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The Economic Mechanisms of Artificial Intelligence Resources Affecting Green Risk Management: Empirical Evidence from Chinese Listed Firms

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ABSTRACT

Against the backdrop of the digital economy, artificial intelligence (AI) has become a critical strategic resource for firms. Beyond enhancing economic performance, AI has opened new pathways for addressing environmental externalities. Drawing on the resource-based view (RBV), this paper examines the economic mechanisms through which AI resources influence firms' green risk management (GRM) practices. The empirical results show that AI attention has a negative impact on GRM, whereas AI depth and AI-driven innovation exert positive effects. Further analysis indicates that AI technology attention and software depth are the main factors driving the negative impact. A resource crowding-out effect exists between AI attention and green attention, but this effect is weakened when financing constraints are low. Although no crowding-out effect is observed between AI depth and green depth, environmental uncertainty promotes the emergence of such an effect. At the same time, green innovation is identified as an indispensable mediating variable in the process through which AI attention and AI depth influence GRM. Further analysis confirms that environmental subsidies and tax incentives, as key economic policy instruments, can complement AI resources and effectively promote green risk management.

1. Introduction

Firm-level green risks originate from the negative environmental externalities of firms' economic activities. With the tightening of environmental regulations, the strengthening of market green preferences, and the intensification of climate physical impacts [1], negative externalities are accelerating their internalization. This then transforms into a comprehensive risk that affects the long-term economic value of firms [2]. Research on green risk management (GRM) essentially explores how firms under resource constraints optimize their economic activities to address the

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internalization of externalities. With the development of the digital economy, artificial intelligence (AI) is regarded as a key economic production factor driving a new round of industrial transformation and economic growth [3]. Some studies suggest that AI should be viewed as a strategic resource that can shape a sustainable competitive advantage for firms [4]. Existing research has not been lacking in attention to the role of AI in the public governance of the ecological environment [5,6]. However, there is a lack of research that reveals the economic mechanisms of AI's role in the green risk management process from a microeconomic perspective. This research gap constitutes the starting point of this study.

1.1 Research Motivation

The research motivation stems from the theoretical and practical demands of environmental economics and business management. From a theoretical perspective, under the dual pressures of the digital economy trend and the internalization of environmental externalities, traditional economic management theories need to be further integrated. The resource-based view (RBV) offers a new economic management theoretical perspective for understanding how firms can fully utilize strategic digital intelligence resources to achieve sustainable development. From a practical perspective, for the state to use macroeconomic policy tools to promote the green transformation of the economy, it requires support and feedback from the microeconomic level. Moreover, under the constraint of limited resources, firms are prone to fall into the dilemma of investment and allocation decisions regarding AI resources.

1.2 Practical and Methodological Objectives

The practical objective of this research is to provide a reference for enterprise managers to rationally allocate AI resources, and to offer empirical support at the microeconomic level for the government to improve policies for green economic development. To achieve this, the research sets methodological goals: on the one hand, based on the RBV theory derived from economics, AI resources are classified into attention, depth and innovation resources from three dimensions: enterprise cognitive resources, basic resources and accumulated resources; on the other hand, examine the overall impact of AI resources on GRM and analyze the specific economic mechanisms in the process of influence. Such as differentiated action paths, internal economic condition constraints, and external economic policy shocks. This study adopts econometric methods and uses data from listed firms in China as samples for empirical tests at the microeconomic level.

Based on the above objectives, this study aims to explore the following core issues: (1) Do heterogeneous dimensions of AI resources (attention, depth, and innovation) exert differential impacts on firms' GRM? (2) Is there a competitive or crowding-out relationship between AI resources and green resources? (3) Which internal and external economic factors, as well as economic policies, moderate the relationship between AI and GRM?

1.3 Research Contributions

The theoretical contribution lies in enriching the application of RBV theory in the intersection of digital intelligence and green transformation. The methodological contribution is to construct an analytical framework that includes multiple effects and mechanisms, enriching the methodological paradigm for studying the role of AI in environmental governance and other management fields. The practical and policy contribution is that the research conclusions can guide firms to make more precise AI investment decisions and provide targeted inspirations for the government to promote AI-enabled green development.

1.4 Research Structure

The framework of the following research is as follows: The second part is a literature review. It reviews and analyzes relevant theories and materials from the perspective of economics, and proposes empirical research hypotheses. The third part is the research design. It elaborates on the data sources, variable selection, model setting, and measurement methods. The fourth part is the empirical results. It reports the benchmark regression and economic mechanism test results. The fifth part is the research conclusion. It summarizes the research results, discusses the research contributions, clarifies the limitations of this study, and points out the future research directions.

2. Literature Review

2.1 Economic Research on AI and Green Development

2.1.1 Economic Logic of AI in Empowering Macro-Level Green Development

The core economic logic of AI promoting green development at the macro level lies in enhancing the resource allocation efficiency and innovation rate of the economic system. It not only creates space for green economic development but also drives the green transformation of the economic structure. First, AI can reduce risk pricing and costs in green finance, thereby mitigating financing constraints [7]. While AI incurs operational energy consumption, the improvements in green economic efficiency driven by AI can offset a portion of such energy-related costs [8]. Second, AI facilitates green technological innovation and industrial structure upgrading, thereby boosting green total factor productivity of the socio-economic system [9]. Research at the regional economic level has empirically verified a positive correlation between the development level of AI and the efficiency of low-carbon transformation in urban economic systems [10]. Finally, the big data function of AI can enhance the information transparency of the social economic system. It can help capital flow more precisely into green projects [7]. Moreover, it exhibits a spatial spillover effect among regions, which can drive up the green efficiency of neighboring regions [8]. At the overall social and economic level, it can achieve a rational allocation of green production factors.

2.1.2 Economic Mechanisms of AI in Reshaping Firms' Green Operations

AI is becoming a key element in driving the green transformation of the enterprise economy. AI technology helps firms reduce the cost of green innovation and alleviate financing pressure, providing economic support for their green operations [11]. There are three specific microeconomic mechanisms. First, by elevating technological capabilities and optimizing management paradigms, AI can directly incentivize corporate green investment [12]. AI can also create new value growth points for firms by promoting green innovation [13]. Second, by enabling intelligent monitoring and optimization of production processes, AI enhances the green total factor productivity of firms and promotes the green transformation of their economic structure [14]. Third, AI enhances internal decision-making and reinforces external oversight. AI-powered data analytics capabilities can help curb the short-sightedness of enterprise management, encouraging them to make decisions that focus more on the long-term sustainable development of the enterprise's economy [12]. Overall, AI is innovating the internal operation mechanisms of micro firms, thereby leading the entire industrial economy towards the goal of carbon neutrality [15].

2.1.3 Economic Connotation of GRM

The economic essence of GRM stems from the need to internalize the negative externalities of firms on the environment. From an economic theory perspective, it is essentially an interwoven field of environmental economics and enterprise management. Its core lies in integrating environmental factors into the economic management and decision-making framework of firms to achieve Pareto improvement in economic resource allocation. To manage the risk associated with the internalization of environmental negative externalities, some firms implement organizational restructuring strategies. Such as transferring pollution-intensive businesses to lower-level subsidiaries, or using limited liability forms to avoid potential environmental regulatory and litigation risks faced by the parent company [16]. Other firms enhance environmental performance and reduce risks through green innovation activities [17]. These measures indicate that GRM has transcended the traditional realm of environmental compliance. It has become an important part of enterprise strategic decision-making and operational management [18]. The capital market also tends to reward firms that perform better in environmental risk management [19]. This further confirms the economic function of GRM in creating long-term value.

2.2 Advancing Economic Theory: AI and GRM from a RBV Perspective

The resource-based view represents an extension of economic theory within the domain of strategic management. It posits that the source of a firm's sustained competitive advantage lies in the development of high-value strategic resources [20,21]. AI is becoming a key strategic resource in enterprise economic management with its irreplaceable value creation characteristics [22]. Most firms in the digital economy are paying particular attention to AI. However, according to the attention-based view, the cognitive resources of the management are limited. Excessive focus on a single field may lead to the neglect of strategic planning in other fields [23]. Especially when the attention of firms to AI remains in the stage of scattered exploration, it will seriously dilute the cognitive resources of managers [24]. Moreover, it may further occupy the energy of firms that could be used to formulate green strategies [25,26]. In addition, without clear green guidance and standards, AI investment of firms may be disconnected from long-term sustainable development goals [27]. The huge energy consumption generated by over-investment and inefficient deployment of AI may offset corporate environmental benefits and increase ecological footprint [3].

Therefore, this study proposes Hypothesis 1 (H1): AI attention has a negative impact on the green risk management of firms.

How can AI enable firms to advance their green initiatives? This needs to be analyzed in combination with AI depth, that is, the degree of integration of AI with the operational processes of the enterprise. The AI assets formed through deep integration represent foundational assets as defined by the RBV. These assets enable firms to take green risk management actions in intangible or tangible form. For example, an AI-driven automated carbon accounting system can integrate data from the entire supply chain, thereby accurately identifying potential areas for emission reduction [28]. Similarly, deep AI models can also implement predictive maintenance of equipment, thus reducing resource waste and accident risk [29]. Due to its high integration with organizational processes, AI assets are more likely to form sustainable competitive advantages [20,22]. Firms may face human-machine collaboration problems in the early stage of AI application [30]. Through comprehensive management, business process reengineering and continuous deep learning, these challenges will eventually become sustainable development advantages of firms [22].

Therefore, this study proposes Hypothesis 2 (H2): AI depth has a positive impact on the green risk management of firms.

After experiencing the stage of AI cognition and deep integration, can firms form cumulative AI resources? AI innovation is a typical example of such cumulative resources. In enterprise green risk management, the core value of AI innovation lies in exploring risk control schemes to cope with unknown environmental challenges. For example, an active AI-powered closed-loop material recycling system that transcends traditional automated recycling workflows, and a generative climate simulation model that advances conventional climate data analytics [4,31]. These are at the forefront of AI innovation. AI innovation can also meet the dynamic capability needs of firms [32]. To help firms grasp ecological environmental problems, environmental protection policy changes and green technology innovation more keenly and proactively. Empirical studies also show that energy-based firms actively engaged in AI innovation have achieved significant emission reduction results [2].

Therefore, this study proposes Hypothesis 3 (H3): AI innovation has a positive impact on the green risk management of firms.

2.3 Critical Analysis and Definition of Research Gaps

While existing materials have established a foundational basis for investigating the economic logics and mechanisms linking AI and green development, they exhibit three distinct limitations: (1) an overemphasis on AI's technical attributes, with insufficient in-depth analysis of its resource-based characteristics and evolutionary phases; (2) a technological optimism bias, where discussions of AI's application barriers and high-cost challenges in ecological governance remain confined to theoretical and ethical domains; and (3) a narrow focus on technological application outcomes, coupled with a paucity of research on micro-level economic mechanisms.

To address the identified research gap, this study conducts an empirical analysis using microeconomic-level data from Chinese listed firms: analyzing and quantifying AI through an economic lens centered on its resource attributes; testing the heterogeneous impact of AI resources on green risk management; unpacking the specific economic mechanisms underlying the effect of AI resources on green risk management.

3. Methodology

3.1 Sample and Data

This study draws its microeconomic-level empirical sample from A-share firms listed on the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) over the period 2010–2023. The research data are compiled from multiple databases and platforms, then matched and integrated using stock codes and listing years to construct the required panel dataset. Data on corporate annual reports, social responsibility report texts, and patent application and authorization records were retrieved from the China Research Data Service Platform (CNRDS) [33]. Information on corporate governance structures and financial structures was obtained from the China Stock Market and Accounting Research Database (CSMAR) [34]. Macro-level data on regional economic conditions and policy systems were sourced from the China Statistical Yearbook [35]. To mitigate the confounding effects of severe data scarcity or outliers, this study implemented the following data screening and processing procedures: excluded samples of firms in ST or *ST status during the observation year; removed samples with missing values for key variables; applied 1% Winsorization to all research variables. A final valid sample of 29,285 firm-year observations was obtained.

3.2 Variables and Model

3.2.1 Dependent Variable

Referring to the ISO 31000 risk management standard in modern risk management theory [36], this study constructs a multi-index comprehensive index measurement model of GRM. The selection criteria for each dimension are operationalized as follows: (1) Risk identification: assesses firms' perceived external ecological pressures and internal cognitive awareness of environmental risks; (2) Risk assessment: objectively measures the extent of firms' active disclosure on the negative ecological impacts of their operational activities; (3) Management measures: focuses on examining firms' concrete resource inputs and emission reduction initiatives implemented to mitigate environmental risks; (4) Risk prevention: evaluates whether firms have integrated ecological risk management into their organizational structure and institutional framework; (5) Management effectiveness: quantifies the efficacy of risk management practices using indicators such as accident-related incentives and penalties.

These dimensions are further measured by 32 sub-indices. The detailed index evaluation basis can be seen in Table 1.

Table 1
Corporate green risk management evaluation system

Primary Indicator	Secondary Indicators	Basis for Indicator Measurement
Risk Identification	Key Polluting Entities Under Supervision	1 if nationally key monitored; otherwise 0
	Environmental Disclosure in Annual Reports Environmental Disclosure in CSR Reports	1 if disclosed; otherwise 0
	Standalone Environmental Report	1 if published; otherwise 0
	Green Investors	1 if present; otherwise 0
	CEO's Environmental Experience	1 if CEO has experience; otherwise 0
Risk Assessment	Wastewater Discharge Volume COD Emission Volume SO_2 Emission Volume CO_2 Emission Volume Soot and Dust Emission Volume Industrial Solid Waste Generation	1 if disclosed; otherwise 0
Management Measures	Waste Gas Emission Reduction Management Wastewater Emission Reduction Management Dust and Soot Control Solid Waste Utilization and Disposal Noise, Light Pollution, and Radiation Control Cleaner Production Implementation	1 if disclosed; otherwise 0
Risk Prevention	Environmental Protection Philosophy (philosophy/structure/models) Environmental Protection Goals (status/future goals) Environmental Management System (systems/regulations) Environmental Education and Training Special Environmental Campaigns (public welfare) Special Environmental Campaigns (emergency/treatment) Three Simultaneities System (implementation)	1 if disclosed; otherwise 0
Management Effectiveness	Green Agency Problem	1 if environmental governance costs are not charged to the operational budget; otherwise 0
	Pollutant Emissions	1 if meet national standards; otherwise 0
	Sudden Environmental Accidents Environmental Violations	1 if none occurred; otherwise 0
	Environmental Complaints	1 if none filed; otherwise 0
	ISO 14001 Certification	1 if certified; otherwise 0
	Environmental Honors/Awards	1 if received; otherwise 0

The weights of these indices are objectively determined using the Entropy-CRITIC method. The entropy method determines the weight of each index based on the degree of dispersion (information entropy) of the observed values of each index. The greater the dispersion, the greater the weight. The CRITIC method determines the weight of each index based on the difference (standard deviation) and correlation (correlation coefficient) between the indices. The greater the difference and the smaller the correlation, the greater the weight. The Entropy-CRITIC method combines the characteristics of both and is more robust than using a single objective weighting method [37]. To eliminate the influence of dimensions, this study has dimensionless processed all sub-indices before measurement

3.2.2 Independent Variables

From the perspective of the three attributes of cognitive, fundamental and accumulative nature of resources, the enterprise AI resources in this study specifically refer to three indicators: AI attention (Ai_A), which is measured by the frequency of AI-related words in the enterprise's information disclosure [38]; AI depth (Ai_D), which is measured by the AI-related capital intensity per employee [39]; and AI innovation (Ai_I), quantified through binary processing of patent holdings [38].

Further, to isolate the effects of other firm-internal economic factors on GRM, this paper incorporates a suite of control variables across four dimensions: firm resource endowment, financial structure, governance structure, and investment activities. Detailed variable definitions are presented in Table 2.

Table 2
Variable definitions

Type	Name	Symbol	Connotation
Dependent Variable	Green Risk Management	GRM	Constructed through an indicator system; comprehensive value calculated using entropy-CRITIC weight method
Independent Variables	AI Attention	Ai_A	Natural logarithm of (1 + count of AI-related keywords in corporate annual reports)
	AI Depth	Ai_D	Book Value of AI-Related Assets / Number of Employees
	AI Innovation	Ai_I	Assigned "1" if the enterprise holds AI-related patent applications; otherwise "0"
Control Variables	Firm Age	Age	Natural logarithm of firm's years since establishment
	Firm Size	Size	Natural logarithm of total number of employees
	Return on Equity	Roe	Net Profit / Average Owners' Equity
	Capital Structure	Lev	Total Liabilities at Year-End / Total Assets at Year-End
	Revenue Growth	Growth	(Current year operating revenue / Previous year operating revenue) - 1
	Cash Flow	Cash	Cash and Cash Equivalents at Period-End / Current Liabilities
	Board Size	Board	Natural logarithm of number of board members
	Investment Intensity	Invest	Net Cash Flow from Investing Activities / Total Assets at Period-Begin

The descriptive statistics in Table 3 show that there are significant differences in the dispersion of each variable. Notably, among all the variables, the standard deviation of Ai_A is the largest (1.256), indicating that there are significant differences in the attention paid to AI among different firms.

Table 3
Descriptive statistics

Variable	Sample Size	Mean	Standard Deviation	Min	Max
GRM	29285	0.260	0.201	0.030	0.807
Ai_A	29285	0.990	1.256	0.000	4.644
Ai_D	29285	0.011	0.020	0.000	0.134
Ai_I	29285	0.182	0.386	0.000	1.000
Age	29285	2.959	0.316	1.946	3.555
Size	29285	7.811	1.193	5.273	11.208
Roe	29198	0.056	0.140	-0.694	0.363
Lev	29285	0.431	0.201	0.063	0.913
Growth	29285	0.155	0.371	-0.514	2.217
Cash	29285	0.736	1.062	0.024	6.840
Board	29227	2.116	0.197	1.609	2.639
Invest	29284	0.142	0.164	-0.137	0.868

3.2.3 Model

To examine the impact of AI on GRM, this study established the following regression estimation model:

$$GRM_{i,t} = \alpha_0 + \alpha_1 Ai_{i,t} + \alpha_2 \sum Controls_{i,t} + \lambda_t + \delta_j + \varepsilon_{i,t} \quad (1)$$

Where *i* represents the company and *t* represents the year; μ_i is the firm fixed effect; λ_t is the year fixed effect; $\varepsilon_{i,t}$ is the random error term; $\Sigma Controls_{i,t}$ represents all control variables.

This study adheres to methodological rigor but is not without limitations. First, the measurement of the GRM relies primarily on firms' public disclosures. This may overlook the "greenwashing" behavior of firms that conceal pollution facts for compliance purposes. Research on such greenwashing behavior can provide supplementary insights [40]. Second, while the model incorporates control variables for firms' economic attributes and year fixed effects, the omission of unobserved confounding factors may still introduce estimation bias. This necessitates robustness checks and endogeneity mitigation during empirical testing. Third, the sample is restricted to Chinese A-share listed firms, meaning empirical findings may lack direct generalizability to non-listed firms or alternative institutional contexts. Future research could extend the sample to include non-listed firms or conduct cross-country comparative analyses to address this limitation.

4. Results

4.1 Overall Relationship Test

Table 4 presents the overall empirical test results based on the regression model. The test results of benchmark regression (1) show that, regardless of whether the influence of control variables is considered or not, AI attention (Ai_A) has a significantly negative impact on the GRM of firms, verifying Hypothesis H1. The test results of benchmark regression (2) show that, regardless of whether the influence of control variables is considered or not, AI depth (Ai_D) has a significantly positive impact on the GRM of firms, verifying Hypothesis H2. Similarly, the test results of benchmark regression (3) show that, regardless of whether the influence of control variables is considered or not, AI innovation (Ai_I) has a significantly positive impact on the GRM of firms, verifying Hypothesis H3.

Table 4
Overall relationship test results

Variable	Benchmark Regression (1) GRM		Benchmark Regression (2) GRM		Benchmark Regression (3) GRM	
Ai_A	-0.004*** (-3.526)	-0.008*** (-7.890)				
Ai_D			0.112** (2.068)	0.255*** (4.822)		
Ai_I					0.014*** (6.186)	0.009*** (4.193)
Age		0.002 (0.380)		0.005 (0.807)		0.005 (0.777)
Size		0.052*** (39.168)		0.0516*** (38.779)		0.051*** (38.234)
Roe		0.0564*** (9.271)		0.057*** (9.413)		0.056*** (9.226)
Lev		-0.011 (-1.488)		-0.009 (-1.283)		-0.010 (-1.355)
Growth		-0.006*** (-3.183)		-0.006*** (-3.124)		-0.006*** (-3.093)
Cash		0.0043*** (4.288)		0.004*** (4.444)		0.004*** (4.430)
Board		0.023*** (3.910)		0.0216*** (3.741)		0.022*** (3.824)
Invest		0.012** (2.266)		0.011** (2.141)		0.011** (2.221)
Year/ Industry	YES	YES	YES	YES	YES	YES
Sample Size	29285	29139	29285	29139	29285	29139
R^2	0.218	0.381	0.216	0.377	0.220	0.376

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t-statistics are reported in parentheses.

4.2 Robustness Tests and Endogeneity Mitigation

4.2.1 Robustness Tests

Considering the potential time lag in the effect of AI resources, this study set a one-year lag for the AI variables, forming the variables L.Ai_A, L.Ai_D, and L.Ai_I. Moreover, to account for the impact of variable calculation methods on empirical results, this study adjusted the calculation method of the GRM variable to sum the indicator values and take the logarithm.

As shown in Table 5, the coefficient signs and significance of the variables are consistent with the benchmark estimation results in Table 4. This indicates that the baseline estimation results remain valid, thereby strengthening confidence in the validity of the empirical results.

Table 5
Robustness test results

Variable	Replace the Dependent Variable			Lag the Independent Variable		
	GRM			GRM		
Ai_A	-0.008*** (-7.777)					
Ai_D		0.231*** (4.672)				
Ai_I			0.009*** (4.185)			

Table 5
Continued

Variable	Replace the Dependent Variable			Lag the Independent Variable		
	GRM			GRM		
L.Ai_A				-0.008*** (-7.107)		
L.Ai_D					0.121** (2.010)	
L.Ai_I						0.010*** (3.992)
Control Variables	YES	YES	YES	YES	YES	YES
Year/ Industry	YES	YES	YES	YES	YES	YES
Sample Size	29139	29139	29139	23907	23907	23907
R^2	0.377	0.374	0.374	0.387	0.383	0.383

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t-statistics are reported in parentheses.

4.2.2 Endogeneity Mitigation

There may be a bidirectional causal relationship between the application of AI at the enterprise level and the effect of GRM, which could lead to endogeneity problems. This study uses the instrumental variable method to obtain the net effect of AI resources on GRM. This study adopts the density of AI firms in the city where the enterprise is located (Ai_e) and the external evaluation of the quality of enterprise information disclosure (Qid) as instrumental variables. These two variables capture the external industrial economic environment faced by firms and the internal quality of firms' economic management, respectively.

Table 6 shows that since the instrumental variables Ai_e and Qid significantly strengthened the enterprise's AI-driven factors in the first-stage regression (correlation test), they meet the correlation criteria. The p-values of the Anderson LM statistic and the Cragg-Donald Wald F statistic for testing the correlation of instrumental variables both reject the null hypothesis ($p < 0.01$), indicating that the instrumental variables are significantly correlated with the endogenous variables and have passed the correlation test. Moreover, the Sargan statistic of the over-identification test is significantly greater than the 10% critical value of Stock-Yogo (the critical value standard for judging weak instrumental variables), proving the validity of the instrumental variables. The results of the second-stage regression (causal effect estimation) further indicate that after adjusting for endogeneity, the coefficients of Ai_A, Ai_D, and Ai_I still show significant negative, positive, and positive values, respectively, consistent with the regression results in Table 4.

Table 6
Instrumental variable test results

Variable	First Stage			Second Stage		
	Ai_A	Ai_D	Ai_I	GRM		
Ai_A				-0.066*** (-8.886)		
Ai_D					1.616** (2.176)	
Ai_I						0.076** (2.228)
Ai_e	0.000*** (20.86)	0.000*** (7.14)	0.000*** (8.71)			
Qid	0.034*** (2.80)	0.002*** (7.11)	0.037*** (8.72)			

Table 6
Continued

Variable	First Stage			Second Stage		
	Ai_A	Ai_D	Ai_I	GRM		
Anderson LM	444.953 [0.000]	108.920 [0.000]	162.478 [0.000]			
Cragg-Donald Wald F	226.651	54.621	81.681			
Stock-Yogo (10%)	19.93	19.93	19.93			
Sargan	260.610 [0.000]	365.796 [0.000]	369.335 [0.000]			
Control Variables	YES	YES	YES	YES	YES	YES
Year/Industry	YES	YES	YES	YES	YES	YES
Sample Size	21276	21276	21276	21276	21276	21276
R^2	0.372	0.117	0.216	0.351	0.406	0.412

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t-statistics are reported in parentheses.

4.3 Economic Mechanisms of GRM Affected by AI Attention Resources and Deep Resources

4.3.1 Resource Segmentation

Based on the different directions of strategic attention of firms, the resources of attention to AI can be divided into two dimensions: technical attention (Ai_At) and application attention (Ai_Aa). The technical attention to AI is measured by the frequency of core technology-related keywords of AI (such as machine learning, algorithm, etc.) in the annual reports of firms; the application attention is measured by the frequency of keywords related to the application scenarios of AI (such as intelligent manufacturing, intelligent customer service, etc.) [41]. And based on the different forms of capital investment, the depth of AI resources can be divided into two dimensions: software depth (Ai_Ds) and hardware depth (Ai_Dh). The software depth of AI is measured by the book value of intangible assets related to AI (such as software, patents, etc.) in the financial statements; the hardware depth is measured by the book value of fixed assets related to AI (such as equipment, servers, etc.) [42].

The empirical test results after the detailed classification of AI attention and depth resources are shown in Table 7. In terms of AI attention resources, Ai_At has a greater negative impact on enterprise GRM; while Ai_Aa shows a positive influence. As for AI depth resources, the relationship between Ai_Ds and GRM does not reach a significant level, but Ai_Dh presents a significant positive effect.

Table 7
Empirical results from subdividing AI attention and depth resources

Variable	Subdivision of AI Attention Resources		Subdivision of AI Depth Resources	
	GRM		GRM	
Ai_At	-0.001^{***} (-8.715)			
Ai_Aa		0.000^{*} (1.838)		
Ai_Ds			0.027 (0.281)	
Ai_Dh				0.634^{***} (7.119)
Control Variables	YES	YES	YES	YES

Table 7
Continued

Variable	Subdivision of AI Attention Resources		Subdivision of AI Depth Resources	
	GRM		GRM	
Year/Industry	YES	YES	YES	YES
Sample Size	29139	29139	29139	29139
R^2	0.377	0.375	0.376	0.377

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t-statistics are reported in parentheses.

4.3.2 Crowding-Out Effect

The coefficient of the interaction term can be used to explain the crowding-out or competitive relationship between variables. In this relationship, when one variable increases, it reduces the marginal effect of another variable on the dependent variable, which precisely conforms to the basic characteristics of resource allocation constraints. The enterprise's green attention (Green_A) is quantified using a similar method to that of AI attention, that is, by calculating the natural logarithm of the frequency of green-related keywords in the annual report [43,44]. The green depth (Green_D) is measured by the ratio of environmental investment to assets [45, 46].

The regression results in Table 8 show that the interaction term between AI attention and green attention (Ai_A × Green_A) presents a significant negative correlation, indicating that there is a crowding-out effect between AI attention and green attention. This crowding-out effect is particularly evident in the interaction term between AI technology attention and green attention (Ai_At × Green_A). In contrast, the interaction term between AI application attention and green attention (Ai_Aa × Green_A) shows a significant positive correlation, suggesting a synergy between AI application attention and green attention.

The interaction term between the depth of AI and the green depth (Ai_D × Green_D) is not significant, indicating that there is neither a crowding-out effect nor a synergy between the depth of AI and the green depth. Similarly, the interaction term between the hardware depth of AI and the green depth (Ai_Dh × Green_D) does not exhibit either of these two relationships. However, the interaction term between the software depth of AI and the green depth (Ai_Ds × Green_D) shows a significant negative correlation, suggesting that there is a crowding-out effect between the software depth of AI and the green depth.

Table 8
Resource crowding-out effect test results

Variable	Attention Resource Crowding-out			Attention Resource Crowding-out		
	GRM			GRM		
Green_A	0.040^{***}	0.040^{***}	0.040^{***}			
	(31.804)	(31.797)	(31.737)			
Ai_A	-0.009^{***}					
	(-9.105)					
Ai_A×Green_A	-0.002^{***}					
	(-2.735)					
Ai_At		-0.001^{***}				
		(-9.784)				
Ai_At×Green_A		-0.001^{***}				
		(-5.287)				
Ai_Aa			0.000			
			(0.380)			
Ai_Aa×Green_A			0.000^{**}			
			(2.129)			

Table 8
Continued

Variable	Attention Resource Crowding-out			Attention Resource Crowding-out		
	GRM			GRM		
Green_D				0.004*** (25.479)	0.004*** (24.745)	0.004*** (25.437)
Ai_D				0.244*** (4.675)		
Ai_D×Green_D				-0.012 (-1.307)		
Ai_Ds					-0.014 (-0.151)	
Ai_Ds×Green_D					-0.082*** (-3.769)	
Ai_Dh						0.601*** (6.837)
Ai_Dh×Green_D						0.004 (0.357)
Control Variables	YES	YES	YES	YES	YES	YES
Year/Industry	YES	YES	YES	YES	YES	YES
Sample Size	29139	29139	29139	29139	29139	29139
R^2	0.422	0.420	0.418	0.405	0.404	0.405

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t-statistics are reported in parentheses.

4.3.3 Resource Allocation Reference Points

Considering that financing constraints and environmental uncertainty may affect the resource allocation decisions of firms, this study examines whether these two factors are reference points for the allocation of AI resources and green resources. The financing constraint indicator is measured by the SA index, which is used to measure the cost difference between internal and external financing sources. Environmental uncertainty is quantified through the volatility of enterprise operating performance [47].

Table 9 presents the allocation patterns of AI and green resources under different situational dimensions. When financial constraints are relatively small, firms face less financial pressure and can maintain both AI and green concerns simultaneously. Therefore, no crowding-out effect is observed between the attention to AI and green concerns (Green_A×Ai_A is not significant). However, when financial pressure is high, there is a conflict in resource allocation, and a crowding-out effect emerges between the attention to AI and green concerns (Green_A × Ai_A is significantly negative). Additionally, in a stable environmental state for firms, they can steadily and deeply advance both AI and green investments simultaneously. Thus, no crowding-out effect is found between the depth of AI and green investments (Green_D×Ai_D is not significant). Conversely, in a situation with high environmental uncertainty, firms tend to adopt conservative strategies and find it difficult to increase investments in both AI and green management simultaneously, resulting in a crowding-out effect between the two (Green_D×Ai_D is significantly negative).

Table 9
Regression results under financing constraints and environmental uncertainty

Variable	Low Financing Constraints	High Financing Constraints	Strong Environmental Uncertainty	Weak Environmental Uncertainty
	GRM	GRM	GRM	GRM
Green_A	0.041***	0.038***		
	(23.141)	(20.686)		
Ai_A	-0.007***	-0.009***		
	(-5.348)	(-5.994)		
Green_A×Ai_A	-0.001	-0.003***		
	(-0.955)	(-2.692)		
Green_D			0.005***	0.004***
			(14.776)	(21.393)
Ai_D			0.262***	0.284***
			(3.293)	(4.123)
Green_D×Ai_D			-0.047***	-0.003
			(-2.636)	(-0.315)
Control Variables	YES	YES	YES	YES
Year/Industry	YES	YES	YES	YES
Sample Size	14566	14573	9714	19425
R^2	0.478	0.376	0.391	0.417

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t-statistics are reported in parentheses.

4.4 Economic Mechanisms of GRM Affected by AI Innovation Resources

4.4.1 Mediation effect

Table 10 presents the results of the mediation effect test using the Bootstrap method (to examine whether green innovation is a mediating variable for the improvement of GRM level by AI innovation). Green innovation (Green_I) is measured by the situation of green patent applications, where 1 indicates the existence of green patent applications and 0 indicates the absence of green patent applications. The coefficient of the direct path in this mediation effect is significantly positive, while the coefficient of the indirect path is significantly negative, indicating that AI innovation has a direct enhancing effect on GRM, but it also has an indirect inhibitory effect due to the occupation of resources needed for green innovation. The two effects offset each other, resulting in the positive impact of AI innovation on GRM being partially weakened.

Table 10
Path creation effects of AI innovation

Effect	coef	z	BootLLCI	BootULCI
Indirect Effect	-0.003	-3.74	-0.005	-0.002
Direct Effect	0.040	15.34	0.035	0.045

Note: BootLLCI denotes the lower bound of the bootstrap confidence interval, while BootULCI denotes the upper bound of the bootstrap confidence interval.

4.4.2 Chain-Mediated Effect

Table 11 reports the results of the chain mediation effect test, illustrating the sequential mediating role of AI innovation and green innovation in the pathway through which AI attention and AI depth influence the GRM. Path 1 of the chain mediation framework reveals that while the direct effect of AI attention on green innovation management is significantly negative (coefficient < 0; 95% confidence interval [CI] excludes 0), two statistically significant indirect facilitation paths exist (coefficients of Mediation Paths 1 and 2 > 0; 95% CIs exclude 0). The first path operates through stimulating AI innovation to enhance green innovation management levels. The second path functions via AI innovation further driving green innovation, which in turn elevates green innovation management levels.

Path 2 of the chain mediation framework indicates that the direct effect of AI depth on GRM is statistically significant and positive (coefficient > 0; 95% CI excludes 0). However, AI depth does not enhance GRM via AI innovation (the coefficient of mediation effect 1 > 0; 95% CI includes 0). Instead, significant reinforcement of GRM is contingent on the further integration of AI depth resources into firms' green innovation practices (the coefficient of mediation effect 2 > 0; 95% CI excludes 0).

Table 11
Serial mediation path test results

Effect	Path Test 1			Path Test 2		
	Coefficient	P	BC	Coefficient	P	BC
Direct Effect	-0.014	[-0.016, -0.013]	[-0.016, -0.013]	0.232	[0.154, 0.366]	[0.154, 0.366]
Mediation Effect 1	0.001	[0.000, 0.001]	[0.000, 0.001]	0.003	[-0.002, 0.009]	[-0.001, 0.009]
Mediation Effect 2	0.002	[0.001, 0.002]	[0.001, 0.002]	0.044	[0.029, 0.053]	[0.039, 0.053]
Total Effect	-0.012	[-0.013, -0.010]	[-0.013, -0.010]	0.279	[-0.203, -0.404]	[-0.216, -0.404]

Note: P denotes the percentile confidence interval, while BC represents the bias-corrected confidence interval.

4.5 Economic Policy Shocks from Environmental Tax Reform and Subsidies
4.5.1 Environmental Tax Reform

In 2018, the promulgation of the Environmental Protection Tax Law in China marked a new stage in China's tax system reform [48]. In this study, the environmental tax reform is used as the economic policy variable (Tax), and the interaction term is formed with the artificial intelligence resource variable to analyze the impact of policy shocks [49].

As shown in Table 12, the environmental tax system reform policy can amplify the positive impact of firms' attention to AI at the application level on the level of GRM (the coefficient of Tax×Ai_Aa is significantly positive). Similarly, the environmental tax system reform policy can amplify the positive impact of the depth of AI in hardware on the level of GRM (the coefficient of Tax×Ai_Dh is significantly positive). Additionally, the environmental tax system reform policy can also amplify the positive impact of AI innovation on the improvement of the level of GRM (the coefficient of Tax×Ai_I is significantly positive).

Table 12
AI-driven effects under environmental tax policy shocks

Variable	Synergistic Interplay of AI Attention			Synergistic Interplay of AI Depth	Synergistic Interplay of AI Innovation
	GRM			GRM	GRM
Tax×Ai_A	0.001 (0.191)				
Tax×Ai_At		-0.001 (-1.528)			
Tax×Ai_Aa			0.007^{***} (3.418)		
Tax×Ai_D				0.081 (1.120)	

Table 12
AI-driven effects under environmental tax policy shocks

Variable	Synergistic Interplay of AI Attention			Synergistic Interplay of AI Depth			Synergistic Interplay of AI Innovation
	GRM			GRM			GRM
Tax×Ai_Ds					-0.031 (-0.233)		
Tax×Ai_Dh						0.308** (2.326)	
Tax×Ai_I							0.011*** (2.811)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Year/Industry	YES	YES	YES	YES	YES	YES	YES
Sample Size	29139	29139	29139	29139	29139	29139	29139
R^2	0.376	0.376	0.375	0.376	0.376	0.376	0.376

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t-statistics are reported in parentheses.

4.5.2 Environmental Subsidies

As a financial incentive mechanism in China's economic system, environmental subsidy policy aims to encourage firms to take environmental protection measures [50]. In this study, the government environmental subsidy is used as an economic policy variable (Subsidy), and the amount of government environmental financial support received by firms in a fiscal year is used as a measure.

As shown in Table 13, environmental subsidy policies can amplify the positive impact of firms' attention to AI at the application level on the level of GRM (the coefficient of Subsidy×AI_Aa is significantly positive). Similarly, environmental subsidy policies amplify the positive impact of the depth of AI application, especially hardware depth, on the level of GRM (the coefficients of Subsidy×AI_D and Subsidy×AI_Dh are significantly positive, and the coefficient of Subsidy×AI_Dh is larger). Environmental subsidy policies also amplify the positive impact of AI innovation on the improvement of GRM level (the coefficient of Subsidy×AI_I is significantly positive).

Table 13
AI-driven effects under environmental subsidy policy shocks

Variable	Synergistic Interplay of AI Attention			Synergistic Interplay of AI Depth			Synergistic Interplay of AI Innovation
	GRM			GRM			GRM
Subsidy×Ai_A	0.002 (1.270)						
Subsidy×Ai_At		-0.000 (-1.620)					
Subsidy×Ai_Aa			0.001*** (3.086)				
Subsidy×Ai_D				0.244*** (3.101)			
Subsidy×Ai_Ds					0.068 (0.369)		
Subsidy×Ai_Dh						0.399*** (3.394)	
Subsidy×Ai_I							0.012*** (3.130)

Table 13
AI-driven effects under environmental subsidy policy shocks

Variable	Synergistic Interplay of AI Attention			Synergistic Interplay of AI Depth			Synergistic Interplay of AI Innovation
	GRM			GRM			GRM
Control Variables	YES	YES	YES	YES	YES	YES	YES
Year/Industry	YES	YES	YES	YES	YES	YES	YES
Sample Size	28353	29139	29139	29139	29139	29139	29139
R^2	0.376	0.376	0.376	0.377	0.376	0.377	0.377

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t-statistics are reported in parentheses.

5. Conclusions

This study is based on the RBV theory, a development in the field of business economic management derived from economic theory. It explores the impact of AI resources on corporate green risk management and its internal economic mechanism. This research not only enriches the economic management theory under the background of green development and digital economy, but also deepens the practical verification of the impact of artificial intelligence on green development at the microeconomic level.

The empirical results confirm that different dimensions of AI resources have differentiated impacts on firms' GRM: AI attention (cognitive resources) has a negative impact on GRM, while AI depth (basic resources) and AI innovation (accumulated resources) show positive effects. In addition, Chinese firms can directly improve GRM only by focusing on AI application and deepening hardware investment.

Economic mechanism analysis shows that at the cognitive resource level, AI crowds out green resources, thereby suppressing GRM. However, it can have a positive impact on GRM through the chain mediating path of AI innovation and green innovation. At the basic resource level, AI has no obvious effect on green resources and the crowding-out effect. Its promoting effect on GRM also depends on the mediating effect of green innovation. This reveals that the realization of the green value of AI resources lies in whether it can effectively guide green innovation. In addition, environmental tax system reform and subsidies at the economic policy level can both enhance the positive impacts of AI application attention, AI hardware deployment depth, and AI-driven innovation on firms' GRM. This verifies the effectiveness of China's macroeconomic green development policies.

The above research findings have five major contributions: (1) By classifying enterprise AI resources based on their attributes, this study advances research on the conceptualization and measurement of AI [51]; (2) It supports the critical research on "technological determinism" [52], confirming that the promoting effect of AI on green development does not only depend on its technical attributes; (3) It highlights the importance of resource specificity, indicating that only AI resources that form dedicated fixed assets can sustainably enhance green performance [53,54]; (4) It identifies the resource crowding-out dilemma that firms may face when managing digital technologies under resource constraints [55], and validates the academically consensus conclusion that green innovation is the core driver for firms to achieve environmental objectives [56]; (5) It demonstrates the effectiveness of economic policy tools such as environmental taxes and subsidies.

Several limitations exist in this study, which point out directions for future research. Although the endogeneity problem in the empirical test has been mitigated, the greenwashing behavior of firms may still lead to data bias. In addition, the research sample focuses on Chinese listed firms, which limits the generalizability of the research results in different institutional and economic environments. The analysis time span is from 2010 to 2023, failing to cover the latest developments of generative AI such as ChatGPT. Future research should explore more precise performance evaluation index systems related to green risks and can expand the research scope to non-listed firms or different countries and regions.

This study not only provides a reference for firms to allocate artificial intelligence resources to achieve green transformation, but also offers microeconomic evidence for the government to build an economic policy system that promotes the synergy between AI and the green economy. For firms, it is necessary to recognize that different types of AI resources have differentiated economic mechanisms in GRM. They should avoid remaining at the technical level and increase substantive investment in the application scenarios of AI. Moreover, they should actively establish a collaborative transformation mechanism between AI innovation and green innovation. At the policy level, government departments should design more targeted environmental regulations and economic incentive policies when promoting the digitalization and greening of the economic system. They should guide the flow of AI resources towards investment and innovation activities with clear environmental benefits.

Author Contributions

Conceptualization, Y.H. and S.S.; Methodology, S.S.; Software Z.Z.; Validation, Y.H., Z.Z. and S.S.; Formal analysis, Y.H.; Data curation, Z.Z.; Writing-review and editing, Y.H.; Visualization, Z.Z.; Supervision, Z.Z.; Project administration, Z.Z.; Funding acquisition, Z.Z. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

For corporate annual reports, social responsibility reports, as well as patent application and authorization information, the data are drawn from the China Research Data Service Platform (CNRDS) [30], available at https://www.cnrds.com. Corporate governance structure and financial data are obtained from the China Stock Market & Accounting Research Database (CSMAR) [31], accessible at https://data.csmar.com. Macro-level regional economic and policy data are derived from the China Urban Statistical Yearbook [32], published by the National Bureau of Statistics of China at https://www.stats.gov.cn/sj/ndsj/. In addition, the original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest

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

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References

[1] Halkos, G., & Nomikos, S. (2021). Corporate social responsibility: Trends in global reporting initiative standards. *Economic Analysis and Policy, 69*, 106-117. https://doi.org/10.1016/j.eap.2020.11.008

[2] Khanra, S., Kaur, P., Joseph, R. P., Malik, A., & Dhir, A. (2022). A resource-based view of green innovation as a strategic firm resource: Present status and future directions. *Business Strategy and the Environment, 31*(4), 1395-1413. https://doi.org/10.1002/bse.2961

[3] Wu, C. J., Raghavendra, R., Gupta, U., Acun, B., Ardalani, N., Maeng, K., ... & Hazelwood, K. (2022). Sustainable ai: Environmental implications, challenges and opportunities. *Proceedings of Machine Learning and Systems, 4*, 795-813. https://proceedings.mlsys.org/paper_files/paper/2022/file/462211f67c7d858f663355eff93b745e-Paper.pdf

[4] Mariani, M. M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation, 122*, 102623. https://doi.org/10.1016/j.technovation.2022.102623

[5] Gaur, L., Afaq, A., Arora, G. K., & Khan, N. (2023). Artificial intelligence for carbon emissions using system of systems theory. *Ecological Informatics, 76*, 102165. https://doi.org/10.1016/j.ecoinf.2023.102165

[6] Priyadarshini, S., Dash, S., & Priyadarshini, S. (2024). Leveraging Artificial Intelligence in Climate Change Interpretation: Overcoming Challenges in Risk Management Approach. *AI for Climate Change and Environmental Sustainability*, 145-159. https://doi.org/10.1201/9781003452393

[7] Wang, Q., Sun, T., & Li, R. (2025). Does Artificial Intelligence (AI) enhance green economy efficiency? The role of green finance, trade openness, and R&D investment. *Humanities and Social Sciences Communications, 12*(1), 1-22. https://doi.org/10.1057/s41599-024-04319-0

[8] Song, Z., & Deng, Y. (2025). The impact of artificial intelligence on green economy efficiency under integrated governance. *Scientific Reports, 15*(1), 25919. https://doi.org/10.1038/s41598-025-03817-8

[9] Hassan, S. T., & Hassan, M. U. (2025). Assessing the dynamics of artificial intelligence, renewable energy investment, and policy uncertainty in promoting green growth in China. *Energy Reports*. https://doi.org/10.1016/j.egyr.2025.08.020

[10] Cheng, Y., Zhang, Z., Hu, L., & Duan, X. (2025). Research on the impact of artificial intelligence development on urban low-carbon transformation. *Scientific Reports, 15*(1), 20438. https://doi.org/10.1038/s41598-025-05330-4

[11] Wang, A., Luo, K., & Nie, Y. (2024). Can artificial intelligence improve enterprise environmental performance: Evidence from China. *Journal of Environmental Management, 370*, 123079. https://doi.org/10.1016/j.jenvman.2024.123079

[12] Akram, R., Shi, X., Khalid, F., & Srivastava, M. (2025). Artificial intelligence (AI) adoption and green investment: driving corporate environmental responsibility. *Business Strategy and the Environment, 34*(7), 9188-9202. https://doi.org/10.1002/bse.70069

[13] Hussain, M., Yang, S., Maqsood, U. S., & Zahid, R. A. (2024). Tapping into the green potential: The power of artificial intelligence adoption in corporate green innovation drive. *Business Strategy and the Environment, 33*(5), 4375-4396. https://doi.org/10.1002/bse.3710

[14] Li, H. (2025). Artificial intelligence, green transition and green total factor productivity in enterprises. *Scientific Reports, 15*(1), 33248. https://doi.org/10.1038/s41598-025-18878-y

[15] Chotia, V., Cheng, Y., Agarwal, R., & Vishnoi, S. K. (2024). AI-enabled Green Business Strategy: Path to carbon neutrality via environmental performance and green process innovation. *Technological Forecasting and Social Change, 202*, 123315. https://doi.org/10.1016/j.techfore.2024.123315

[16] Lee, J., & Bansal, P. (2024). Sweeping it under the rug: Positioning and managing pollution-intensive activities in organizational hierarchies. *Strategic Management Journal, 45*(6), 1151-1179. https://doi.org/10.1002/smj.3582

[17] Liu, L. (2024). Green innovation, firm performance, and risk mitigation: evidence from the USA. *Environment, Development and Sustainability, 26*(9), 24009-24030. https://doi.org/10.1007/s10668-023-03632-z

[18] Yazo-Cabuya, E. J., Ibeas, A., & Herrera-Cuartas, J. A. (2024). Integration of sustainability in risk management and operational excellence through the VIKOR method considering comparisons between multi-criteria decision-making methods. *Sustainability, 16*(11), 4585. https://doi.org/10.3390/su16114585

[19] Dal Maso, L., Gianfagna, L., Maglione, F., & Lattanzi, N. (2024). Going green: Environmental risk management, market value and performance. *Corporate Social Responsibility and Environmental Management, 31*(1), 122-132. https://doi.org/10.1002/csr.2556

[20] Barney, J. B. (2000). Firm resources and sustained competitive advantage. *Economics Meets Sociology in Strategic Management, 17*, 203–227. https://doi.org/10.1016/S0742-3322(00)17018-4

[21] Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal, 5*(2), 171-180. https://doi.org/10.1002/smj.4250050207

[22] Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal, 44*(6), 1425-1452. https://doi.org/10.1002/smj.3387

[23] Ocasio, W. (1997). Towards an attention-based view of the firm. *Strategic Management Journal, 18*(S1), 187-206. https://doi.org/10.1002/(SICI)1097-0266(199707)18:1+<187::AID-SMJ936>3.0.CO;2-K

[24] Joseph, J., Laureiro-Martinez, D., Nigam, A., Ocasio, W., & Rerup, C. (2024). Research frontiers on the attention-based view of the firm. *Strategic Organization, 22*(1), 6-17. https://doi.org/10.1177/14761270231223397

[25] Obschonka, M., & Audretsch, D. B. (2020). Artificial intelligence and big data in entrepreneurship: a new era has begun. *Small Business Economics, 55*, 529-539. https://doi.org/10.1007/s11187-019-00202-4

[26] Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change, 162*, 120392. https://doi.org/10.1016/j.techfore.2020.120392

[27] Akter, S., Hossain, M. A., Sajib, S., Sultana, S., Rahman, M., Vrontis, D., & McCarthy, G. (2023). A framework for AI-powered service innovation capability: Review and agenda for future research. *Technovation, 125*, 102768. https://doi.org/10.1016/j.technovation.2023.102768

[28] Alqahtani, A. S. H. (2023). Application of Artificial Intelligence in Carbon Accounting and Firm Performance: A Review Using Qualitative Analysis. *International Journal of Experimental Research and Review, 35*, 138-148. https://doi.org/10.52756/IJERR.2023.V35SPL.013

[29] Peretz-Andersson, E., Tabares, S., Mikalef, P., & Parida, V. (2024). Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach. *International Journal of Information Management, 77*, 102781. https://doi.org/10.1016/j.ijinfomgt.2024.102781

[30] Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192-210. https://doi.org/10.5465/amr.2018.0072

[31] Feroz, A. K., Zo, H., & Chiravuri, A. (2021). Digital transformation and environmental sustainability: A review and research agenda. *Sustainability, 13*(3), 1530. https://doi.org/10.3390/su13031530

[32] Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509-533. https://doi.org/10.1002/(sici)1097-0266(199708)18:7<509::aid-smj882>3.0.co;2-z

[33] China Research Data Services Platform. (2025). *CNRDS*. Retrieved September 13, 2025, from https://www.cnrds.com

[34] China Stock Market & Accounting Research Database. (2020). *CSMAR*. Retrieved September 11, 2025, from https://data.csmar.com

[35] National Bureau of Statistics of China. (2011-2024). *China urban statistical yearbook*. China Statistics Press. Retrieved September 3, 2025, from https://www.stats.gov.cn/sj/ndsj/

[36] De Oliveira, U. R., Marins, F. A. S., Rocha, H. M., & Salomon, V. A. P. (2017). The ISO 31000 standard in supply chain risk management. *Journal of Cleaner Production, 151*, 616-633. https://doi.org/10.1016/j.jclepro.2017.03.054

[37] Salaj, & Kumari, M. (2025). A multi-criteria approach to blockchain in supply chain management assessment: entropy-CRITIC weight method and MCDM for enhanced decision support. *International Journal of System Assurance Engineering and Management*, 1-14. https://doi.org/10.1007/s13198-025-02764-x

[38] Yao, J., Zhang, K., Guo, L., & Feng, X. (2024). How does artificial intelligence improve firm productivity? Based on the perspective of labor skill structure adjustment. *Journal of Management World, 40*(2), 101-116. https://link.cnki.net/doi/10.19744/j.cnki.11-1235/f.2024.0018

[39] Ho, J. L., Wu, A., & Xu, S. X. (2011). Corporate governance and returns on information technology investment: Evidence from an emerging market. *Strategic Management Journal, 32*(6), 595-623. https://doi.org/10.1002/smj.886

[40] Huang, Y., & Sun, S. (2025). Research on the Relationship among Audit Opinion, Corporate Governance and Green-washing: Based on the Two-stage Moderating Effect of Executives' Digital Background and Regional Digital Environment. In *Proceedings of the 2025 International Conference on Artificial Intelligence and Digital Finance* (pp. 1-8). https://dl.acm.org/doi/full/10.1145/3764727.3764729

[41] Grashof, N., & Kopka, A. (2023). Artificial intelligence and radical innovation: an opportunity for all companies? *Small Business Economics, 61*(2), 771-797. https://doi.org/10.1007/s11187-022-00698-3

[42] Yu, F., Wang, L., & Li, X. (2020). The effects of government subsidies on new energy vehicle enterprises: The moderating role of intelligent transformation. *Energy Policy, 141*, 111463. https://doi.org/10.1016/j.enpol.2020.111463

[43] Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of Management Review, 20*(4), 986-1014. https://doi.org/10.5465/amr.1995.9512280033

[44] Ding, X., Xu, Z., Petrovskaya, M. V., Wu, K., Ye, L., Sun, Y., & Makarov, V. M. (2023). Exploring the impact mechanism of executives' environmental attention on corporate green transformation: evidence from the textual analysis of Chinese companies' management discussion and analysis. *Environmental Science and Pollution Research, 30*(31), 76640-76659. https://doi.org/10.1007/s11356-023-27725-4

[45] Chen, Y., & Ma, Y. (2021). Does green investment improve energy firm performance? *Energy Policy, 153*, 112252. https://doi.org/10.1016/j.enpol.2021.112252

[46] Nakamura, E. (2011). Does environmental investment really contribute to firm performance? An empirical analysis using Japanese firms. *Eurasian Business Review, 1*, 91-111. https://doi.org/10.14208/BF03353800

[47] Cheng, J. L., & Kesner, I. F. (1997). Organizational slack and response to environmental shifts: The impact of resource allocation patterns. *Journal of Management, 23*(1), 1-18. https://doi.org/10.1016/S0149-2063(97)90003-9
[48] Liu, Y., Wang, A., & Wu, Y. (2021). Environmental regulation and green innovation: Evidence from China's new environmental protection law. *Journal of Cleaner Production, 297*, 126698. https://doi.org/10.1016/j.jclepro.2021.126698
[49] Bi, G., Jin, M., Ling, L., & Yang, F. (2017). Environmental subsidy and the choice of green technology in the presence of green consumers. *Annals of Operations Research, 255*, 547-568. https://doi.org/10.1007/s10479-016-2106-7
[50] Bian, J., & Zhao, X. (2020). Tax or subsidy? An analysis of environmental policies in supply chains with retail competition. *European Journal of Operational Research, 283*(3), 901-914. https://doi.org/10.1016/j.ejor.2019.11.052
[51] Bahoo, S., Cucculelli, M., & Qamar, D. (2023). Artificial intelligence and corporate innovation: A review and research agenda. *Technological Forecasting and Social Change, 188*, 122264. https://doi.org/10.1016/j.techfore.2022.122264
[52] Morozov, E. (2013). *To save everything, click here: The folly of technological solutionism*. PublicAffairs. https://media-1.carnegiecouncil.org/cceia/import/studio/To_Save_Everything_Click_Here.pdf
[53] Williamson, O. E. (2008). The economic institutions of capitalism. *The Political Economy Reader: Markets as Institutions*, 27. https://www.academia.edu/1084272/The_economic_institutions_of_capitalism
[54] Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99-120. https://doi.org/10.1016/S0742-3322(00)17018-4
[55] He, J., & He, Z. (2025). Digital transformation effects on Chinese heavily polluting firms internalising environmental costs. *Sustainability Accounting, Management and Policy Journal, 16*(3), 946-972. https://doi.org/10.1108/SAMPJ-11-2023-0863
[56] Orjuela-Ramirez, G., Zuluaga-Jimenez, J. C., & Urbano, D. (2024). Drivers of eco-innovation: the role of appropriability strategies and complementary assets. *Science and Public Policy, 51*(2), 309-323. https://doi.org/10.1093/scipol/scad072