

In summary, Figure 1 displays the research framework.

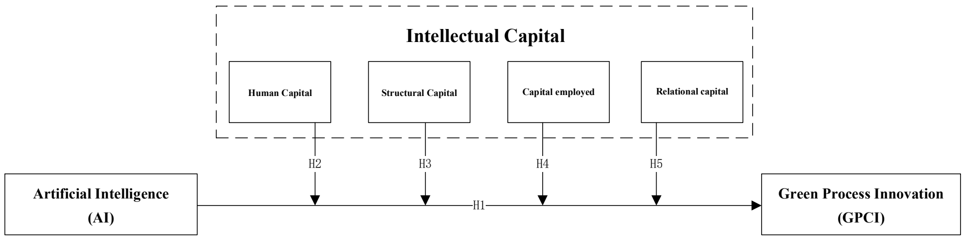

Figure 1. The research framework.

3. Methods

3.1. Data and Sample

This study used data on Chinese A-share-listed companies from 2013 to 2022 as the research sample. Since 2013, more than 60% of global AI investments have been made in China, which has greatly contributed to its development, and China has become the largest AI market in the world [79]. This also makes the sample used in this study highly representative, although the sample starting time is realistic given the conditions. Based on data availability, the data of Chinese listed companies were updated to 2022, and the data of Chinese listed companies in the last ten years were selected for statistical analysis to improve the comprehensiveness of this study.

To ensure the accuracy and reliability of this study, this study referred to the relevant literature [80,81]. Based on the characteristics of listed companies in China, data cleaning and processing were performed according to the following rules: (1) exclude the data from the financial industry; (2) exclude the data of the companies categorized as ST, ST*, and PT due to their abnormal financial status; and (3) exclude data with missing values. After preliminary data processing, 5681 observations were obtained. To avoid the influence of extreme values on the statistical analysis, we shrank all continuous variables by 1% (Zhang et al., 2023). The data used in this study were obtained from the China Stock Market and Accounting Research Database (CSMAR), WIND Database (WIND), Chinese Research Data Services WIND Database (WIND), Chinese Research Data Services (CNRDS), and Juchao Information Network (CNINFO). The software used in this research included Stata 17.0 and Python 3.8.

3.2. Definition and Measurement of Variables

3.2.1. Explained Variable

Green process innovation (GPCI): Existing studies on the measurement of corporate green process innovation have mainly used the questionnaire method [18,82], but when this method is used, it often leads to research bias due to the small sample size and heterogeneity of the background of the sample population [83]. Among the proxy variables for corporate green innovation, patent data are the most commonly used; however, patent indicators often have a time lag and cannot accurately measure enterprises' green innovation level in the current year [84]. Recent studies used textual analysis to analyze CSR reports and assign scores to values according to established criteria for measuring corporate process innovation [85,86]. CSR reports contain information on corporate policies, practices, and social, environmental, and governance performance [87]. Therefore, this methodology can more comprehensively reflect corporate green process innovation.

Synthesizing and drawing on the existing literature [50,85,88,89], this study measured the green process innovation of enterprises mainly in terms of cleantech innovation and end-processing innovation. Three project questions were used to assess cleantech innovation, and two were used to assess end-of-pipe processing innovation. All the project questions are listed in Table 1. The steps were as follows: First, Java PDFbox3.0 captured the text of 2013–2022 Chinese-listed corporate social responsibility reports to form a text master database. Compared with the financially indicative description of corporate annual reports, CSR reports can reflect corporate social and environmental behaviors more comprehensively [90]. Second, Python software was used to clean and split the words involving each item's indicator to avoid unnecessary information interference. Third, the CBOW model in the Word2Vec algorithm (word-to-vector) was used to train the vectors for each project's issue. Fourth, the trained model was applied to the total text database for cosine similarity calculations, and preliminary calculation results were obtained. Fifth, according to the calculation criteria in the existing literature [85,89], a value of 0, 1, or 2 was assigned according to when the item question was disclosed in the CSR report, where 0 meant that the item question was not disclosed in the CSR report, 1 meant that a simple textual description was provided, and 2 meant that detailed information, such as specific numerical indicators, was provided. Finally, corporate green process innovation was measured using the item question's mean value.

Table 1. Questions related to GPCI.

Variable	Type	Question
Green Process Innovation (GPCI)	Clean Technological Innovation	Q1: Aim to reduce the consumption of resources and energy and improve resource energy efficiency
		Q2: Consider environmental issues in the processes of production planning and control
		Q3: Use recycled materials, recycling techniques, and environmental technologies
	End-of-pipe Technological Innovation	Q4: Use pollution control equipment
		Q5: Adopt pollution control projects or technologies

3.2.2. Explanatory Variables

Artificial intelligence (AI): Since digital technology permeates all aspects of the enterprise operation process and as the annual reports of listed enterprises disclose detailed information, such as the company's operation status, it was more intuitive to adopt text analysis methods to reflect the company's application of digital technology [91]. Drawing on the existing literature, this study measured the level of AI by constructing an AI thesaurus and measuring the level of AI by its word frequency in annual corporate reports [3]. This study constructed a thesaurus of keywords related to the use of AI by enterprises with reference to relevant government documents, research reports, important policy reports, and academic literature, including artificial intelligence, image understanding, machine learning, and natural language processing. First, this study drew on the existing literature to construct a thesaurus for enterprise AI [92], as shown in Table 2. Second, the annual reports of the listed enterprises from 2013 to 2022 were manually collected and organized. Finally, Python was used to analyze the text content of annual reports of listed companies, extract relevant keywords, and perform statistics on word frequency to obtain the AI index of the companies. The AI thesaurus was matched and searched against the text database of annual corporate reports to obtain the word frequencies of the AI terms. As such data have right-skewed characteristics [93], this study used logarithmic processing to obtain the AI indicators.

Table 2. Keywords of 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

3.2.3. Moderating Variables

Intellectual capital (IC): Pulic (2000) introduced the value-added intellectual capital coefficient (VAIC) to measure intellectual capital. Subsequently, scholars have revised this coefficient for different research topics [94–96]. Drawing on existing studies [60,97,98] and considering research applicability, this study adopted the modified value-added intellectual capital coefficient (MVAIC) to measure intellectual capital and used the human capital coefficient (HCE), structural capital coefficient (SCE), coefficient of employed capital (CEE), and coefficient of relational capital (RCE) to perform human capital (HC), structural capital (SC), employed capital (CE), and relationship capital (RC) measurements. The formula used was as follows:

$$MVAIC = HCE + SCE + CEE + RCE$$

$$VA = OUT - IN$$

$$HCE = \frac{VA}{HC}$$

$$SCE = \frac{SC}{HC}$$

$$CEE = \frac{VA}{CE}$$

$$RCE = \frac{RC}{VA}$$

where the economic value added (VA) of a firm for a year is represented by the difference between the firm's total outputs (OUT) and total inputs (IN) [99]. HC represents a firm's total expenditure on its employees, which mainly includes employee compensation and benefits [98], and HCE represents the value generated per unit of human capital input. SC is expressed as the difference between a firm's economic value added and human capital, and SCE represents the efficiency of a firm's utilization of structural capital to produce economic value [100]. CE is expressed as the difference between the total and intangible assets of the enterprise [101], and CEE represents the value added to the enterprise per unit of physical capital. RC is usually expressed as the cost of goods sold, and RCE represents the efficiency of the enterprise in producing enterprise value from the costs invested in marketing and sales [99].

3.2.4. Control Variables

In addition to the above variables, other variables can affect the dependent variable. To reduce the influence of omitted variables, this study referred to the existing literature [102–104] and selected firm size (Size), years of listing (ListAge), return on assets (ROA), board size (Board), the proportion of female directors (sex), and environmental regulation (ISO14001) as control variables. In addition, this study provided two-way controls for individual firms and time to improve linear regression accuracy. Table 3 displays the study variables and their names, symbols, and definitions.

Table 3. Definition and measurement of the variables.

Type	Variables	Symbol	Definitions
Dependent variable	Green process innovation	GPCI	Text analysis and evaluation of CSR report
Independent variable	Artificial intelligence	AI	The logarithm of the frequency of AI terms in corporate annual reports

Table 3. *Cont.*

Type	Variables	Symbol	Definitions
Moderating variables	Human capital efficiency	HCE	HCE = VA/HC
	Structural capital efficiency	SCE	SCE = SC/VA
	Capital employed efficiency	CEE	CEE = VA/CE
	Relational capital efficiency	RCE	RCE = RC/VA
Control variables	Size of firm	Size	Logarithm of total assets
	Listed years	ListAge	Years the enterprise has been listed
	Return on asset	ROA	Net profit/average balance of total assets
	Size of board	Board	Logarithm of the number of board members
	Sex ratio of board	Sex	Number of female directors/number of board members
	Environmental regulation	ISO14001	1 for ISO14001-certified and 0 otherwise

3.3. Models

A Hausman test was conducted before setting up the model. The results showed that the fixed-effects model was applicable. Therefore, this study conducted two-way fixed effects, controlling for individuals and time, to reduce model endogeneity. Five linear regression models were used to test the research hypotheses. In order to verify the impact of artificial intelligence on corporate green process innovation and the moderating role of multidimensional intellectual capital, this study constructed the following five bidirectional fixed-effects models. In the four models, $GPCI_{i,t}$ was the explanatory variable representing the level of green process innovation of firm i in year t, $\Sigma Control_{i,t}$ represented the overall level of control variables in the model, φ_i and γ_t represented the individual fixed effects and time fixed effects controlled in the model, and $\varepsilon_{i,t}$ represented the residual term.

Equation (1) tested Hypothesis 1 to verify whether enterprise artificial intelligence impacts enterprise green process innovation. β_1 represents the level of the impact of enterprise artificial intelligence on enterprise green process innovation. If the coefficient is positive and passes the significance test, this indicates that the level of enterprise artificial intelligence promotes green process innovation. Thus, Hypothesis 1 would be supported. Hypothesis 1 does not hold if the coefficient is negative or does not pass the significance test.

$$GPCI_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \Sigma Control_{i,t} + \varphi_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

Equations (2)–(5) were used to test Hypotheses 2 to 4 to verify whether the level of corporate intellectual capital affects the relationship between corporate artificial intelligence and green process innovation. Taking Equation (2) as an example, if the coefficient β_2 of the interaction term is significantly positive while the coefficient of the independent variable is significantly positive, corporate human capital positively regulates the positive impact of artificial intelligence on corporate green process innovation. Thus, Hypothesis 2 is valid. If the coefficient of the interaction term β_2 is significantly negative while the coefficient of the independent variable is significantly positive, corporate human capital negatively regulates the positive impact of artificial intelligence on corporate green process innovation. Thus, Hypothesis 2 is invalid. As long as β_1 does not pass the significance test, the moderating effect does not exist, regardless of whether the coefficient of the interaction term is significant. Equations (3)–(5) tested the moderating effects of SCE, CEE, and RCE, respectively. The model interpretations were no different from those of Equation (2) and are thus not repeated here.

$$GPCI_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 AI_{i,t} \times HCE_{i,t} + \beta_3 HCE_{i,t} + \Sigma Control_{i,t} + \varphi_i + \gamma_t + \varepsilon_{i,t} \quad (2)$$

$$GPCI_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 AI_{i,t} \times SCE_{i,t} + \beta_3 SCE_{i,t} + \Sigma Control_{i,t} + \varphi_i + \gamma_t + \varepsilon_{i,t} \quad (3)$$

$$GPCI_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 AI_{i,t} \times CEE_{i,t} + \beta_3 CEE_{i,t} + \Sigma Control_{i,t} + \varphi_i + \gamma_t + \varepsilon_{i,t} \quad (4)$$

$$GPCI_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 AI_{i,t} \times RCE_{i,t} + \beta_3 RCE_{i,t} + \Sigma Control_{i,t} + \varphi_i + \gamma_t + \varepsilon_{i,t} \quad (5)$$

4. Results

4.1. Descriptive Statistics

Table 4 shows the descriptive statistical results of the analysis of all the variables. Regarding corporate green process innovation, the minimum value was 0.000, the maximum value was 1.600, and the standard deviation was 0.418, indicating that there were large differences in the green process innovation among Chinese listed companies and that certain companies have not demonstrated green process innovation. Regarding the level of enterprise artificial intelligence, the minimum value was 0.000, the median was 0.000, and the maximum value was 2.197, indicating that, in general, the level of artificial intelligence application in Chinese enterprises was still in the preliminary stage. In contrast, the standard deviation was 0.523, indicating a large difference in the level of artificial intelligence application among enterprises. The other findings are consistent with the findings in the existing literature and are not repeated here.

Table 4. Descriptive statistics.

Variable	N	Mean	SD	Min	Median	Max
GPCI	5681	0.70	0.418	0.000	0.800	1.600
AI	5681	0.24	0.523	0.000	0.000	2.197
HCE	5681	3.01	1.982	1.103	2.378	9.693
SCE	5681	0.55	0.219	0.033	0.579	0.932
CEE	5681	0.17	0.110	0.027	0.139	0.571
RCE	5681	0.22	0.180	0.002	0.173	0.771
Size	5681	23.15	1.388	20.523	23.032	26.994
Board	5681	2.16	0.202	1.609	2.197	2.708
ListAge	5681	2.45	0.771	0.000	2.708	3.367
ISO14001	5681	0.38	0.485	0.000	0.000	1.000
ROA	5681	0.05	0.049	−0.100	0.040	0.227
Sex	5681	0.15	0.127	0.000	0.111	0.500

4.2. Correlation

To avoid the multicollinearity problem between the variables, this study calculated the variance inflation factor (VIF), and the results showed that the VIF was less than three, indicating no multicollinearity problem in this study. This study conducted a heteroscedasticity test, showing no heteroscedasticity in the sample. In addition, this study examined the correlation between the variables using Pearson's correlation coefficient. As shown in Table 5, the correlation coefficient between artificial intelligence (AI) and corporate green process innovation (GPCI) was 0.106, and it passed the significance test at the 1% level, preliminarily confirming a positive correlation between the two. It is worth noting that there was a strong correlation between the moderating variables. For example, the correlation coefficient between the human capital coefficient (HCE) and the structural capital coefficient (SCE) was 0.824, which is a strong correlation. However, no adjustment was needed because highly correlated variables did not appear in the same regression model simultaneously. Correlations between the other variables satisfied the requirements and are not repeated here.

Table 5. Correlations.

	GPCI	AI	HCE	SCE	CEE	RCE	Size	Board	ListAge	ISO14001	ROA	Sex
GPCI	1											
AI	0.106 ***	1										
HCE	0.025 *	−0.113 ***	1									
SCE	0.031 **	−0.095 ***	0.824 ***	1								
CEE	0.068 ***	0.028 **	0.186 ***	0.248 ***	1							
RCE	−0.007	−0.003	−0.071 ***	0.017	0.431 ***	1						
Size	0.244 ***	0.036 ***	0.183 ***	0.158 ***	−0.244 ***	−0.199 ***	1					
Board	0.068 ***	−0.018	−0.032 **	−0.035 ***	−0.059 ***	−0.052 ***	0.213 ***	1				
ListAge	−0.014	−0.064 ***	0.053 ***	0.006	−0.181 ***	−0.018	0.337 ***	0.104 ***	1			
ISO14001	0.148 ***	0.036 ***	−0.125 ***	−0.104 ***	0.064 ***	−0.018	−0.171 ***	−0.025 *	−0.162 ***	1		
ROA	0.069 ***	0.01	0.332 ***	0.345 ***	0.606 ***	−0.125 ***	−0.104 ***	−0.012	−0.186 ***	0.053 ***	1	
Sex	0.012	−0.011	0.054 ***	0.060 ***	0.061 ***	0.055 ***	−0.159 ***	−0.101 ***	−0.058 ***	0.055 ***	0.074 ***	1

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3. Regression Results and Analysis

The first column in Table 6 presents this study's main effects and results. The estimated regression coefficient for artificial intelligence (AI) was 0.0266, which passed the significance test, indicating a significant positive facilitating effect of the independent variable on the dependent variable. This indicated that the application of AI in enterprises effectively improved their level of green process innovation, thus verifying Hypothesis 1.

Table 6. Regression results.

Variables	(1) GPCI	(2) GPCI	(3) GPCI	(4) GPCI	(5) GPCI
AI	0.0266 ** (2.3023)	0.0297 ** (2.5782)	0.0291 ** (2.4791)	0.0255 ** (2.2542)	0.0264 ** (2.2993)
HCE		0.0021 (0.2946)			
AI × HCE		0.0088 * (1.9227)			
SCE			−0.0059 (−0.0975)		
AI × SCE			0.0727 * (1.7618)		
CEE				0.0646 (0.4436)	
AI × CEE				0.2533 ** (2.3417)	
RCE					0.1533 (1.5704)
AI × RCE					0.1204 * (1.9089)
Size	0.0679 *** (3.3383)	0.0673 *** (3.2859)	0.0678 *** (3.2807)	0.0663 *** (3.2478)	0.0687 *** (3.3795)
Board	0.0312 (0.5850)	0.0321 (0.6018)	0.0321 (0.6003)	0.0324 (0.6099)	0.0337 (0.6338)
ListAge	0.0524 * (1.7308)	0.0530 * (1.7488)	0.0521 * (1.7185)	0.0488 (1.6137)	0.0513 * (1.6916)
ISO14001	0.0724 *** (4.9078)	0.0727 *** (4.9211)	0.0729 *** (4.9389)	0.0727 *** (4.9364)	0.0718 *** (4.8773)
ROA	0.1509 (1.0315)	0.1320 (0.7400)	0.1656 (0.9148)	0.1106 (0.5658)	0.2775 * (1.6664)

Table 6. *Cont.*

Variables	(1) GPCI	(2) GPCI	(3) GPCI	(4) GPCI	(5) GPCI
Sex	0.0135 (0.1936)	0.0133 (0.1911)	0.0119 (0.1716)	0.0133 (0.1917)	0.0141 (0.2028)
Constant	−1.0987 ** (−2.4093)	−1.0942 ** (−2.3982)	−1.0935 ** (−2.3942)	−1.0653 ** (−2.3234)	−1.1602 ** (−2.5262)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	5681	5681	5681	5681	5681
R-squared	0.0885	0.0889	0.0907	0.0960	0.0969

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

The results in the second column in Table 6 show that the estimated coefficient of the regression of artificial intelligence (AI) was 0.0297, which also passed the standard level of significance test, and, at the same time, the coefficient of AI × HCE was significantly positive, which indicated that the positive moderating effect of human capital did exist. This indicated that the better an enterprise's human capital performance, the stronger the positive effect of AI on the enterprise's green process innovation, which verified Hypothesis 2. The regression results in the last three columns in Table 6 demonstrate the moderating effects of structural, utilized, and relational capital. While the regression coefficients of the independent variables were positive and significant, the coefficients of the interaction terms were positive and significant, indicating that all three positively regulated the positive impact of AI on the enterprise's green process, thus verifying Hypotheses 3, 4, and 5. All the hypotheses in this study are valid. A summary of the research hypothesis results is shown in Table 7.

Table 7. Research hypothesis results.

	Hypothesis	Result
H1	Artificial intelligence has a positive impact on corporate green process innovation.	Supported
H2	Human capital promotes the positive impact of AI on corporate green process innovation.	Supported
H3	Structural capital promotes the positive impact of AI on corporate green process innovation.	Supported
H4	The capital employed promotes AI's positive impact on corporate green process innovation.	Supported
H5	Relational capital promotes the positive impact of AI on corporate green process innovation.	Supported

4.4. Robustness Test

Robustness testing was conducted using the instrumental variable method and the replacement of the dependent variable measure. Among the AI measurements, in addition to the word frequency calculation method used above, studies used the ratio of the length of AI terms to the length of the text in the company's annual report [105]. In this study, the replacement measurement method's independent variable (AI1) was applied to all the models for testing. The results are summarized in Table 8. In the regression results in Equations (1)–(5), the independent variable (AI1) had a significant positive effect on the dependent variable (GPCI). Meanwhile, multidimensional intellectual capital reinforced the positive influence of the independent variable on the dependent variable, and the moderating effect was still significant, which again validated all of the hypotheses in this study and further improved the accuracy of the results.

Table 8. Robustness test: replacing the measurement of AI.

Variable	(1) GPCI	(2) GPCI	(3) GPCI	(4) GPCI	(5) GPCI
AI1	0.5845 *** (2.5851)	0.6935 *** (2.9781)	0.6718 *** (2.8887)	0.5272 ** (2.4233)	0.5559 ** (2.5256)
HCE		0.0014 (0.1998)			
AI1 × HCE		0.2210 * (1.8950)			
SCE			0.0100 (0.1619)		
AI1 × SCE			1.9241 ** (2.2646)		
CEE				0.0675 (0.4489)	
AI1 × CEE				4.1293 * (1.8860)	
RCE					0.1408 (1.3936)
AI1 × RCE					2.3199 * (1.8776)
Size	0.0633 *** (3.1135)	0.0629 *** (3.0658)	0.0627 *** (3.0377)	0.0624 *** (3.0434)	0.0642 *** (3.1463)
Board	0.0341 (0.6320)	0.0356 (0.6590)	0.0358 (0.6632)	0.0352 (0.6539)	0.0358 (0.6649)
ListAge	0.0464 (1.5025)	0.0476 (1.5430)	0.0478 (1.5502)	0.0459 (1.4854)	0.0458 (1.4777)
ISO14001	0.0711 *** (4.7803)	0.0715 *** (4.8028)	0.0714 *** (4.7984)	0.0712 *** (4.7930)	0.0703 *** (4.7450)
ROA	0.1409 (0.9758)	0.1351 (0.7650)	0.1297 (0.7224)	0.0914 (0.4642)	0.2580 (1.5581)
Sex	0.0202 (0.2854)	0.0206 (0.2914)	0.0190 (0.2684)	0.0199 (0.2828)	0.0191 (0.2699)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	5672	5672	5672	5672	5672
R-squared	0.0944	0.0949	0.0949	0.0993	0.1000

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

Endogeneity, which may affect the accuracy of research findings, has received increased research attention [106]. The instrumental variable method is used to avoid endogeneity bias [107]. The correlation between the current period's explanatory variables and the current period's disturbance term mainly causes the endogeneity problem. As the independent variables in the lagged period did not correlate with the disturbance term in the current period, the independent variables in the lagged period (AI_{t-1}) were used as the instrumental variables to be examined in this study [3].

Table 9 presents the instrumental variable regression and test results. The value of the Cragg–Donald Wald F statistic was 351.522, significantly greater than the standard critical value of 16.38, indicating that it passed the weak instrumental variable test; that is, AI_{t-1} was not a weak instrumental variable. Meanwhile, the p-value of the unidentifiable test was 0.000, indicating that the instrumental variable passed the underidentification test. In addition, the overidentification test was not necessary because the instrumental variables having the same numbers as the independent variables were chosen in this study. As shown in Table 8, after correcting for endogeneity bias, the regression coefficient of AI was 0.0858, which passed the significance test, reconfirming the positive impact of AI on green process innovation in enterprises.

Table 9. Robustness test: instrumental variable method.

Variable	(1) AI	(2) GPCI
AI_{t-1}	0.3369 *** (9.1681)	
AI		0.0858 ** (1.9990)
Size	0.0364 (1.2525)	0.0696 *** (2.9200)
Board	−0.0443 (−0.5387)	0.0132 (0.2369)
ListAge	0.1732 ** (2.4010)	0.0165 (0.3276)
ISO14001	−0.0012 (−0.0560)	0.0592 *** (3.3893)
ROA	−0.2308 (−1.0492)	0.1035 (0.5999)
Sex	−0.0488 (−0.4853)	−0.1405 * (−1.8220)
Constant	−1.0483 (−1.5099)	−0.9410 * (−1.7689)
Firm FE	YES	YES
Year FE	YES	YES
N	3834	3834
R-squared	0.181	0.094
Underidentification test *p*-value	0.000	
Cragg–Donald Wald F statistic	351.522	
Kleibergen–Paap rk Wald F statistic	98.851	
10% maximal instrumental variable size	16.38	

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

5. Discussion and Conclusions

5.1. Discussion

As the role of the green innovation of enterprises in effectively solving environmental problems and vigorously responding to environmental challenges has been gradually highlighted [108], it is important to explore ways to improve enterprises' green innovation capabilities. Current scholars have studied effective ways of enhancing corporate green innovation from multiple perspectives, including social factors [109], legal factors [81], policy factors [110], and technological factors [111]. With the globalization of the digital economy, it has become possible for digital technology to empower green enterprise development [14]. This study explored digital methods of enhancing green innovation in enterprises, further enriching the related research on this topic from the perspective of technological factors, and provides reference and guidance for relevant organizations and institutions such as enterprises.

The effect of digitization on corporate green innovation was initially confirmed [112,113]. However, gaps remain in the research on digital technology and corporate green innovation. Most scholars have focused on the impact of the overall level of corporate digitalization on green corporate innovation. For example, there is a relationship between enterprise digital transformation and green innovation [114,115]. Although this provides a preliminary understanding of the relationship between digital technology and green enterprise innovation, the impact varies due to the complexity and diversity of digital technology [116]. A holistic perspective alone is insufficient for clarifying the internal logic of the relationship between the two; hence, there is a need to study the impact of specific types of digital technology on enterprise green innovation. In addition, in AI outcome studies, research has mostly focused on the macro-level perspective [20,117]. This study shifted the research perspective to the micro level, taking Chinese listed companies as the research object and using a two-way research fixed-effects model to study the impact of AI on corporate green innovation in an attempt to improve the understanding of the effects of AI. Based on resource-based theory, this study aimed to determine the impact of artificial intelligence on corporate green process innovation to fill this gap. The findings of this study are consistent with the notion of most scholars that AI can provide the technological resources needed for the realization of green process innovations in companies, both from a cleantech perspective and an end-processing perspective.

Resource-based theory was the central theoretical foundation in this study. In this theoretical category, the IC's firm-based view of intellectual capital is important [43]. Meanwhile, the relationship between intellectual capital and dynamic markets has become an important branch of intellectual capital research that focuses on the role of innovation and knowledge-based intellectual capital in dynamic and technological markets [54]. In this context, the inclusion of intellectual capital in the study of the relationship between AI and corporate green process innovation is in line with academic expectations, validating the applicability of the resource-based view of intellectual capital in corporate practice and enriching the research stream of intellectual capital in dynamic technology markets. More importantly, existing studies have extensively examined the direct role of intellectual capital at the macro level [118–120] and micro level [121] but have not paid enough attention to the indirect impacts of intellectual capital. This study found that human capital, structural capital, capital employed, and relational capital all enhance the positive impact of AI on firms' green process innovation, broadening the breadth of the research on the indirect role of intellectual capital from a micro perspective.

5.2. Conclusions

Environmental issues are currently of international concern [122,123]. The effective improvement in the corporate green innovation level has become the focus of academia and industry as an important way to solve environmental problems and cope with environmental challenges. Digital waves have provided new possibilities for enterprises' green practices. This study focused on the relationship between artificial intelligence (AI) and enterprise green process innovation to contribute new perspectives. Based on the sample characteristics, data availability, and method applicability, this study selected China's A-share-listed enterprises as the research object, selected 2013–2022 as the sample observation period, adopted ordinary least squares (OLS) and two-stage least squares (2SLS) methods, and applied a two-way fixed-effects model to study the impact of artificial intelligence on enterprise green process innovation and conditional differences in the level of intellectual capital.

The results showed that artificial intelligence significantly positively impacted green process innovation of enterprises. The level of AI application in enterprises could effectively enhance green process innovation. The findings also validated resource-based theory in that enterprises can use AI as a key resource to enhance their green innovation level, help them gain advantages in green practices, and achieve sustainable development.

In addition, this study found a moderating role of intellectual capital in the relationship between artificial intelligence and green process innovation in enterprises. First, human capital could positively modulate the positive impact of AI on firms' green process innovation. The higher the education level, skills, and experience of employees, the more the empowerment of AI could promote firms' green process innovation. Second, structural capital had a positive moderating effect. The complete organizational structure, excellent operational processes, and advanced culture and philosophy of enterprises were, to some extent, conducive to applying AI technology to improve green process innovation. Third, employed capital could strengthen the positive effects of AI on green process innovation. An enterprise's investment in capital provides continuous material resources for the enterprise, increases digital technology's role in the enterprise's green practices, and guarantees the enhancement in AI's role in the enterprise's green process innovation. Finally, relational capital contributed to the facilitating role of AI in green process innovation. Solid relational capital helped enterprises obtain valuable resources related to AI and facilitates risk sharing when enterprise AI empowered green process innovation. Consequently, the multiple dimensions of intellectual capital reinforced the positive impact of AI on corporate green process innovation.

5.3. Implications

5.3.1. Theoretical Implications

First, this study found a positive impact of AI on firms' green process innovation, which enriches the literature on digital technologies and firms' green practices, especially by expanding the understanding of the impact of specific types of digital technology on firms' green innovation and revealing digital pathways to enhancing firms' green process innovation. Second, by applying resource-based theory, this study examined listed firms in the Chinese context, which both extends the empirical validation of the theory in the research on AI outcomes and expands the boundaries of AI research at the micro level, compensating for the shortcomings of existing studies, which have mostly focused on the macro and meso levels. Third, this study adopted the text analysis method to collect the data for the dependent variable, which further enriches the application of machine learning methods in linear research. Moreover, at the same time, this research method makes up for the gaps in the existing studies, which have mostly adopted the questionnaire survey method for collecting data on the dependent variable, which not only enlarges the sample size but also avoids subjective bias and increases the accuracy and universality of the research conclusions. Fourth, this study considered the intellectual capital perspective, clarified the conditional differences between AI and green process innovation under different types of intellectual capital, filled the gap regarding the lack of research on the indirect effects of intellectual capital in the established literature, and confirmed the scope of the application of intellectual capital in the digital green practices of enterprises.

5.3.2. Practical Implications

(1) From a business perspective, this study found that the application of AI technology can significantly improve the green process innovation of enterprises, which is conducive to increasing the attention of enterprises on the application of digital technology, providing a reference for the application of AI in green practices in the areas of cleantech and end-of-pipe treatment, and providing a digital reference for enterprises to improve their level of environmental protection governance. Enterprises and professionals should actively explore and implement practical applications of AI technology in green processes, form specialized teams, and establish systematic evaluation and monitoring mechanisms.

(2) From the government's point of view, this study provides direction for the relevant government departments formulating digital-technology-guided policies and norms. This is conducive to mitigating the current environmental challenges the international community is facing in achieving sustainable development. Governments can formulate relevant policies, such as tax incentives and increased subsidies, to encourage enterprises to adopt AI technologies for green process innovation. At the same time, governments should promote cooperation among government departments, research

institutions, and enterprises to share data and resources and jointly develop green technology solutions.

(3) From the research perspective, this study preliminarily confirms that digital technology can become an important force helping enterprises to cope with environmental challenges and playing an important role in their green practices. Scholars should further explore the relationships between technology and the environment, establish more systematic theoretical frameworks and methodologies, and provide a scientific basis for green technology innovation. At the same time, interdisciplinary research should pay attention to the social and environmental responsibilities of enterprises beyond economic development.

5.4. Limitations and Future Research

However, there are still issues with this study that must be addressed. To fully capture the impact of digital technology on green corporate practices, this study only examined the role of artificial intelligence in corporate green process innovation. This is insufficient as other types of digital technology exist, which may be added to linear research in the future. Nevertheless, this study expands the literature on digital technology and green corporate development. Further research must be conducted on samples of various types of enterprises in different countries and regions to verify the accuracy of the findings. This study is based on listed enterprises in the Chinese context, and the findings may not be applicable to nonlisted enterprises in China or enterprises in other countries and regions. Ultimately, this study found that artificial intelligence (AI) positively affects corporate process innovation. However, the precise mechanism underlying this impact is unclear. Additional mediating and moderating variables may be added to fully identify the underlying logic.

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