A Study on the Influence Mechanism of AI Development Level and Digital Transformation Degree on Corporate ESG Coordinated Development

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Abstract. Existing research predominantly relies on aggregate ESG scores to assess corporate sustainability performance. However, such metrics often fail to accurately capture the synergistic interplay among the Environmental, Social, and Governance (ESG) pillars, leading to an inadequate reflection of the actual implementation status of corporate sustainability strategies. To address this research gap, this study introduces the "ESG Coupling Coordination Degree" as a core evaluation metric to systematically investigate the mechanism through which the level of Artificial Intelligence (AI) development and the degree of digital transformation influence corporate ESG coordinated development. Using a sample of Chinese A-share listed companies from 2009 to 2023, this research first constructs a coupling coordination degree model to measure the level of corporate ESG coordinated development and reveals its temporal evolution characteristics. The empirical results indicate that: the overall ESG coupling coordination degree of firms shows a steady upward trend, albeit with significant industry and regional disparities. Both the depth of digital transformation and the breadth of AI application exert a significant positive impact on corporate ESG coordinated development. This mechanism operates by enhancing the efficiency of internal information flows, which in turn promotes the balanced development of environmental management systems, social responsibility fulfillment, and corporate governance structures. Further analysis reveals that this synergistic effect is more pronounced in firms located in the eastern region and in technology-intensive industries, whereas firms with weaker digital infrastructure exhibit greater potential for improvement in ESG coordination. These findings provide empirical evidence and policy implications for policymakers aiming to foster the deep integration of the digital economy and sustainable development.

Keywords: Corporate ESG Coordinated Development, Artificial Intelligence Development, Digital Transformation, Econometric Analysis.

1. Introduction

In recent years, with the profound global penetration of the sustainable development concept, ESG has progressively emerged as a core criterion for evaluating corporate sustainability and overall competitiveness. Ding and Liu (2025) summarized the developmental trajectory and future prospects of ESG theory, noting that ESG has evolved from an investment philosophy into a central component of corporate strategic management [1]. He et al. (2025) further emphasized that ESG performance serves as a crucial dimension for assessing a firm's new quality productivity and resilience [2]. Empirical evidence demonstrates that superior ESG performance not only enhances a firm's resilience to external risk shocks and improves its image in the capital market but also lays a solid foundation for long-term development by optimizing resource allocation efficiency and elevating risk management capabilities. Both academia and industry have conducted systematic, multi-dimensional, and multi-perspective research on corporate ESG. These efforts have not only established diverse evaluation systems and measurement methods but have also delved into the impact of ESG performance on key operational indicators such as firm performance, financing constraints, and investment efficiency. For instance, Zheng and Zhao (2025) empirically tested the positive effect of digital transformation on corporate ESG performance using regression models [3]. Peng and Liao

(2025) analyzed the mechanism through which interlocking shareholding structures positively promote corporate green innovation and ESG performance [4].

Concurrently, the rapid evolution of big data technology and the surge of the digital economy are fundamentally transforming corporate business models and governance logic. Emerging technologies such as cloud computing, blockchain, and large language models are accelerating the processes of informatization and intellectualization within firms, with digital transformation and Artificial Intelligence (AI) application becoming key engines driving strategic upgrades. Specifically, digital infrastructure significantly enhances a firm's internal data processing capabilities and information transparency, providing technical support for innovating environmental governance methods and strengthening external oversight mechanisms while optimizing resource allocation. Meanwhile, AI technology, through algorithmic analysis and predictive modeling, precisely identifies potential carbon emission risks, green supply chain management shortcomings, and weaknesses in social responsibility fulfillment, offering data-driven solutions and optimization opportunities for corporate decision-making. Existing studies have indicated that by leveraging intelligent algorithms to optimize carbon auditing processes and enhance governance transparency, firms can effectively improve the execution efficiency and coordination level of their ESG strategies [5-6]. These technological advancements collectively provide instrumental support for firms to balance environmental protection, social responsibility, and governance structures, helping them build more efficient and sustainable operational models. Scholars have begun to explore the mechanisms underlying these relationships. For example, Chen and Kai (2025) pointed out a significant bidirectional feedback loop between technological innovation and ESG performance, where AI can optimize environmental governance strategies and improve corporate governance transparency [7].

However, the existing literature predominantly relies on composite scores to quantify corporate ESG development or focuses on analyzing the environmental, social, and governance dimensions in isolation. While such research has advanced the ESG theoretical framework, it often overlooks the interactive relationships and synergistic effects among these three pillars. In practice, a sustainable strategy lacking coordinated support across its environmental, social, and governance dimensions will struggle to translate single-dimension improvements into a systemic competitive advantage. Consequently, an aggregate score may fail to authentically reflect the balanced state of sustainable development within a firm. Xu and Ren (2025), in their study of smart home appliance manufacturers, employed the coupling coordination degree method to measure the alignment between digital and green transformations, demonstrating the method's superiority in capturing multi-dimensional synergistic development [8]. By contrast, the corporate ESG coupling coordination degree can more precisely measure the balanced development state among the environmental, social, and governance elements within a firm's sustainability strategy, objectively reflecting the complementarity and interactivity of resource allocation and governance measures across these dimensions. Constructing a scientifically sound coupling coordination degree index system can not only reveal structural imbalances in corporate sustainable development but also provide quantitative guidance for firms to identify areas for improvement and optimize strategic planning.

In light of this, our study first innovatively introduces the coupling coordination degree index, building upon existing ESG evaluation theories, to quantify the synergistic development level of firms across the environmental, social, and governance dimensions. We then construct a two-way fixed-effects model to systematically investigate the impact of AI and digital transformation on the corporate ESG coupling coordination degree, verifying the robustness and applicability of our results through multi-dimensional tests. Additionally, this research further examines whether heterogeneous impact mechanisms exist across different industries and regions. Our empirical findings reveal that: the overall ESG coupling coordination degree of firms exhibits a steady upward trend, yet with significant industry and regional disparities. Both the depth of digital transformation and the breadth of AI application exert a significant positive influence on corporate ESG coordinated development. This mechanism operates by optimizing the efficiency of internal information flows, thereby fostering the balanced development of environmental management systems, social responsibility fulfillment, and corporate governance structures. Further analysis indicates that the synergistic effect is more pronounced in firms located in the eastern region and in technology-intensive industries, while firms with weaker digital infrastructure show greater potential for improvement in ESG coordination. These conclusions not only provide a theoretical basis for firms to formulate synergistic strategies for digital upgrades and green development but also offer empirical support for policymakers aiming to promote the deep integration of digital technology and sustainable development.

2. Theory and Methods

2.1. Hypothesis Development

AI Drives Green Innovation, Optimizing Resource Allocation and Carbon Reduction. Artificial Intelligence (AI) enhances the integration and management of data resources, enabling real-time monitoring of energy consumption and pollution in production environments. By leveraging machine learning and advanced algorithms, AI can extract valuable information from environmental data to build predictive models that identify potential environmental risks [9], dynamically adjust resource allocation to reduce unit energy consumption, and optimize the proportion of renewable energy to minimize carbon emissions. AI has a significant driving effect on technological innovation, with intelligent manufacturing technologies demonstrating a positive impact on both short-term and long-term firm performance [10], wherein the enhancement of green innovation capabilities is directly linked to improved environmental performance. Concurrently, in addressing climate change, AI supports carbon footprint measurement and climate risk assessment, assisting firms in setting carbon neutrality goals and guiding biodiversity conservation projects. This process improves resource utilization efficiency, strengthens the scientific rigor and responsiveness of environmental management, and promotes corporate sustainability by reducing the ecological footprint. Through real-time analysis of environmental data, AI helps firms lower their carbon emission intensity, ultimately contributing to a positive shift in their coupling coordination degree.

AI Empowers Social Responsibility Management, Enhancing Fairness and Execution Efficiency. AI services can improve customer experience and alleviate operational pressures by providing real-time, effective advice and assistance to clients [11]. This, in turn, enhances metrics related to employee rights, supply chain management, and community impact. AI systems can automatically flag non-compliant behaviors, optimize welfare distribution, and refine the corporate labor structure through job reallocation, skills upgrading, retraining, and fostering the development of emerging professions [11]. Furthermore, AI improves delivery and operational efficiency, thereby strengthening the fulfillment of social responsibility in products and services. AI algorithms analyze corporate demand data to optimize localized hiring and diversity initiatives, helping firms achieve gender balance and enhance their influence and inclusivity. These applications boost the efficiency of social responsibility execution. By mitigating discrimination risks and fostering stakeholder engagement, AI ensures the dynamic alignment of social objectives with corporate strategy, significantly enhancing the overall coordination of ESG by improving fairness and responsiveness.

AI Strengthens Governance Transparency and Risk Control, Fortifying the Cornerstone of Corporate Compliance. AI optimizes corporate decision-making mechanisms and compliance by enhancing governance transparency and risk control capabilities. In information disclosure and risk management, firms can use data integration tools to automate the generation of ESG reports, ensuring the complete disclosure of key indicators such as carbon emissions and supply chain audit records. Machine learning models can be employed to identify corporate risks in real-time and implement dynamic prevention and control strategies, thereby improving corporate governance performance through increased information transparency. AI breaks down internal information silos and facilitates information gathering from both internal and external stakeholders via cloud platforms, thus broadening governance channels [12]. Intelligent systems can automatically track major administrative penalties and litigation records and analyze shareholder meeting voting data to protect the rights of minority shareholders and enhance the fairness of profit distribution. The application of this technology reduces compliance risks and solidifies the foundation of corporate governance through scientific decision-making and institutional optimization. By empowering multiple dimensions, AI achieves synergistic optimization at the objective level, fostering a closer positive linkage among the ESG elements. Based on the preceding analysis, this paper proposes Hypothesis 1.

H1: The level of Artificial Intelligence has a significant positive impact on the corporate ESG coupling coordination degree.

Digital Transformation Cultivates a Green Innovation Environment and Enhances Corporate Environmental Performance. Digital technologies reshape corporate resource allocation pathways, enabling precise control over energy consumption and emissions [13]. Through digital systems, firms can integrate and reorganize resources to optimize their configuration and improve utilization rates. Notably, digital finance promotes corporate green innovation by optimizing the structure of factor allocation. It not only assists firms in developing or adopting energy-saving equipment and eco-friendly production processes but also provides online trading services for green investment products like green bonds and loans. This enhances production efficiency while reducing pollution, directly contributing to lower energy and water intensity and the implementation of emission reduction measures. Furthermore, digital inclusive finance significantly improves corporate ESG performance by alleviating financing constraints and fostering green innovation [14]. Such green technological innovation must be supported by a robust environmental management system, where digital tools are used to dynamically track environmental compliance, thereby creating an institutional closed-loop for green innovation [15].

Digital Transformation Strengthens Social Responsibility Fulfillment and Boosts Corporate Social Reputation. By optimizing internal management and resource allocation, digital transformation enables firms to implement employee training and welfare programs using digital tools. This helps attract and retain R&D talent and positively reflects a commitment to labor contract compliance, compensation, benefits, and occupational health training. It encourages standardized employment practices and utilizes digital systems to improve workplace safety monitoring, thereby reducing injury rates. Digital inclusive finance contributes to social equity and inclusive development by expanding financial service accessibility, particularly for vulnerable groups such as SMEs and in underdeveloped regions. Moreover, by enhancing information transparency and external communication efficiency, digital transformation helps firms respond more precisely to societal demands for fairness and inclusivity. The reinforcement of such social responsibility practices boosts a firm's internal drive, builds a positive social reputation, and enhances market competitiveness. As indicated by relevant research, the development of corporate digital technologies signals operational excellence to external investors and stakeholders, enabling firms to better understand and respond to stakeholder needs, which in turn increases transparency and trust in their fulfillment of social responsibilities.

Digital Transformation Optimizes Corporate Governance Structure and Reduces Financing Costs. Through the application of digital technologies like big data and cloud computing, digital transformation helps firms accurately assess their financial and market conditions and efficiently match funding needs with financing channels. High-efficiency data processing and analysis tools enable firms to monitor the implementation of internal controls and their risk status, signaling low risk to external parties and thereby reducing required risk premiums and financing costs. Digital transformation also enhances the effectiveness of external supervision, mitigating agency problems by reducing the scope for managerial opportunism. Specifically, it can optimize internal control systems, promote a shift towards flatter and more networked organizational structures, and improve departmental collaboration, decision-making efficiency, and innovation capabilities. This limits managerial discretion, enhances operational stability, and strengthens risk control. By improving data processing capabilities, it increases operational transparency, alleviates internal information asymmetry, constrains opportunistic managerial behavior, and further mitigates agency problems, ultimately enhancing the quality of corporate governance and internal control. Based on this analysis, digital transformation can simultaneously empower the environmental, social, and governance dimensions of ESG, promoting their synergistic development. Therefore, this paper proposes Hypothesis 2.

H2: The degree of Digital Transformation has a significant positive impact on the corporate ESG coupling coordination degree.

The Digital Foundation Empowers the Precision of AI-driven Environmental Governance. A unified data platform enables the centralized management and sharing of financial and operational data, which should possess robust processing, analytical, and visualization capabilities to meet diverse business needs [16]. This foundation drives the optimization of environmental resources and the management of social risks. As Yao (2022) pointed out, digital technologies like the Internet of Things (IoT) and blockchain provide reliable data support for AI-driven environmental risk assessments, such as carbon emission prediction and pollution source tracking. Blockchain technology, for instance, can create a decentralized ledger where all transactions are recorded immutably, ensuring data authenticity and integrity [17]. Wang et al. (2023) developed a digital and intelligent green packaging solution library, using blockchain to trace the origin of raw materials and guarantee the authenticity of environmental data [18]. A digital carbon management platform with automated alert rules can trigger reduction plans and generate compliance reports when emissions exceed limits, significantly reducing the risk of human intervention. This allows AI algorithms to dynamically optimize environmental management strategies. For example, predictive maintenance systems can identify equipment risks in advance, enhancing the responsiveness of resource consumption monitoring and pollutant reduction. With a well-developed digital infrastructure, big data platforms can achieve "precise monitoring and intelligent control of energy consumption and pollutant emissions," fully unleashing the potential of AI in corporate carbon footprint measurement and climate change response.

Data Integration Drives AI-powered Synergy in Social Responsibility. Digital transformation facilitates the integration of multi-source data and breaks down departmental barriers, allowing for the centralized management of scattered information related to supply chains, employee rights, and community impact. This enables AI-driven assessments of social responsibility, such as labor rights monitoring and supply chain compliance audits, to be more comprehensive and precise. This process is often supported by government innovation incentives, such as special funds and technical renovation loans, which accelerate the implementation of green technologies in the social responsibility domain [19]. Digital technologies effectively "dismantle departmental silos" to promote cross-functional collaboration. Blockchain-based supplier traceability systems further "ensure supplier behavior is traceable," strengthening the enforcement of anti-forced labor policies. A higher degree of digital transformation allows AI-powered evaluations of key metrics like diversity, inclusion, and local community hiring to be more targeted, thereby enhancing the overall coordination of social responsibility initiatives.

Trustworthy Data Enhances the Effectiveness of AI-driven Risk Control Decisions. By providing real-time, verifiable data streams, digital systems integrate governance data such as shareholder behavior and compliance records. Digital transformation reduces insiders' incentives to conceal adverse information, thereby mitigating the risk of stock price crashes by enhancing information verifiability [16]. The core of this moderating effect lies in how digital transformation improves corporate data transparency, reduces information asymmetry in investment and financing processes [19], saves agency costs, and ensures the traceability of intelligent corporate data. Regarding corporate assets, intelligent internal control systems can automatically detect and flag financial anomalies, reducing the scope for managerial information manipulation. Concurrently, "strengthened shareholder protection mechanisms" within data governance frameworks can enhance the participation of minority shareholders. An advanced level of digital transformation, leveraging technologies like blockchain's distributed ledger, improves data verifiability. This makes AI interventions in business ethics reviews and operational compliance monitoring more effective in managing governance risks. Consequently, it enables the synergy of intelligent environmental risk monitoring, automated social responsibility execution, and real-time intelligent auditing of governance processes, significantly boosting the role of AI in risk identification and decision optimization. Based on the foregoing analysis, this paper proposes Hypothesis 3.

H3: Digital Transformation positively moderates the impact of Artificial Intelligence on the corporate ESG coupling coordination degree.

2.2. Methodology

(1) Construction of the ESG Coupling Coordination Index System

Adhering to the principles of scientific rigor, systematic design, and practical applicability, this study constructs a three-level ESG coupling coordination index system comprising a "Target Layer," a "Criterion Layer," and an "Indicator Layer," as shown in Table 1.

Table 1. ESG Coupling Coordination Index System

Level 1 Indicator	Level 2 Indicator	Level 3 Indicator
Environment (E)	Environmental Management	Environmental Policies and Targets
		Environmental Management System Certification
	Resource Consumption	Energy/Water Use Intensity
		Proportion of Renewable Energy
	Pollutant Emissions	Greenhouse Gas, Wastewater, Waste Gas, Solid Waste Emissions and Reduction Measures
	Climate Change Response	Carbon Footprint Measurement
		Carbon Neutrality Goals
		Climate Risk Assessment
	Biodiversity Protection	Impact of Operations in Ecologically Sensitive Areas
		Ecological Restoration Projects
Social (S)	Employee Rights	Labor Contract Compliance
		Compensation and Benefits
		Working Hours Management
		Anti-Discrimination and Anti-Harassment
	Health and Safety	Investment in Production Safety
		Work-related Injury Rate
		Occupational Health Training
	Supply Chain Management	Supplier ESG Audits
		Protection of Labor Rights
		Anti-Forced Labor Policies
	Product Responsibility	Product Quality and Safety
		Customer Privacy Protection
		Consumer Complaint Handling
	Community Impact	Philanthropic Donations
		Investment in Community Projects
		Localized Hiring
	Diversity and Inclusion	Gender Equality
		Protection of Minority Rights
Governance (G)	Board Governance	Proportion of Independent Directors
		Board Diversity
		Establishment of Specialized Committees
	Business Ethics	Anti-Corruption Policies
		Records of Commercial Bribery Penalties
		Whistleblower Mechanism
	Information Disclosure Quality	Transparency of ESG Reports
		Completeness of Key Data Disclosure
	Risk Management	ESG Risk Identification Mechanism
		Data Security and Privacy Protection
	Shareholder Rights	Protection of Minority Shareholders
		Participation in Shareholder Meetings
		Fairness of Profit Distribution
	Compliance Operations	Major Administrative Penalties
		Litigation and Arbitration Records
		Tax Compliance

The Target Layer is the "ESG Coupling Coordination Degree," which reflects the synergistic development level among the three sub-systems: Environmental (E), Social (S), and Governance (G). The Criterion Layer corresponds to the E, S, and G sub-systems. The Indicator Layer directly utilizes the secondary indicators from the criterion layer. The calculation process is as follows:

(1) Standardize the positive and negative indicators using the min-max normalization method.

(2) Employ the CRITIC method to determine the weight of each indicator. The CRITIC method is favored for its dual benefits: it objectively quantifies conflicts between indicators through negative correlation, while simultaneously capturing information intensity via standard deviation. This approach effectively avoids subjective bias, making it particularly suitable for assessing both synergistic and conflicting relationships within multi-dimensional ESG systems. Subsequently calculating the composite scores for the E, S, and G sub-systems and the coordination index.

(3) Calculate the interaction strength among the sub-systems using a coupling degree model.

(4) Finally, derive the ESG Coupling Coordination Degree.

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad X_{\text{normalized}} = \frac{X_{\max} - X}{X_{\max} - X_{\min}} \tag{1}$$

$$\mathrm{T} = \omega_{\mathrm{E}} \cdot \mathrm{U_E} + \omega_{\mathrm{S}} \cdot \mathrm{U_S} + \omega_{\mathrm{G}} \cdot \mathrm{U_G} \tag{2}$$

$$\mathrm{C} = \frac{(\mathrm{U_E} \cdot \mathrm{U_S} \cdot \mathrm{U_G})^{1/3}}{(\mathrm{U_E} + \mathrm{U_S} + \mathrm{U_G})/3} \tag{3}$$

$$\mathrm{D} = \sqrt{\mathrm{C} \cdot \mathrm{T}} \tag{4}$$

(2) Selection of Core Explanatory and Control Variables

To measure Artificial Intelligence (AI) development level, existing studies have proposed different evaluation dimensions. Gu and Ma (202x) built an index system based on "environmental support, knowledge creation, and industrial competitiveness" but ignored the AI application dimension [20]. Ye and Ou (202x) focused on "technological level, AI industrialization, and industrial intelligence" (capturing core tech and application aspects) yet excluded essential AI development infrastructure [21]. In contrast, CAICT (2022) emphasized that AI development core lies in industrial growth, integrated applications, and technological innovation, with infrastructure as a critical prerequisite [22]. Thus, this paper constructs a composite "Artificial Intelligence Level" index via weighted synthesis (standardized sub-indicators multiplied by entropy weight method-determined weights, enhancing credibility, objectivity, and accuracy) to proxy AI development level. Measuring digital transformation degree requires recognizing its multi-dimensionality—it is not just a technological upgrade but a comprehensive revolution in organizational structure, business processes, and corporate culture [23], covering core attributes (subject, scope, method, expected outcomes [24]) and key aspects (entity, technological scope, transformation domain, effects [25]). Prior common methods (text analysis, financial indicators, survey scales) oversimplify this concept and fail to capture its core essence [26]. Therefore, drawing on standardized indicator development logic [27], this study constructs a composite "Digital Transformation" index via weighted synthesis of standardized word frequency data (from firms' annual reports) and corresponding weights, aiming to comprehensively capture digital transformation's multi-dimensional characteristics for measurement.

To eliminate the influence of other potential variables on the research findings, and following the practices of Zhou and Gui (2025) [9] and Zhang and Huang (2025) [13], this paper includes the following variables in its empirical analysis: Stock Code (id); Year (year); Province Code (ui); Coupling Degree (y1); Coordination Index (y2); Coupling Coordination Degree (y3); Digital Transformation (x1); AI Level (x2); Listing Age (x3); Firm Size (x4); Operational Capability (x5); Leverage (x6); Return on Assets (ROA) (x7); Proportion of Independent Directors (x8); Log of (Sum of MD&A Digital Transformation Keywords A + 1) (x11); Sum of MD&A Digital Transformation Keywords A (x12); Log of (Sum of MD&A Digital Transformation Keywords B + 1) (x13); Sum of MD&A Digital Transformation Keywords B (x14); Log of (Sum of MD&A Digital Transformation Keywords C + 1) (x15); Sum of MD&A Digital Transformation Keywords C (x16).

(3) Econometric Model Construction

In econometric model construction, the two-way fixed-effects model is primarily used to control for time-invariant individual characteristics and time trends that do not vary across individuals. In parallel, density estimation methods, such as Kernel Density Estimation, are often employed to characterize the distributional features of variables, which can provide prior information on the data distribution for model specification. Kernel Density Estimation (KDE) is a non-parametric method used to estimate the probability density function of a random variable when its underlying distribution is unknown. The fundamental idea is to place a kernel function at each data point and then sum these functions to obtain an overall estimate of the probability density. Assuming a sample of n data points, x_1, x_2, ..., x_n, the kernel density estimate of the probability density function at any given point x, denoted as $\hat{f}(x)$, is expressed by the following formula:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \quad (5)$$

Therefore, the following core econometric model, a "two-way fixed-effects model," is constructed to examine the impact of the level of AI development and the degree of digital transformation on corporate ESG coupling coordination degree:

$$\begin{aligned} \mathrm{norm\_y3}_{it} = {} & \beta_0 + \beta_1 \cdot \mathrm{norm\_x2}_{it} + \gamma_1 \cdot \mathrm{x15}_{it} + \gamma_2 \cdot \mathrm{norm\_x4}_{it} + \gamma_3 \cdot \mathrm{norm\_x5}_{it} + \gamma_4 \cdot \\ & \mathrm{norm\_x6}_{it} + \gamma_5 \cdot \mathrm{norm\_x7}_{it} + \gamma_6 \cdot \mathrm{norm\_x8}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (6)$$

Where i denotes the firm and t denotes the year; ESG_ccd_{it} is the ESG coupling coordination degree of firm i in year t; AI_{it} is the level of AI development of firm i in year t; DT_{it} is the degree of digital transformation of firm i in year t; $Controls_{it}$ represents a set of control variables for firm i in year t; μ_i and λ_t are the individual and time fixed effects, respectively; and ε_{it} is the random error term. In this study, Kernel Density Estimation is used to visually present the distributional characteristics (e.g., skewness and peak distribution) of the AI development level, the degree of digital transformation, and the ESG coupling coordination degree. This analysis provides a basis, grounded in the shape of the data distributions, for specifying the relationships between variables in the two-way fixed-effects model.

3. Empirical Analysis

3.1. Data Source and Pre-processing

The empirical analysis data for this study are derived from the merging and processing of two core databases: 1. Corporate ESG Performance Data: This was sourced from the "Sino-Securities ESG Ratings for Listed Companies" module of the Wind database. We selected the annual ESG rating data for all A-share listed companies for the period from 2009 to 2023. This dataset contains firm-level composite ratings and scores, as well as disaggregated ratings and scores for the three dimensions: Environmental (E), Social (S), and Governance (G). This data serves as the foundation for constructing the core dependent variable of this study. 2. Corporate AI, Technological Innovation, and Financial Data: This was sourced from the "Research Database on AI Development Level and Technological Innovation of Listed Companies" on the Macrodatas platform (s. macrodatas.cn). This database references the methodology from the study by Li (2024). AI application levels, and a series of key financial and corporate control variables for listed companies from 2007 to 2023.

To construct the final research panel dataset, we performed the following sample screening and processing steps: 1. We matched the two aforementioned databases using "stock code" and "year" as common keys to create an initial pooled panel dataset. 2. Considering that the ESG data is available from 2009 onwards, we set the study period from 2009 to 2023. 3. We excluded the following: listed companies in the financial industry due to the unique nature of their financial statements and business models; firms designated as ST (Special Treatment) or *ST and those that were delisted during the sample period to ensure the operational stability of the sample firms; and samples with missing values for any core variables (including the subsequently constructed composite indices). To ensure the balance and comparability of the data, this study only retained listed companies with complete observations for all 15 years from 2009 to 2023, thereby constructing a balanced panel. After these processing steps, we obtained a final balanced panel dataset containing 47,049 firm-year observations.

Furthermore, to mitigate issues of data skewness and heteroskedasticity, we took the natural logarithm (ln) of variables such as firm size (total assets) and firm age. For patent data that contain a large number of zero values (such as the number of invention patent applications), we applied a log transformation after adding one (ln(x+1)). Finally, to eliminate the interference of extreme outliers on the regression results, we applied Winsorization to all major continuous variables (including the dependent, independent, and control variables) at the 1st and 99th percentiles. Through these steps, we constructed a variable system and dataset comprising a total of 22 variables for the final empirical analysis. The descriptive statistics are presented in Table 2.

Table 2. Descriptive Statistics of Major Variables

Variable Name	Variable	N	Mean	Std. Dev.	Min	Max
Coupling Degree	y1	20,370	0.953	0.068	0	1.000
Coordination Index	y2	20,370	0.554	0.111	0.170	0.944
ESG Coupling Coordination Degree	y3	20,370	0.724	0.093	0	0.970
Digital Transformation	x1	20,250	0.059	0.076	0	0.489
AI Level	x2	20,340	15.377	46.944	0	498.302
Listing Age	x3	20,370	16.987	6.545	1	34
Firm Size	x4	20,370	2,633.249	11,700	8.482	290,000
Operational Capability	x5	20,370	14.733	11.741	-5.983	99.999
Leverage	x6	20,370	51.571	107.914	0.173	13,837.77
Return on Assets (ROA)	x7	20,370	2.780	43.120	-5,194.684	2,200.512
Proportion of Independent Directors	x8	20,369	37.349	5.787	0	100

Specifically, the mean of the core variable, ESG Coupling Coordination Degree (y3), is 0.724, with a standard deviation of 0.093. This indicates that during the sample period, the ESG pillars of listed companies in China are, on the whole, at a relatively high level of coordinated development, and the performance among firms is relatively concentrated, with no extreme disparities.

Regarding the explanatory variables, the mean of Digital Transformation (x1) is 0.059, and its maximum value is only 0.489, suggesting that the digitalization process for most listed companies in the sample was still in its initial stages. The mean of AI Level (x2) is 15.377, while its standard deviation is as high as 46.944. The high standard deviation reveals significant disparities in the level of AI development among the sample firms; this may reflect that a few leading firms have made substantial progress in this area, while the majority are still in their early stages of development, highlighting a phenomenon of divergence in the application of this technology among firms. In summary, all variables in this study possess the necessary variability for empirical research, with clear distributional characteristics and reliable quality, laying a solid foundation for the subsequent analysis. To further investigate the dynamic evolution of the ESG coupling coordination degree for listed companies, we have plotted its kernel density distribution for the period 2009-2023 (as shown in Figure 1).

This figure visually reveals two core trends. First, there has been a significant improvement in the overall level accompanied by a reduction in internal divergence. From a time-series perspective, the kernel density curves exhibit a clear trend of an "overall rightward shift" and "higher, steeper peaks." This indicates that the average ESG coupling coordination level for listed companies in Guangdong Province (represented by the red dots in the figure) has been rising annually. Meanwhile, the disparities among firms have continuously narrowed, demonstrating a distinct "catch-up" and "convergence" effect. Second, high-level coordination has become the norm. Especially in the later part of the sample period (2018-2023), the distribution is markedly left-skewed, meaning that the ESG coordination degree for the vast majority of firms is concentrated in the high-quantile range above 0.7.

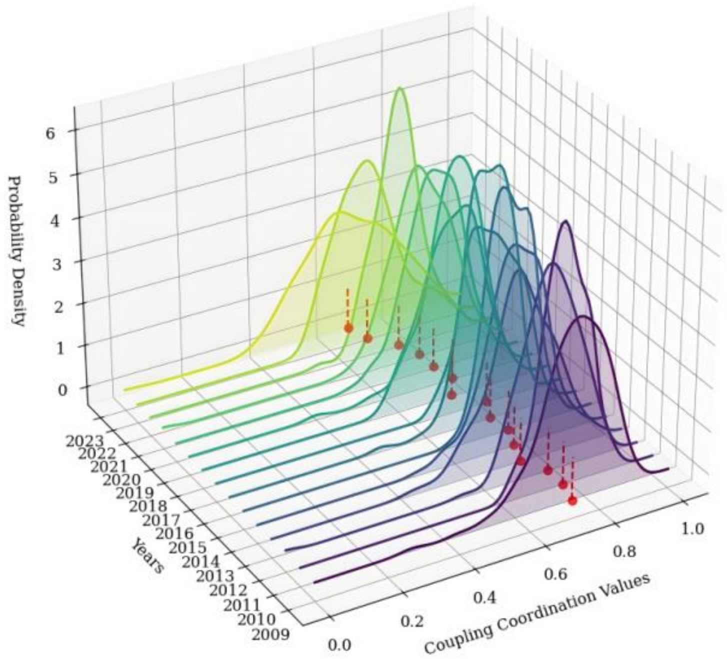

Figure 1. Dynamic Evolution of ESG Coupling Coordination Degree for Listed Companies in Guangdong Province (2009-2023)

This continuously improving trend provides an ideal empirical background for the present study. It raises a key question: what specific driving forces contributed to the general improvement and structural optimization of ESG coordinated development for firms in Guangdong Province during this period? This provides a strong empirical basis and a crucial point of entry for our subsequent examination of the role played by emerging technological forces, such as the level of AI development and digital transformation.

3.2. Mechanism Analysis

This section aims to delve into the mechanism through which corporate AI level and digital transformation affect their ESG coupling coordination degree. We begin by establishing the relationship between the core variables using a baseline regression model. Subsequently, a series of endogeneity and robustness tests are conducted to ensure the reliability of the findings. Finally, heterogeneity analysis is performed to explore how this impact varies across different regions.

(1) Baseline Regression Analysis

To examine the impact of AI and digital transformation on the corporate ESG coupling coordination degree, this paper constructs the following two-way fixed-effects model. The baseline regression results are presented in Table 3.

Column (1) presents a simple regression without any control variables or fixed effects, Column (2) adds control variables, and Column (3) shows our final adopted model, the two-way fixed-effects model. The results in Column (3) show that after controlling for both year and firm individual fixed effects, the regression coefficient for AI Level (x2) is 0.186 and is statistically significant at the 10% level; the regression coefficient for Digital Transformation (x15) is 0.003 and is statistically significant at the 1% level. This finding initially suggests that enhancing the level of AI development and accelerating the process of digital transformation can both significantly promote the synergistic and high-quality development of a firm's three ESG pillars.

The potential underlying reasons are as follows: AI technology can systematically enhance the synergy of ESG performance by optimizing energy efficiency (E), monitoring supply chain labor rights (S), and conducting risk pre-warning through big data (G). Digital transformation, by improving operational transparency and strengthening communication efficiency with stakeholders, enables firms to be more coordinated and consistent in their environmental information disclosure, social responsibility fulfillment, and corporate governance optimization, thereby increasing the ESG coupling coordination degree.

Table 3. Baseline Regression Results

Y (ESG)	Baseline Regression	With Controls	Two-Way Fixed Effects
x2	0.012* (1.75)	0.014** (2.04)	0.186* (1.75)
x15	0.002*** (4.48)	0.002*** (4.12)	0.003*** (5.02)
x4		0.259 (15.27)	0.291*** (7.95)
x5		-0.011 (-1.87)	0.002* (0.39)
x6		-0.230 (-1.63)	-0.253** (-2.08)
x7		0.360* (1.91)	-0.071* (-0.46)
x8		0.006 (0.55)	0.024* (1.96)
Year	No	No	Yes
Id	No	No	Yes
R2	0.0011	0.0146	0.5462
N	20,243	20,242	20,242
F	11.63	42.80	26.56
Prob > F	0	0	0

Notes: t-statistics are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Regarding the control variables, the coefficient for Firm Size (x4) is significantly positive at the 1% level, indicating that as a firm's size expands, its ESG synergistic performance improves. Similarly, the coefficient for the Proportion of Independent Directors (x8) is also significantly positive, suggesting that for the same company, increasing the proportion of independent directors helps to promote the coordinated development of its ESG. This is consistent with theoretical expectations that firm growth and the improvement of corporate governance structures are key internal drivers of ESG performance. It is noteworthy that after including two-way fixed effects, the model's R-squared significantly jumps from 0.0146 in Column (2) to 0.5462. On one hand, this indicates that time-invariant individual fixed effects (such as corporate culture, industry attributes, etc.) are crucial factors in explaining the variation in corporate ESG performance, which again highlights the necessity and appropriateness of using a fixed-effects model to control for such omitted variables.

The baseline regression results may be affected by reverse causality (i.e., firms with better ESG performance are more capable of investing in AI) or omitted variable bias. To address this, this paper, referencing relevant studies, employs the Two-Stage Least Squares (2SLS) method to handle the potential endogeneity issue. The results of the endogeneity test are as follows: In the first-stage regression, the coefficient of the instrumental variable (Lx2) on its endogenous variable (norm_x2) is 0.886 and is highly significant at the 1% level (p-value = 0.000). This indicates that the chosen instrumental variable is a strong instrument, satisfying the relevance condition. In the second-stage regression, after controlling for endogeneity, the coefficient for the core explanatory variable (norm_x2, the normalized AI level) on ESG performance is 0.298, which remains statistically significant and positive at the 1% level (p-value = 0.003). Therefore, we can conclude that after accounting for potential endogeneity, the positive promotional effect of AI level on corporate ESG coupling coordination degree remains robust, and the conclusion of the baseline regression is reliable.

(2) Robustness Tests

To further ensure the reliability of the research conclusions, this paper conducts a series of robustness checks, as shown in Table 4. First, we replace the original dependent variable (y3) with its logarithmic form (ln(y3)) and re-run the regression. As shown in Column (1) of Table 3, the coefficients for AI Level (x2) and Digital Transformation (x15) remain significantly positive at the 1% level. Next, we substitute the proxy variable for digital transformation from x15 to another indicator, x11. As shown in Column (2) of Table 3, the coefficients for AI Level (x2) and the new digital transformation indicator (x11) are also significantly positive at the 1% level. The results from these robustness checks indicate that regardless of whether we change the measurement of the dependent variable or the core explanatory variable, the direction and significance of their impacts do not undergo any substantive change. This strongly suggests that the conclusions of this study are highly robust and are not driven by specific variable measurement methods.

Table 4. Robustness Test Results

ESG	Log of y3	Log of y3, replacing x15 with x11
x2	0.329*** (2.63)	0.322** (2.58)
x15/x11	0.004*** (4.94)	0.005*** (5.16)
x4	0.417*** (8.31)	0.415*** (8.30)
x5	0.005 (0.67)	0.005 (0.69)
x6	-0.482*** (-2.86)	-0.482*** (-2.86)
x7	-0.238 (-1.18)	-0.237 (-1.17)
x8	0.034** (2.06)	0.035** (2.08)
Year	No	No
R2	0.5700	0.5700
N	20202	20202
F	24.41	24.39

Notes: t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

(3) Heterogeneity Analysis

Considering the significant disparities in regional economic development across China, the infrastructure and application environments for AI and digital transformation may differ, which could lead to heterogeneous effects on corporate ESG performance. To investigate this, this paper divides the sample into two groups based on geographical location—coastal provinces and inland provinces—and conducts sub-sample regressions. The results are presented in Table 5.

Table 5. Heterogeneity Analysis Results

ESG	Inland	Coastal
x2	0.080 (0.54)	0.309** (2.11)
x15	0.003*** (4.33)	0.001** (2.13)
x4	1.324*** (9.68)	0.178*** (5.70)
x5	-0.004 (-0.58)	0.010 (1.13)
x6	-0.284 (-0.70)	-0.370*** (-2.62)
x7	-0.184 (-0.32)	0.178 (0.75)
x8	0.054*** (3.48)	0.005 (0.27)
Year	No	No
R2	0.5584	0.5432
N	11000	9242
F	0	0

Notes: t-statistics are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

First, the regression results for AI Level (x2) reveal significant regional heterogeneity in its empowering effect on the ESG coupling coordination degree. Specifically, in the coastal region sub-sample, the coefficient of x2 is 0.309 and is statistically significant at the 5% level. However, in the inland region sub-sample, this coefficient is not statistically significant. The underlying reason for this finding may be that coastal regions typically possess more developed digital infrastructure, a more abundant pool of technological talent, and more intense market competition. These superior external conditions provide the necessary foundation and motivation for firms to translate cutting-edge AI technologies into enhanced management efficiency and ESG performance. This suggests that the positive impact of AI on corporate ESG is not unconditional but is highly dependent on a mature regional innovation ecosystem.

Second, in contrast to AI, the impact of Digital Transformation (x15) is more universal. As shown in Table 4, the regression coefficient for x15 is significantly positive at the 1% level in both the inland and coastal sub-samples. This indicates that regardless of a firm's location, advancing the fundamental process of digitalization (such as moving business operations online and implementing data-driven management) is a universally effective path to improving its ESG coordinated development. This may be because basic digital transformation is more focused on optimizing and increasing the transparency of existing business processes, making it less dependent on the external environment compared to high-tech AI applications that require substantial investment.

In summary, the heterogeneity analysis reveals a crucial conclusion: basic digital transformation serves as a "standard requirement" for enhancing ESG coordinated performance and has broad applicability. In contrast, more advanced AI technology acts as a "premium enhancement," and the realization of its empowering effects requires regional economic and technological development to reach a certain "threshold."

4. Conclusion

This study utilizes panel data from A-share listed companies from 2009 to 2023 to empirically analyze the impact and mechanisms of the corporate AI development level and the degree of digital transformation on their ESG coupling coordination degree. By constructing an ESG coupling coordination index system, quantifying the degree using the CRITIC objective weighting method, and employing a two-way fixed-effects model for empirical analysis, this study finds the following:

(1) The ESG coupling coordination degree shows an upward trend but exhibits heterogeneity: The overall ESG coupling coordination degree of firms is on a rising trend, reflecting the synergistic optimization of the environmental, social, and governance dimensions. However, the coordination degree is higher in coastal regions than in inland areas, and higher in technology-intensive industries than in traditional manufacturing, underscoring regional and industrial developmental imbalances.

(2) The three primary driving pathways of Artificial Intelligence: The level of AI development significantly enhances the ESG coordination degree. Specifically, this is achieved by optimizing resource allocation and reducing environmental management costs via intelligent algorithms; lowering the incidence of ESG risk events through AI-powered risk warning systems; and improving the quality of information disclosure using Natural Language Processing (NLP) technology.

(3) The synergistic effect and inclusive value of digital transformation: The ESG coordination degree progressively increases as digital transformation deepens. Furthermore, the promotional effect of digital transformation in inland regions confirms the inclusive value of digital infrastructure. Meanwhile, the synergistic effect of both technologies in technology-intensive industries leads to a significantly higher improvement in the ESG coupling coordination degree compared to resource-intensive industries.

Based on the research findings above, the following implications can be drawn:

(1) At the policy level, implementing regionally differentiated support strategies is recommended: To address the weak digital infrastructure in inland regions, and drawing on the experience of smart city pilot policies, dedicated funds for digital transformation should be established to prioritize the construction of 5G base stations and computing power centers in central and western provinces. For coastal regions, "Intelligent ESG Integration Demonstration Zones" could be established to promote models for optimizing factor allocation structures, and VAT credits could be offered to firms that adopt AI-driven carbon footprint monitoring systems.

(2) At the corporate practice level, it is essential to simultaneously advance technological integration and organizational change: On the environmental dimension, deploy AI-driven real-time carbon emission monitoring systems and integrate them with the Internet of Things (IoT) to achieve dynamic optimization of energy consumption. On the social dimension, apply digital technologies to construct supply chain responsibility maps, enabling end-to-end traceability of supplier ESG behavior. On the governance dimension, develop ESG risk warning platforms based on large language models (LLMs) to enhance decision-making efficiency.

Future research can be extended in three directions. From a theoretical perspective: explore the dynamic interaction effects between AI and digital transformation, quantify the long-term contribution of technological iteration to the ESG coordination degree, and conduct cross-country comparisons to verify the impact of institutional differences. From a methodological perspective: introduce Large Language Models (LLMs) to build a semantic analysis framework for ESG to capture risk signals, and combine intelligent technologies to analyze the cognitive mechanisms of decision-making. From an application perspective: develop ESG risk stress testing models for the financial and service industries to expand the depth and breadth of practical application scenarios.

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