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Article

How green intellectual capital shapes competitive advantage through AI-driven green innovation: an empirical study in the manufacturing industry

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ABSTRACT

Amid increasingly stringent environmental regulations and rapid global digitalization, the role of green intellectual capital in forging competitive advantage for firms in the manufacturing industry has become a growing concern. This study aims to propose an integrated framework for examining the mediating effect of green innovation and the moderating impact of the application of artificial intelligence on the relationship between green intellectual capital and competitive advantage. Grounded in the natural resource-based theory and the dynamic capabilities theory, the research uses data collected from 163 Chinese manufacturing enterprises and applies partial least squares structural equation modeling, with machine learning techniques such as XGBoost-SHAP. The results reveal that all three dimensions of green intellectual capital, namely green human capital, green structural capital, and green relational capital, are positively associated with both green product innovation and green process innovation, with green structural capital exhibiting the strongest effect. Green innovation partially mediates the relationship between green intellectual capital and competitive advantage. The application of artificial intelligence positively moderates the relationship between green intellectual capital and green innovation, particularly through the green relational capital pathway. Notably, machine learning analysis uncovers a threshold effect whereby an artificial intelligence application must reach a critical level before generating positive impacts on competitive advantage. This study contributes to the literature by extending the natural-resource-based view to digital contexts and demonstrating complementary insights through the integration of explanatory and predictive analytical approaches.

1. Introduction

Driven by the global agenda of sustainable development, the manufacturing industry faces unprecedented pressure to adopt environmentally sustainable practices. Pressing environmental policies and rising awareness of environmentally friendly practices in the consumer market are forcing companies to reconsider their approaches to production and competitiveness, while scarce resources and carbon-emission policies are undermining the long-term feasibility of traditional competitive advantages [1, 2]. In this context, Green Intellectual Capital (GIC), as a strategic resource that combines environmentally friendly knowledge, skills, and ecological relationships, is increasingly attracting the attention of both academicians and practitioners. In contrast to traditional intellectual capital that emphasizes the purely economic value of knowledge, GIC underscores the irreplaceable role of knowledge resources in environmentally friendly practices and sustainable development, thereby offering a novel theoretical approach that enables companies to create a distinctive competitive advantage in the field of green competition [3]. Previous studies have established a positive relationship between GIC and Competitive Advantage (CA) in a variety of industry settings [4,5]. However, the mediating role of green innovation in this correlation remains a long-standing unresolved issue and currently requires a novel theoretical approach to address the following question: In what ways does GIC lead to a sustainable CA? What is the value-creation process in such a process? Meanwhile, the extensive adoption of Artificial Intelligence (AI) in industry is also reshaping enterprises' innovation trends. AI-enabled green knowledge resources can be more efficiently transformed into innovation outputs, and industrial intelligence is a major catalyst for enterprises' green innovation [6, 7]. Nevertheless, in current studies on the connection between GIC and CA, it is generally treated as a static, linear process, without accounting for the boundary effects that the presence of AI, as a critical contextual variable, could introduce. Moreover, in methodological approaches, studies in this area have generally used Structural Equation Modeling (SEM) to test hypotheses, while few have applied machine learning techniques to investigate nonlinear relationships or assess variable importance in nonlinear settings [8, 9].

Based on the research gaps, this study aims to examine the impact of GIC on the CA of manufacturing companies via Green Innovation (GI), to test the moderating role of AI application in the process, and to compare the explanatory power of Partial Least Squares Structural Equation Modeling (PLS-SEM) with that of the XGBoost-SHAP hybrid approach. Theoretically, the proposed research clarifies the value transformation process of GIC via the GI mediator and extends the application of the Natural Resource-Based View (NRBV) theory to the digital economy paradigm [10,11]. Methodologically, the proposed research develops a hybrid analytical approach for management studies, integrating structural equation modeling and machine learning. Finally, the proposed research offers practical implications, providing insights for manufacturing companies on leveraging GIC and AI.

2. Literature review and research hypotheses

2.1 Green intellectual capital and green innovation

GIC is defined as the total amount of knowledge resources accumulated during the management and green development of companies, which includes three dimensions [3]. Green Human Capital (GHC) refers to the employees' green knowledge, green skills, and awareness of green innovations, which provide the intellectual basis for companies to undertake green practices. Green Structural Capital (GSC) refers to the organizational structures, green operational processes, and green knowledge management systems that enable the effective storage, transfer, and utilization of green knowledge within the organization. Green Relational Capital (GRC) encompasses the cooperative networks and trust-building on green matters among companies and their stakeholders, including suppliers, customers, governments, and other stakeholders. These relationships provide companies with external green information and green technology inputs [12]. The above-mentioned capitals are not independent; rather, they are interdependent and interact dynamically to build a green knowledge ecosystem. Green skills of employees, for example, cannot function effectively without organizational structures, and external networks provide a constant stream of green information to renew green knowledge within the organization.

From a knowledge-based perspective, GIC represents an integral knowledge input for GI. GHC provides the intellectual support and creativity for innovation. Employees with environmental knowledge have a greater understanding of green technology, facilitating the translation of that knowledge into viable, innovative solutions. GSC helps reduce coordination costs and minimize knowledge loss throughout the innovation process, often through standardized environmental management protocols and knowledge-sharing platforms. Meanwhile, GRC assists in gaining timely industry knowledge of environmental trends and knowledge of partners' green practices, thereby expanding the knowledge boundaries for innovation [13]. The theoretical logic has been empirically proven in most studies. For instance, in SMEs, GIC has significantly increased GI levels and absorptive capacity [14]. For hotels and tourism organizations, the three constituent aspects of GIC positively affect green supply chain performance [15]. Longitudinal studies in post-pandemic situations have shown that the Industrial Internet of Things (IIoT) has an indirect effect on GI. It has rebuilt GIC into three aspects. GRC has had the most nonlinear effect [16]. Although such studies have greatly enriched the understanding of the effects of GIC on innovation, there exist important gaps in the current literature: first, the current studies have primarily treated GIC as an aggregated variable and have seldom compared the different mechanisms of the three dimensions of GIC; second, the current studies have primarily focused on the service field, and the relevant empirical studies in the manufacturing field have been relatively limited, which is the key battleground for green transformation. Based on the above analysis, this study proposes:

H1: GIC positively influences GI
H1a: GHC positively influences GI
H1b: GSC positively influences GI
H1c: GRC positively influences GI

2.2 Green innovation and competitive advantage

GI encompasses two primary dimensions: environmental innovation and process innovation. Environmental innovation refers to the development of green products and the improvement of the environmental qualities of existing products, while process innovation involves the implementation of clean production technology to decrease the use of energy and the release of pollutants [17]. The NRBV theory forms a theoretical foundation for explaining the competitive advantage gained through GI. This theory argues that the relationship between the firm and nature can be a source of sustained CA. This is achieved through three interconnected strategic capabilities: pollution prevention, product stewardship, and sustainable development, each corresponding to different levels of environmental capability [10]. With the development of novel green products and efficient clean production methods through GI, these achievements are often characterized by causal ambiguity and path dependency, which are difficult for imitators to completely emulate in the short run and thus fulfill the criteria of value, rarity, inimitability, and non-substitutability, which are highlighted by the Resource-Based View(RBV) [11, 18].

From the perspective of competitive advantage, GI concurrently shapes both cost structure and differentiation positioning strategies. Green Process Innovation (GPcI) creates cost leadership advantages through process optimization and minimizing resource use and waste disposal, which plays a major role in the energy-driven manufacturing sector [19]. GPdI creates differentiation advantages through responding to consumers' rising environmental values and creating a responsible brand image, allowing organizations to realize green benefits. Cross-national comparative studies have found that GI's positive impact on organizational performance has been confirmed in both G7 and BRICS nations, and the underlying influence patterns differ, where product innovation plays a major role in developed nations, and process and organizational innovation are more relevant to emerging nations [20].

In addition, GI is posited as a crucial mediating variable between GIC and CA. As a knowledge capital, GIC does not create market value directly and should be translated into particular product enhancements, technological achievements, or process enhancements, which eventually shape the recognizable competitiveness. The "knowledge-innovation-advantage" logic of value conversion has been proven in various industry settings: empirical studies of Spanish wineries have found that green ambidextrous innovation acts as a partial mediator between GIC and environmental performance [15]; there is evidence from the Malaysian manufacturing sector that green innovation capacity is a significant mediator of the relationship between AI capacity and sustainable performance [21]; green supplier management and green brand image have been found as significant mediating factors, which help GIC influence CA [22]. From the foregoing analysis, the following hypothesis is proposed:

H2: GI positively influences CA
H2a: GPdI positively influences CA
H2b: GPcI positively influences CA
H3: GI mediates the relationship between GIC and CA

2.3 The moderating role of AI application

AI technology is driving a paradigm shift in the innovation ecosystem and competition dynamics of manufacturing. In terms of technology adoption progress, while the overall adoption level of AI technology in the United States is less than 6%, its adoption is already widespread in large-scale companies and technology-intensive sectors, and the adoption rate weighted by employment is more than 18% [23]. In the Chinese manufacturing industry, industrial intelligence significantly enhances companies' green transformation, and this influence is more evident among state-owned and manufacturing companies, as well as in eastern provinces. A higher level of marketization can enhance the green transformation influence of industrial intelligence, while excessive government intervention can reduce such a positive influence [24]. Concurrently, the adoption of AI technology in sustainable materials is also accelerating, and it shows great potential in terms of material design and green processing to lifecycle management [25].

Dynamic Capability Theory (DCT) is an effective theory in explaining the moderating role of AI. According to this theory, firms' capabilities to detect opportunities, integrate resources, and adapt business processes in a rapidly changing environment play an important role in sustaining CA [26]. The application of AI technology precisely increases these three capabilities. In terms of sensing capability, machine learning algorithms enable firms to discover market opportunities and technology trends in the environment by analyzing large amounts of data. In terms of integration capabilities, AI-based knowledge management systems facilitate the coding, storage, and sharing of green experience across departments. In terms of reconfiguration capabilities, intelligent optimization platforms enable firms to rapidly change their business processes according to changes in environmental regulations [27]. It has been found in empirical studies that AI capability not only has a direct impact on GI and sustainable performance but also indirectly affects innovation output, with an emphasis on the enhanced role of GIC [28].

In particular, AI technology improves the efficiency of the transformation from GIC to GI in various aspects. From a human capital perspective, natural language processing and knowledge graphs increase the efficiency of acquiring and integrating dispersed environmental knowledge for employees, reducing cognitive barriers to GI. Regarding the structural capital, process automation and decision support systems enabled by AI technology improve the efficiency and responsiveness of environmental management systems. In terms of relational capital, intelligent analysis systems enhance the efficiency of information exchange and collaborative innovation between companies, green suppliers, and environmental organizations. Studies on the Taiwanese manufacturing industry conclude that the generative AI capability has a positive effect on green CA through the dual mechanisms of organizational creativity and green innovation ambidexterity [29]. Survey results from Chinese companies indicate that learning orientation has a positive moderating effect on the association between AI capability and GIC [27]. From the above explanation, the following hypotheses are proposed:

H4: AI application positively moderates the relationship between GIC and GI

2.4 Conceptual model

Based on the above assumptions, the theoretical model in Figure 1 is built. Based on the NRBV and DCT theories, the model treats GIC (including three aspects) as the independent variable, CA as the dependent variable, GI (including two aspects) as the mediating variable, and the application of AI as the moderating variable. This model is designed to address two key research problems: (1) how GIC is converted into CA, and (2) how the application of AI influences the efficiency of the conversion process. Thus, the model offers a comprehensive framework for analyzing the mechanism for the green competitiveness of manufacturing enterprises.

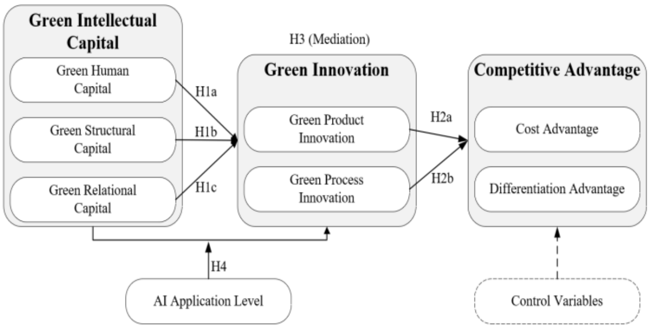

Figure 1. Research Model
Note: For simplified presentation, H1a/H1b/H1c point to the overall GI box, H2a/H2b point to the overall CA box; actual testing is conducted by dimension for each pathway.

3. Research methods

3.1 Sample and data collection

The target population included Chinese manufacturing companies. Middle and senior managers were selected as the target respondents due to their in-depth knowledge regarding the green strategies employed by the companies, knowledge resources, and application of AI in the companies. The stipulated criteria for the sampling population were that the respondents were required to have the following attributes: (1) tenure greater than two years in the organization, (2) position level greater than department manager, and (3) extensive knowledge regarding environmental management and the application of technology status in firms. To enhance measurement reliability, it was requested that two or three qualified managers in each firm provide the required data. Responses from multiple informants per firm were averaged to obtain a single composite score. This process was in accordance with the protocols set in organizational research. The distribution of respondents per firm was as follows: 67 firms (41.1%) had 2 respondents, while 96 firms (58.9%) had 3 respondents, yielding an average of 2.4 respondents per firm (391/163).

To enhance the representativeness of the sample, stratified random sampling was conducted. The sampling frame was constructed from membership directories of provincial manufacturing industry associations in six provinces (Guangdong, Jiangsu, Zhejiang, Shandong, Hubei, and Sichuan). These six provinces accounted for approximately 58% of China's output in the manufacturing industry. Random sampling was achieved by using random numbers. The stratification variables included industry type (equipment manufacturing, electronics and information, chemical materials, and consumer goods manufacturing), firm size (large, medium, and small), and region (eastern, central, and western). These sectors in the manufacturing industry were selected based on the following criteria: (1) they have been recognized as important sectors in the "Made in China 2025" initiative – a state strategy for the development of the Chinese manufacturing industry; (2) they have different levels of intensity in the environmental regulations – high in the chemical materials sector, moderate in the equipment sector, and low in the consumer sector; (3) they have different levels of adoption of AI technology according to studies carried out in the industry recently, which allows us to examine the moderating role of the adoption rate of AI technology in a wide range of technological environments. In the comparison between the sample and the population distribution based on the China Statistical Yearbook 2024, which is presented in Appendix A, it was observed that the deviations in all the stratum values were below 5%. The process of collecting data was performed between July and September 2025, encompassing both a pilot test and a main survey. The pilot testing involved a questionnaire that was completed by 30 managers of 12 firms.

Based on the pilot test results, the items that were removed were one item in the GHC scale that had an item-total correlation of less than 0.40 (r = 0.31), one item in the AI scale that had cross-loadings of more than 0.40 on unintended factors, and one item in the GRC scale that had semantic ambiguity. The retained items satisfied the criteria of having a correlation of 0.50 or higher with other items and a factor loading of 0.60 or higher on that factor. For the main survey, three methods were employed in disseminating questionnaires: member firms of local manufacturing associations, MBA alumni networks, and professional survey platforms. A total of 461 questionnaires were distributed to 178 firms, with 417 responses. The response rates across channels were: local manufacturing associations 87.2% (198/227), MBA alumni 83.5% (147/176), and professional platforms 79.3% (46/58). After removing responses completed in under 3 minutes, those with patterned responses, and incomplete questionnaires, 391 usable responses were obtained (overall response rate: 84.8%), representing 163 firms. A post hoc power analysis using G*Power 3.1 indicated that with n = 163, α = 0.05, and six predictors, the study achieved 0.92 power to detect a medium effect size ($f^2 = 0.15$), exceeding the conventional 0.80 threshold and confirming sample adequacy for PLS-SEM analysis.

3.2 Variable measurement

The core variables in this study included GIC, GI, AI application, and CA. All constructs were modeled as reflective, as the indicators were manifestations of their underlying latent constructs rather than forming them. All items used a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). To ensure the applicability of the scales in the Chinese manufacturing context, the research team first translated the English scales into Chinese, then had another bilingual researcher perform back-translation, eliminating semantic deviations by comparing the original and back-translated texts. The specific sources and structure of variable measurements are shown in Table 1.

Table 1. Summary of variable measurements

Variable	Dimension	Number of Items	Scale Source	Sample Item
GIC	GHC	5	Chen [3]; Yong et al. [12]	Employees in our firm possess sufficient environmental management knowledge and skills
	GSC	5		Our firm has established comprehensive environmental management systems and processes
	GRC	4		Our firm maintains close cooperation with suppliers on environmental issues
GI	GPdI	4	Chen et al. [17]; El-Kassar & Singh [19]	Our firm actively develops environmentally friendly new products
	GPcI	4		Our firm continuously improves production processes to reduce energy consumption and emissions
AI Application	Unidimensional	6	Adapted from TOE framework	Our firm extensively applies machine learning technology in production processes
CA	Cost Advantage	3	Porter [31]; Chen [3]	Our firm's unit product cost is lower than major competitors
	Differentiation Advantage	3		Our firm's products have unique competitiveness in environmental attributes
Control Variables	—	4	—	Firm size, firm age, industry type, ownership type

The assessment of GIC was based on scales developed by Chen [3] and Yong et al. [12]. GHC is assessed based on employees' knowledge stock, green skills, and awareness of ecologically innovative practices. GSC covered organizational environmental management systems, green knowledge databases, and standardized processes for environmental operations. GRC gauged the intensity of collaboration and trust between firms and their key stakeholders, including suppliers, customers, and environmental institutions. The assessment of GI was based on scales developed by Chen et al. [17] and El-Kassar and Singh [19]. GPdI measured the development of environmentally friendly new products and the improvement of green attributes in existing products, while GPcI captured the development of clean production technologies and resource recycling. The research employed the application of AI with the TOE framework. This framework offered a conceptual foundation but did not offer dimensional modeling. The six indicators comprised two dimensions: width, which referred to the scope of AI technology adoption (machine learning, computer vision, natural language processing, intelligent robotics); and depth, which referred to the extent of AI adoption in business processes such as R&D, production, and management. A single dimension referred to the extent of AI adoption.

Porter’s framework [31], together with Chen’s operationalization [3], was utilized to evaluate competitive advantage (CA) in terms of both cost leadership and differentiation strategies. The composite CA score was computed as the average of the two-dimensional scores. Results similar to the above were found when CA was treated as a reflective-reflective second-order construct for sensitivity analysis, as given in Appendix B. The control variables included firm size (the natural logarithm of the number of employees), firm age (the year since the firm's establishment), industry type (three dummy variables for equipment manufacturing, electronics and information, and chemical materials, with consumer goods manufacturing as the reference), and ownership type (two dummy variables for state-owned and foreign invested firms, with private firms as the reference).

3.3 Data analysis

This study adopted a hybrid analytical approach, which combined PLS-SEM and machine learning, given that the approaches aligned with the study objectives as indicated in Appendix C. PLS-SEM was suitable for evaluating complex models with several latent variables, especially when the sample size was moderate, and the data were not normally distributed [30]. XGBoost complemented this by detecting non-linear relationships and providing predictive validation beyond hypothesis testing [32]. This hybrid approach has gained traction in management research, with recent studies applying it to examine GIC-innovation relationships [16]. For hypothesis testing, GI (GPdI and GPcI) was added to the model as two mediating variables to demonstrate the transfer of value. CA was treated as a single construct comprising cost advantage and differentiation advantage, using the average of the two latent variable scores as the composite score for CA.

Since all data were self-reports of the same participants for both independent and dependent variables, Common Method Bias (CMB) was a potential concern. Multiple approaches were employed to assess and mitigate CMB. First, Harman's single-factor test was conducted through exploratory factor analysis on all items; if the first unrotated factor accounted for less than 50% of the variance, CMB was not a serious threat. Second, a full collinearity assessment was performed; Variance Inflation Factor (VIF) values below 3.3 indicated the absence of substantial CMB. Third, procedural controls were implemented during questionnaire design, including anonymity assurance, randomization of item order, inclusion of reverse-coded items, and temporal separation by placing marker items between predictor and criterion variables. Reliability was assessed using Cronbach's alpha and composite reliability (CR), with a threshold of 0.70. In relation to convergent validity, Average Variance Extracted (AVE) with a cut-off level of 0.50 was utilized. Discriminant validity was assessed using two criteria: the Fornell-Larcker criterion, which required that the square root of each construct's AVE exceeded its correlations with other constructs, and the Heterotrait-Monotrait ratio (HTMT), with values below 0.85 indicating adequate discriminant validity. Given the multi-informant design, Intraclass Correlation Coefficients (ICC) were calculated using SPSS 27 following Shrout and Fleiss's [33] one-way random effects model. Both ICC(1) and ICC(2) were computed, with ICC(1) > 0.12 and ICC(2) > 0.70 as benchmarks. Additionally, within-group agreement was assessed using rwg(j); values above 0.70 justified aggregation to the firm level.

Model fit was evaluated using standardized root mean square residual (SRMR < 0.08) and normed fit index (NFI > 0.90). Predictive relevance was assessed using Stone-Geisser's Q^2 via blindfolding, with $Q^2 > 0$ indicating predictive relevance. Multicollinearity in the structural model was examined using VIFs for all structural paths, with values below 5.0 considered acceptable. Hypothesis testing was conducted using SmartPLS 4.0. Direct effects (H1 and H2) were examined using the path coefficients (β) and their respective t-values, with significance set at 0.05. Mediation (H3) employed the bootstrapping method with 5,000 resamples to estimate the indirect effect and its 95% confidence interval. If the intervals did not contain zero, the mediation hypothesis was significant. In addition, the Variance Accounted For (VAF) was computed to identify the type of mediation, which is considered partial (20-80%) and full (>80%). Moderation (H4) was assessed by creating a product term for the interaction variables for the use of AI and the GIC dimension. A significant interaction term indicates moderation. For interpretative purposes, a graph showing the simple slopes for the effect of GIC on GI, holding high and low levels of AI use (at mean + 1 SD and mean - 1 SD, respectively), was employed.

To train machine learning models, the XGBoost algorithm was employed, which enabled predictive modeling [8]. The hyperparameters were: learning rate = 0.1, maximum depth = 4, number of estimators = 100, subsample ratio = 0.8, colsample_bytree = 0.8, and random seed = 42 for reproducibility. Continuous variables were standardized using z-score normalization, and categorical control variables (industry type and ownership type) were one-hot encoded. Five-fold cross-validation was employed to assess model performance using Root Mean Square Error (RMSE) and R^2. Feature importance was interpreted using SHAP (SHapley Additive exPlanations) [9], which quantified each feature's contribution to predictions based on game-theoretic Shapley values. The global importance rankings were calculated using the average absolute SHAP values for all the observations, and SHAP dependence plots were performed to check for non-linear relationships between the features and the target variable.

4. Results

4.1 Sample characteristics and descriptive statistics

The valid sample data were collected from 163 firms, and the distribution characteristics of the sample are shown in Table 2. The distribution of industries was dominated by equipment manufacturing (34.4%), followed by the electronics and information industry (27.6%), the chemical materials industry (21.5%), and the consumer goods manufacturing industry (16.6%).

Table 2. Sample Distribution Characteristics (N=163)

Category	Option	Number of Firms	Percentage (%)
Industry Type	Equipment Manufacturing	56	34.4
	Electronics and Information	45	27.6
	Chemical Materials	35	21.5
	Consumer Goods Manufacturing	27	16.6
Firm Size	Large (≥1000 employees)	50	30.7
	Medium (300-999 employees)	70	42.9
	Small (<300 employees)	43	26.4
Geographic Region	Eastern Region	85	52.1
	Central Region	47	28.8
	Western Region	31	19.0
Ownership Type	State-owned	42	25.8
	Private	95	58.3
	Foreign-invested	26	16.0
Respondent Position	General Manager/Deputy General Manager	30	18.4
	Department Director	59	36.2
	Department Manager	74	45.4

In terms of enterprise size, the majority of the distribution comprised medium-sized enterprises (42.9%), followed by large- and small-sized enterprises (30.7% and 26.4%, respectively). Regarding geographical distribution, the eastern region accounted for 52.1%, followed by the central and western regions (28.8% and 19.0%, respectively). In terms of enterprise ownership, the dominant form was private enterprises, which accounted for 58.3%, followed by state-owned enterprises at 25.8%, and then foreign-invested enterprises at 16.0%. Managers at the department level comprised the majority at 45.4%, with an average length of service of 6.3 years. The descriptive statistics and intervariable correlations for the study are presented in Table 3. The GSC has the highest average of 3.72, while GRC has the lowest at 3.49. The average value of AI is 3.21, with a standard deviation of 0.89. The correlation results show some important findings. The three dimensions of GIC have shown positive and significant correlations with GI, ranging from 0.35 to 0.49. GI has shown positive and significant correlations with CA ranging from 0.37 to 0.52. These results provide preliminary support for the primary research hypotheses. In contrast, the correlation between AI application and GRC, although still statistically significant ($r = 0.18$, $p < 0.05$), is somewhat weaker. This may indicate a less direct or more limited relationship between the firm's AI application and its GRC. Finally, all correlation coefficients are below 0.70, indicating no multicollinearity.

4.2 Reliability and validity testing

The single-factor test suggested by Harman indicated that the variance extracted by the first factor in the unrotated factor analysis was 31.6%, below 50%. Furthermore, the VIF values from a full collinearity ranged from 1.24 to 2.18, which were much lower than 3.3, thus suggesting that CMB was not a concern. The results from the ICC tests showed that the ICC(1) values ranged from 0.71 to 0.84, while the ICC(2) values ranged from 0.78 to 0.89, indicating that there was sufficient inter-rater agreement. The average rwg(j) values ranged from 0.73 to 0.89 for the constructs. This was higher than 0.70, indicating that the values could be reliably used as an average. As shown in Table 4, the results of reliability and validity tests were as follows: the Cronbach's α values ranged from 0.81 to 0.88. Meanwhile, the composite reliability values ranged from 0.86 to 0.91. The average variance extracted values ranged from 0.58 to 0.71.

Table 3. Descriptive statistics and correlation coefficient matrix (N=163)

Variable	Mean	SD	1	2	3	4	5	6	7	8
1. GHC	3.58	0.76	—							
2. GSC	3.72	0.71	0.52***	—						
3. GRC	3.49	0.82	0.44***	0.48***	—					
4. GPdI	3.47	0.79	0.40***	0.45***	0.35***	—				
5. GPcI	3.61	0.74	0.43***	0.49***	0.41***	0.57***	—			
6. AI Application	3.21	0.89	0.32***	0.36***	0.18*	0.39***	0.42***	—		
7. Cost Advantage	3.52	0.78	0.28***	0.34***	0.21**	0.37***	0.47***	0.33***	—	
8. Differentiation Advantage	3.68	0.73	0.36***	0.40***	0.29***	0.52***	0.44***	0.35***	0.49***	—

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Reliability and convergent validity test results

Construct	Item	Factor Loading	Cronbach's α	CR	AVE
GHC	GHC1	0.79	0.86	0.90	0.64
	GHC2	0.82			
	GHC3	0.81			
	GHC4	0.78			
	GHC5	0.80			
GSC	GSC1	0.83	0.88	0.91	0.67
	GSC2	0.85			
	GSC3	0.81			
	GSC4	0.79			
	GSC5	0.82			
GRC	GRC1	0.84	0.85	0.90	0.69
	GRC2	0.86			
	GRC3	0.81			
	GRC4	0.80			
GPdI	GPdI1	0.81	0.84	0.89	0.67
	GPdI2	0.83			
	GPdI3	0.82			
	GPdI4	0.80			
GPcI	GPcI1	0.85	0.87	0.91	0.71
	GPcI2	0.84			
	GPcI3	0.86			
	GPcI4	0.82			
AI Application	AI1	0.77	0.85	0.89	0.58
	AI2	0.75			
	AI3	0.78			
	AI4	0.76			
	AI5	0.74			
	AI6	0.77			
Cost Advantage	CA1	0.85	0.81	0.88	0.71
	CA2	0.84			
	CA3	0.83			
Differentiation Advantage	DA1	0.82	0.82	0.89	0.68
	DA2	0.85			
	DA3	0.80			

Note: Factor loading threshold is 0.70, CR threshold is 0.70, AVE threshold is 0.50

All values satisfied the convergent validity requirements. The standardized factor loadings ranged from 0.74 to 0.86. All values exceeded the 0.70 requirements. Discriminant validity was also assessed using two criteria, and the results are presented in Table 5. The Fornell-Larcker Criterion stated that the square root of the AVE for the constructs (diagonal values) was higher than the correlations between the constructs (below diagonal). The results showed that all constructs met the Fornell-Larcker Criterion. Furthermore, the values of the HTMT(above diagonal) ranged from 0.21 to 0.66, all of which were below 0.85, thus confirming adequate discriminant validity.

An acceptable model fit was found, as all indices were within acceptable ranges. SRMR was 0.062, below 0.08, and NFI was 0.91, above 0.90. The predictive relevance was confirmed, as Q^2 values were 0.31 for GPdI, 0.36 for GPcI, and 0.38 for CA, all above zero. VIF values for all structural paths were between 1.18 and 2.34, which was below 5.0, thus there was no problem of multicollinearity. The explained variance (R^2) was 0.389 for GPdI, 0.436 for GPcI, and 0.476 for CA, thus representing moderate to substantial explanatory power. Effect sizes (f^2) for significant paths ranged from 0.024 to 0.112, indicating small to medium effects.

Table 5. Discriminate validity test results

Construct	GHC	GSC	GRC	GPdI	GPcI	AI	CA	DA
GHC	0.80	0.58	0.52	0.47	0.49	0.37	0.33	0.42
GSC	0.52	0.82	0.55	0.51	0.55	0.41	0.40	0.46
GRC	0.44	0.48	0.83	0.41	0.47	0.21	0.25	0.34
GPdI	0.40	0.45	0.35	0.82	0.66	0.45	0.44	0.61
GPcI	0.43	0.49	0.41	0.57	0.84	0.48	0.55	0.51
AI Application	0.32	0.36	0.18	0.39	0.42	0.76	0.39	0.41
Cost Advantage	0.28	0.34	0.21	0.37	0.47	0.33	0.84	0.58
Differentiation Advantage	0.36	0.40	0.29	0.52	0.44	0.35	0.49	0.82

Note: Bold diagonal values = square root of AVE; below diagonal = Fornell-Larcker correlations; above diagonal = HTMT ratios

4.3 Hypothesis testing

Direct effect test results are shown in Table 6. All three GIC dimensions had significant positive effects on both GPdI and GPcI. GHC had significant effects on GPdI ($\beta = 0.19$, $p < 0.01$) and GPcI ($\beta = 0.22$, $p < 0.01$). GSC had the strongest effects on GPdI ($\beta = 0.28$, $p < 0.001$) and GPcI ($\beta = 0.33$, $p < 0.001$). GRC had relatively weaker effects on GPdI ($\beta = 0.16$, $p < 0.05$) and GPcI ($\beta = 0.19$, $p < 0.01$). Overall, the effects of all three GIC types on GPcI were slightly stronger than on GPdI. H1a, H1b, and H1c were all supported. GPdI ($\beta = 0.34$, $p < 0.001$) and GPcI ($\beta = 0.29$, $p < 0.001$) both had significant positive effects on CA, supporting H2a and H2b.

Bootstrap test results for mediation effects are shown in Table 7. GPdI and GPcI both played significant mediating roles between the three GIC dimensions and CA, with the 95% confidence intervals for all six mediation pathways not containing zero. In terms of indirect effect magnitude, the indirect effect of GSC on CA through GPcI was the strongest (0.096), followed by the pathway through GPdI (0.095). The indirect effect of GRC through GPdI was the weakest (0.054).

VAF values ranged from 23.7% to 27.4%, all indicating partial mediation. Consequently, H3 was supported.

Table 6. Direct effect test results

Hypothesis	Path	β	SE	t	p
H1a	GHC → GPdI	0.19	0.071	2.68	0.008
H1a	GHC → GPcI	0.22	0.072	3.06	0.002
H1b	GSC → GPdI	0.28	0.074	3.78	<0.001
H1b	GSC → GPcI	0.33	0.073	4.52	<0.001
H1c	GRC → GPdI	0.16	0.073	2.19	0.029
H1c	GRC → GPcI	0.19	0.072	2.64	0.009
H2a	GPdI → CA	0.34	0.075	4.52	<0.001
H2b	GPcI → CA	0.29	0.077	3.76	<0.001

Note: Control variables include firm size, firm age, industry type, and ownership type; GPdI R2 = 0.389, GPcI R2 = 0.436, CA R2 = 0.476

Table 7. Mediation effect test results (Bootstrap N=5000)

Mediation Pathway	Indirect Effect	SE	95% CI	VAF	Mediation Type
GHC → GPdI → CA	0.065	0.026	[0.020, 0.121]	24.1%	Partial
GHC → GPcI → CA	0.064	0.025	[0.019, 0.118]	23.7%	Partial
GSC → GPdI → CA	0.095	0.032	[0.039, 0.164]	27.1%	Partial
GSC → GPcI → CA	0.096	0.033	[0.038, 0.167]	27.4%	Partial
GRC → GPdI → CA	0.054	0.023	[0.014, 0.104]	25.7%	Partial
GRC → GPcI → CA	0.055	0.022	[0.016, 0.103]	26.2%	Partial

Note: CI represents confidence interval; VAF represents the proportion of mediation effect to total effect; control variables same as Table 6.

Moderation effect test results are shown in Table 8. The moderating effect of AI application on the relationship between GIC and GI varied by pathway. For GHC, the interaction term with AI had significant positive moderating effects on both GPdI ($\beta = 0.12$, $p < 0.05$) and GPcI ($\beta = 0.15$, $p < 0.05$). For GSC, AI's moderating effect was significant only on the GPcI pathway ($\beta = 0.12$, $p < 0.05$) and not significant on the GPdI pathway ($\beta = 0.09$, $p = 0.115$). For GRC, AI's moderating effects were significant on both pathways, with stronger moderation on GPcI ($\beta = 0.17$, $p < 0.01$ vs $\beta = 0.14$, $p < 0.05$). Overall, AI's moderating effect on GPcI pathways was stronger than on GPdI pathways. H4 was partially supported. Figure 2 presents simple slope analyses for significant moderation effects. Under high AI application contexts (+1 SD), the effects of GHC on GPdI ($\beta = 0.31$) and GPcI ($\beta = 0.37$) were both significantly enhanced compared to low AI contexts (−1 SD; $\beta = 0.07$ for both). The difference in GSC's effect on GPcI between high and low AI contexts was relatively smaller ($\beta = 0.45$ vs 0.21). GRC's effects were significantly enhanced under high AI contexts, showing similar patterns for both GPdI ($\beta = 0.30$ vs 0.02) and GPcI ($\beta = 0.36$ vs 0.02). The slopes under low AI contexts were close to zero, indicating that AI can effectively activate the innovation potential of relational capital. Johnson-Neyman analysis revealed that the moderating effect of AI on the GRC → GPcI relationship becomes significant when AI application exceeds 2.64 on the 5-point scale (18.4% of the sample below this threshold), suggesting that a minimum level of AI deployment is necessary for GRC to translate into process innovation.

Table 8. Moderation effect test results

Interaction Term	β	SE	t	p
AI × GHC → GPdI	0.12	0.058	2.07	0.039
AI × GHC → GPcI	0.15	0.061	2.46	0.015
AI × GSC → GPdI	0.09	0.057	1.58	0.115
AI × GSC → GPcI	0.12	0.060	2.00	0.046
AI × GRC → GPdI	0.14	0.059	2.37	0.018
AI × GRC → GPcI	0.17	0.063	2.70	0.007

4.4 Machine learning analysis

XGBoost model predictive performance is shown in Table 9. With CA as the target variable, the five-fold cross-validation average R2 was 0.573, and RMSE was 0.412, indicating good predictive capability. Figure 3 presents feature importance based on SHAP values. GPcI contributed the most (mean |SHAP| = 0.156), followed by GPdI (0.142), GSC (0.098), AI application (0.087), GHC (0.076), and GRC (0.063). This ranking is largely consistent with PLS-SEM results, validating the central mediating role of GI.

Figure 4 shows the dependence plots for the significant variables using the SHAP values. The GPcI increases with the levels of CA, with the slope diminishing as the levels increase (Figure 4a). On the other hand, the effects of the GPdI decrease with the levels, with the slope increasing dramatically as the levels increase (Figure 4b). The application of AI has shown clear threshold effects. On the 5-point scale, the SHAP values are close to zero or negative for values below 2.7; however, they increase rapidly above 2.7, as shown in Figure 4c. This pattern suggests that there must be a minimum threshold of AI application to produce a substantial positive effect on CA. The steady increase of the mean SHAP values further illustrates the trend: -0.02 for 2.0, 0.04 for 3.0, and 0.11 for 4.0. This pattern suggests that approximately 23.3% of sampled firms (n = 38) had not yet crossed the threshold necessary for AI to contribute positively to competitive advantage.

Table 9. XGBoost model predictive performance

Metric	Mean	SD
R^2	0.573	0.042
RMSE	0.412	0.031

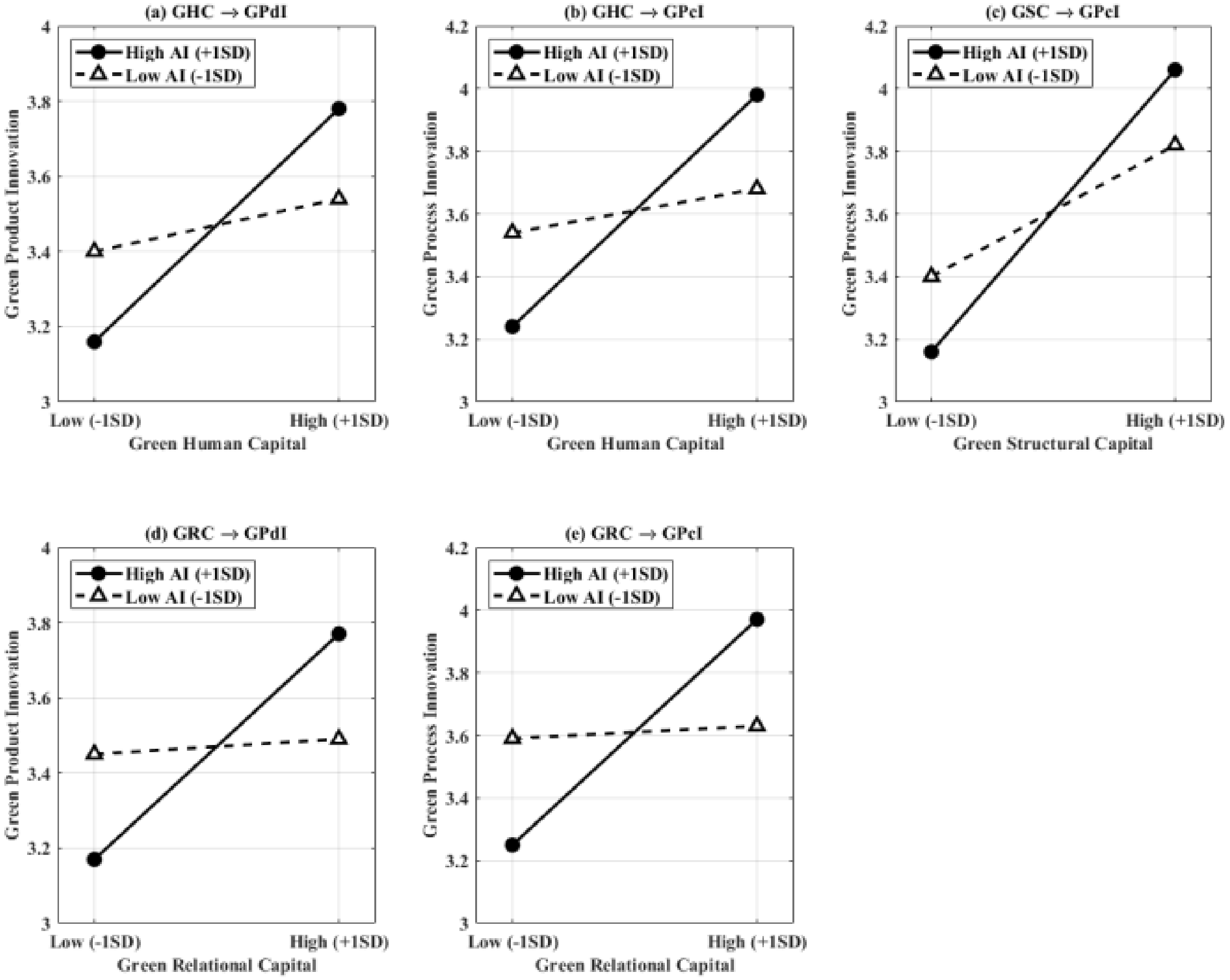

Figure 2. Moderating effects of AI applications

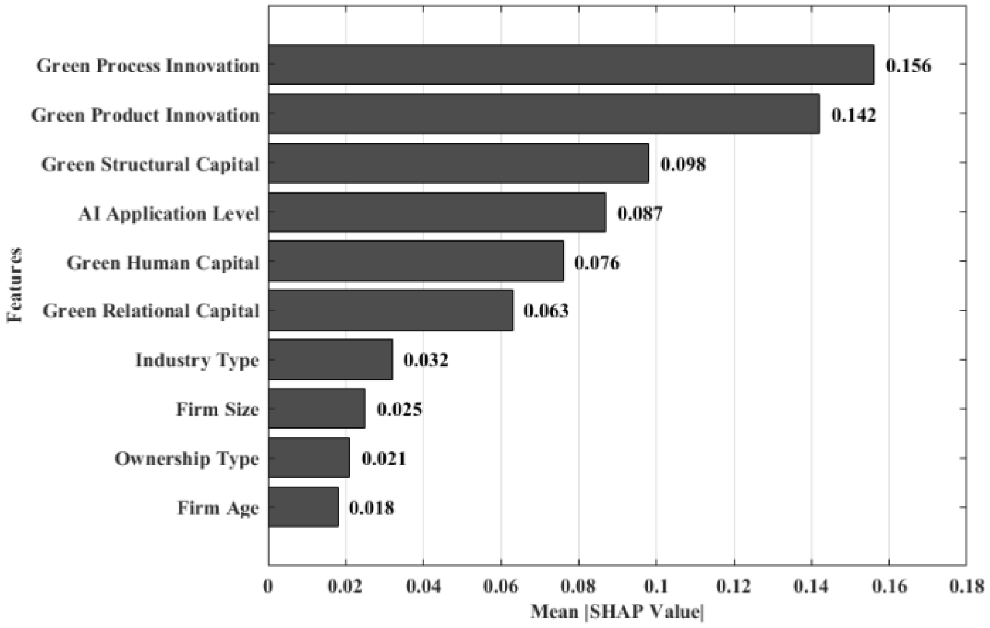

Figure 3. SHAP feature importance

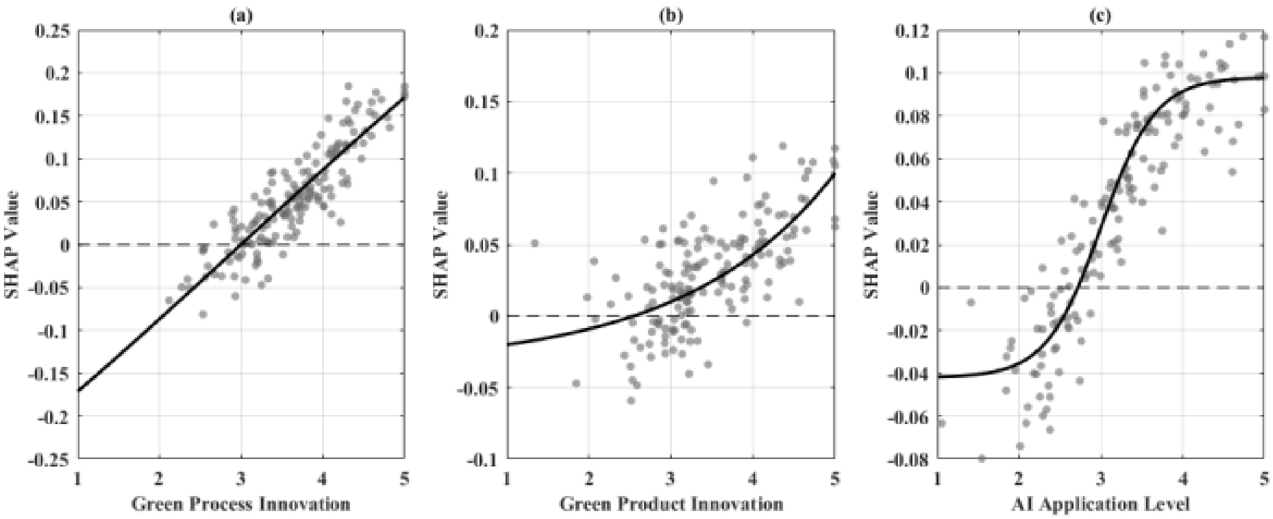

Figure 4. SHAP dependence plots

5. Discussion

This study examined the relationship between GIC and CA, mediated by GI, as well as the boundary role of AI application in this process. The results address theoretical questions in the existing research and offer novel insights into the importance of green knowledge resources in the digital age. The innovation-driving force was the strongest in GSC among the three GIC types. This result extends the current literature. The previous literature generally regarded GIC as a comprehensive variable without comparing the relative weights of its dimensions. This study explicitly indicates that innovation transformation efficiency in knowledge codification systems and environmental management systems in organizations is higher than in personal skills or relationship networks outside organizations. This may be because organizational knowledge storage and sharing systems lower the cost of coordinating innovation. Notably, in the Malaysian SME environment, it was found that GHC did not have a significant influence on business sustainability [34], contrary to the result in this study. This may be because medium- to large-scale manufacturing enterprises have more abundant human capital resources and training systems. The comparison between this study and the above-mentioned literature implies that the weights of GIC dimensions are strongly context-dependent.

The result of GI as a partial mediator illustrates the “knowledge-innovation-advantage” mechanism for transforming resources into value. This is significant because it underscores that value is not created by GIC alone but by actual innovative activities. The VAF values between 23.7% and 27.4% indicate that GI is a significant channel for value transmission, but not the exclusive one. GIC can also directly impact competitive positions through other channels, such as enhancing reputation or trust among stakeholders. It aligns with Mexican manufacturing study outcomes that GI facilitated financial innovation and sustainability [35]. Collectively, the results have significant implications for innovative activities and the ability to convert resources to value. The threshold effect of AI utilization is one of the most significant theoretical contributions of this research. While in regular regression analysis the relationship is linear, in machine learning it is non-linear, indicating that after a certain threshold is reached, a positive relationship exists between AI and CA.

The results of the Johnson-Neyman tests (threshold = 2.64) and SHAP dependence tests (threshold ≈ 2.7) indicate that the application of AI must exceed a moderate level on the measurement scale. Thus, the investment in corporate AI is not input-output in nature, and there is a threshold for technology use. This result is consistent with the emerging literature on “AI readiness,” which emphasizes the importance of developing the right type of infrastructure for data and alignment in improving AI investment [36]. There also appear to be similar non-linear relations in research related to AI and machine-learning patents, as well as the performance of firms, where lag effects appear to be significant [37]. The results appear in a pattern related to the depth of AI usage, rather than over time, and collectively imply that AI-enabled green transformation is also a process requiring continuous investment in key capabilities.

The result related to the moderating impact of AI on GRC pathways is particularly noteworthy. It implies that digital technology can harness the innovation potential in external cooperative networks, lending strength to the belief that companies can increase the value of green supply-chain collaborations by leveraging smart collaboration technology. However, the non-significant moderating effect of AI on the GSC → GPdI pathway (β = 0.09, p = 0.115) warrants theoretical interpretation. GSC, characterized by internal knowledge codification systems and environmental management processes, operates through relatively formalized, routinized mechanisms that are already optimized for efficiency. Consequently, the incremental benefit of AI in enhancing this internally focused, process-oriented capital may be limited compared to externally oriented GRC, where AI-enabled analytics can substantially improve information exchange and collaborative innovation with supply chain partners. Additionally, product innovation (GPdI) may require more tacit knowledge and creative processes that are less amenable to AI augmentation than the standardized procedures underlying process innovation (GPcI). The above findings have practical implications for management practice. This centrality of GSC also indicates that resource allocation should focus on developing systematic environmental management systems and green knowledge databases, rather than on episodic employee training and external collaboration. The threshold effect in AI deployment also indicates that organizations need to avoid superficiality in digital transformation, as such efforts are unlikely to yield significant returns, even in small-scale deployments. Only by undertaking the highest level of integration with technology will the organization be able to cross the threshold and unlock the GIC's innovation potential. Organizations that have developed a strong green cooperative network but lack digitalization may use augmented investment in AI to unlock the value embedded in relational capital.

Several limitations of this study should be noted. The cross-sectional nature of the data makes it difficult to conduct rigorous causal analysis, and the lag effects between GIC accumulation and innovation output are not captured. Therefore, the findings can be considered indicative of relationships but not causal. Further research using multi-wave panel studies with objective CA measures, such as green patents, environmental certifications, and Tobin's Q, will be useful for confirming temporal precedence and inferring causality. With regard to sample coverage, this current research has focused on Chinese manufacturing firms. Using channels such as manufacturing associations and MBA alumni networks may introduce sample bias in favor of technologically advanced and environmentally proactive firms. Comparative studies in the EU or the US can clarify how contextual factors mediate relationships among GIC, GI, and CA, thereby enhancing generalizability. In addition, whereas the current approach uses self-reported data from the manager, it is recommended that objective financial measures, such as return on assets or market share, be used to assess CA. Finally, the unidimensional approach to applying AI does not account for the effects of different types of AI technology on GI. Further experimental or quasi-experimental vignette studies may be conducted to explore the effect of the depth of AI application on GIC activation.

6. Conclusion

This research attempts to address the key question of how the relationship between GIC and CA operates. A theoretical model is proposed to describe the mechanism of knowledge resources, the innovation process, and the digital environment, with GI as the mediator and the application of AI as the moderator. Using data on Chinese manufacturing firms, the results indicate that all three dimensions of GIC are positively related to GI, which in turn relates to the firm's CA, with the strongest effect from GSC. The application of AI has a positive moderating effect on the relationship between GIC and GI, but with an observable threshold effect. The application of PLS-SEM and XGBoost-SHAP analysis helps validate the study and presents a two-fold approach to analysis in management studies that combines explanation and prediction. From a broader perspective, the importance of this study lies in its effort to address how a corporation can maintain its competitive advantage amid the dual pressures of green and digital transformation in the manufacturing industry. The findings suggest that the strategic value of green knowledge resources cannot be fully realized without transforming these resources into new value through innovation and full enablement by digital technology. The study has expanded the application of the NRBV framework to the digital economy era.

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Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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Appendix A

Sample and population distribution comparison

Category	Option	Sample (%)	Population (%)*	Deviation
Industry Type	Equipment Manufacturing	34.4	32.1	+2.3
	Electronics and Information	27.6	28.9	−1.3
	Chemical Materials	21.5	22.7	−1.2
	Consumer Goods Manufacturing	16.6	16.3	+0.3
Firm Size	Large (≥1000 employees)	30.7	28.5	+2.2
	Medium (300-999 employees)	42.9	41.2	+1.7
	Small (<300 employees)	26.4	30.3	−3.9
Geographic Region	Eastern Region	52.1	54.6	−2.5
	Central Region	28.8	26.1	+2.7
	Western Region	19.0	19.3	−0.3

Note: Population data from China Statistical Yearbook 2024, manufacturing sector.

Appendix B

Sensitivity analysis of CA as a second-order construct

To test the robustness of treating CA as a composite score, we re-estimated the model with CA specified as a reflective-reflective second-order construct (Type I in PLS-SEM terminology).

Path	Original Model (Composite CA)	Second-Order CA Model
	β	β
GPdI → CA	0.34***	0.32***
GPcI → CA	0.29***	0.31***
Cost Advantage ← CA	—	0.89***
Differentiation Advantage ← CA	—	0.91***
R^2 (CA)	0.476	0.461

Note: *** p < 0.001. Results are substantively identical, supporting the use of the composite approach in the main analysis.

Appendix C

Comparison of analytical approaches

Aspect	PLS-SEM	XGBoost-SHAP
Primary purpose	Theory testing and hypothesis evaluation	Prediction and pattern discovery
Research question	Do hypothesized relationships hold? What are effect sizes?	Which factors best predict outcomes? Are there non-linear patterns?
Assumption	Linear relationships among constructs	No distributional or linearity assumptions
Strength	Simultaneous estimation of measurement and structural models; handles latent variables	Captures non-linear effects, interactions, and threshold patterns
Limitation	Assumes linearity; limited predictive validation	Limited causal interpretability; requires sufficient sample size
Output	Path coefficients, indirect effects, R^2	Feature importance, SHAP values, dependence plots