

Article

How Does Executive AI Adoption Impact Corporate Persistent Green Innovation? New Evidence from the BERT Model

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Abstract

With the rapid growth of the digital economy, the application of artificial intelligence (AI) technology has injected new momentum into persistent green innovation. Using data on Chinese A-share listed companies from 2010 to 2023, this article aims to investigate whether senior executives' adoption of AI technology influences companies' persistent green innovation and to identify the specific mechanisms underlying this relationship. To improve measurement accuracy, this paper employs the BERT model to conduct an in-depth analysis of corporate annual report texts to construct an executive AI adoption metric. The findings reveal that executive AI adoption significantly promotes corporate persistent green innovation, and this effect is primarily achieved through enhanced data factor allocation capabilities. Moreover, strategic agility positively moderates the relationship between executive AI adoption and corporate persistent green innovation. Specifically, the higher the level of strategic agility, the stronger the mediating role of data factor allocation in the relationship between executive AI adoption and corporate persistent green innovation. In particular, executive AI adoption plays a more significant role in fostering persistent green innovation among firms with higher total factor productivity and those facing intense market competition.

Keywords: executive AI adoption; corporate persistent green innovation; data factor allocation; strategic agility; BERT model

1. Introduction

In recent years, faced with the “dual pressures” of economic growth and environmental protection, the Chinese government has emphasized the need to deeply integrate “scientific and technological innovation” with “ecological civilization construction.” As institutional frameworks at the national level have gradually been refined, a series of green incentive policies, green manufacturing standards, and carbon emissions regulatory mechanisms have been successively introduced and implemented, laying a solid institutional foundation for enterprises to engage in green innovation activities. “Green innovation” generally refers to a systematic process through which companies optimize product design, improve production processes, or reform management models to ultimately achieve efficient resource utilization and improved environmental quality [1]. Unlike traditional green innovation, persistent green innovation places greater emphasis on the dynamic nature of green innovation capabilities and aims to generate long-term benefits through the production of green products and the development of green technologies [2,3]. This process is not merely a technical upgrade but a systematic strategic endeavor. However,



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the green innovation process faces numerous challenges, such as substantial long-term investment requirements, uncertainty regarding technology pathways, and difficulties in integrating resources. These challenges often result in green innovation efforts by some Chinese companies remaining limited to short-term pilot projects or marginal improvements, lacking sustainability.

Driven by the digital economy and the wave of intelligent technology, AI has become a key driver of green innovation in enterprises. The “Draft Outline of the 15th Five-Year Plan for National Economic and Social Development of the People’s Republic of China” explicitly calls for deepening the “AI+” initiative, emphasizing the use of intelligent technologies to enhance green development capabilities. Breakthroughs in AI technology in areas such as perception and recognition, intelligent decision-making, and autonomous control have given rise to a series of advanced algorithms and system platforms, including deep learning, natural language processing, and knowledge graphs. These advancements have not only improved corporate operational efficiency [4] and levels of intelligence [5], but have also provided robust technological support for green innovation [6–8]. However, from a strategic perspective, how to effectively integrate AI technology into long-term development strategies and translate it into green innovation capabilities remains a core practical challenge for enterprises.

The implementation of AI requires not only technical support but also close collaboration between senior executives and the technical team at the strategic level. As the primary decision-makers within an enterprise, executives’ willingness to adopt AI technology not only influences the timing and scale of technology introduction but may also profoundly shape the company’s green innovation performance through mechanisms such as organizational learning, strategic adjustments, and the allocation of innovation resources [7,9–12]. However, due to practical constraints, many executives lack a deep understanding of the fundamental principles of AI technology and its practical applications, which prevents them from fully leveraging the value of data and consequently impacts corporate strategic decision-making [13,14].

Based on existing research, academic discussions on this topic have primarily focused on two areas: first, the factors influencing corporate persistent green innovation. From an internal perspective, scholars have mainly explored the influence of management characteristics [15], technological strategy [2,7], and incentive mechanisms [16] on corporate persistent green technological innovation. From an external perspective, existing research has focused on influencing factors such as government support [17], market competition [18], and environmental regulations [19,20]. Second, there is a body of research examining the relationship between AI and green innovation. Previous literature has analyzed the mechanisms through which AI influences corporate green innovation from the perspectives of knowledge integration [21], organizational learning [22,23], and resource allocation [15,24]. However, there are still certain limitations to the relevant research.

① Research on corporate persistent green innovation has largely focused on factors such as internal governance structures, technology strategies, and external institutional environments, with relatively limited attention paid to the decision-making behavior of senior executives amid the transformation driven by AI technology. As key decision-makers in corporate strategy formulation and resource allocation, senior executives’ technological understanding and adoption decisions may have a significant impact on the long-term path of persistent green innovation within their organizations. ② Existing research on the relationship between AI and green innovation primarily focuses on the level of AI adoption within enterprises, emphasizing how AI promotes green innovation through mechanisms such as knowledge integration, optimized resource allocation, and organizational learning.

However, few studies have analyzed the underlying mechanisms linking AI adoption to green innovation from the perspective of executive AI adoption.

In light of this, drawing on upper echelons theory, the resource-based view, and dynamic capabilities theory, this paper investigates the relationship and underlying mechanisms between executive AI adoption and corporate persistent green innovation from the perspective of green innovation sustainability. Specifically, this study addresses the following questions: Does executive AI adoption affect corporate persistent green innovation? If so, what are the potential mechanisms through which it operates? Furthermore, does the impact of executive AI adoption on persistent green innovation vary across different types of firms? To answer these questions, and taking into account data availability and the observability of core variables, this paper collects data from Chinese A-share listed companies spanning from 2010 to 2023 for empirical testing.

The contribution of this article lies in the following: First, it enriches the body of research on the relationship between AI and corporate persistent green innovation. This article focuses on senior executives as its primary research subjects, systematically analyzing how their adoption of AI technologies influences corporate persistent green innovation. It further contributes to the body of research on the relationship between AI and green innovation, while offering a new strategic perspective for research into pathways for persistent green innovation. Second, by training the BERT model on publicly available corporate text data to extract information regarding executives' AI-related decisions, we developed an executive AI adoption index. This approach moves beyond traditional discrete measurement methods that rely on the number of AI-related keywords or sentences in annual reports, enabling a more quantitative and nuanced assessment of executive AI adoption and providing empirical analysis with more distinctive and continuous indicators. Third, regarding corporate strategic agility, the paper constructs multidimensional proxy indicators based on publicly available data and employs the Critic-entropy weighting method for comprehensive weighting and measurement. This method enhances the objectivity and scientific rigor of strategic agility measurements, providing reliable data support for subsequent mechanism analysis.

2. Theoretical Analysis and Research Hypotheses

2.1. Executive AI Adoption and Corporate Persistent Green Innovation

Persistent green innovation draws on knowledge across multiple fields, including green products, green technologies, and the circular economy. If companies remain confined to existing technical expertise, they may find themselves in information silos, encounter technical bottlenecks, or become trapped in homogenized green innovation. Therefore, only by breaking free from reliance on traditional technical pathways and dynamically updating their knowledge resources can companies sustain long-term, stable green innovation.

In this process, AI—as the core driving force behind the new wave of technological revolution and industrial transformation—can provide crucial empowerment and support for corporate persistent green innovation. On the one hand, AI algorithms—such as deep learning and graph neural networks—can build simulation and optimization models for complex ecosystems, assist in the optimal design of green processes, significantly shorten the R&D cycle for green products, and enhance the sustainability of green innovation [5,25]. On the other hand, AI-driven open collaborative innovation platforms break down information silos between enterprises, facilitate the establishment of an integrated collaborative innovation network spanning industry, academia, research, and application, provide critical support for breakthroughs in cutting-edge green technologies such as carbon capture, carbon conversion, hydrogen energy, and green

refrigeration, and foster a multi-center, multi-stakeholder interactive ecosystem for green technology innovation [26,27]. In addition, by integrating AI into their decision-making systems, companies can enhance their ability to process environmental information and formulate long-term strategic plans, thereby fostering the persistent development of green innovation initiatives [23,28].

Whether AI technology can translate into tangible innovation outcomes for a company depends on whether the company effectively adopts and strategically integrates it. The high-level team theory posits that the demographic characteristics, cognitive foundations, and values of a company's executive team shape their perception and interpretation of the external environment, thereby influencing the company's strategic choices [9,10]. Therefore, executives' level of technical understanding and willingness to adopt AI directly influence the depth of AI's organizational embedding. When executives proactively promote AI technology, companies are more likely to develop technology-driven strategies at the organizational level, thereby fostering the sustained development of corporate persistent green innovation activities [15]. Based on this, we formulate Hypothesis 1:

Hypothesis 1. *Executive AI adoption drives corporate persistent green innovation.*

2.2. Executive AI Adoption, Data Factor Allocation, and Corporate Persistent Green Innovation

According to the resource-based view, a firm's competitive advantage stems from its ability to possess and effectively allocate scarce resources, and data is increasingly becoming a critical strategic resource for firms to achieve breakthroughs in innovation [2,29]. The application of AI technology often relies on large-scale data resources, and the process of training algorithms and making intelligent decisions continuously builds up a company's data assets [30]. When executives drive the adoption of AI technology, companies can not only enhance their application of AI but also improve their data factor allocation capability through data collection, integration, and analysis.

From the perspective of green innovation mechanisms, the data factor allocation capability serves as a crucial bridge linking the adoption of AI technology with sustained green innovation in enterprises. On the one hand, data serves as a critical factor of production within the digital economy, and its effective allocation can promote technological innovation and green development in enterprises [31,32]; on the other hand, data-driven decision-making can optimize the efficiency of resource allocation, increase investment in green R&D, and enhance enterprises' green innovation performance [33]. In addition, data elements can provide a stable resource foundation for corporations to pursue persistent green innovation by enhancing their dynamic knowledge capabilities [34,35]. Based on this, Hypothesis 2 is formulated as follows:

Hypothesis 2. *Executive AI adoption can help companies drive corporate persistent green innovation by enhancing the data factor allocation capability.*

2.3. Executive AI Adoption, Strategic Agility, and Corporate Persistent Green Innovation

In strategic management research, strategic agility is typically defined as an organization's ability to rapidly identify external changes in a dynamic environment, flexibly allocate resources, and promptly adjust its strategic direction to address environmental uncertainty. It requires companies to possess both adaptability and strategic thinking, with the key elements being "speed and stability" [36].

In a rapidly changing technological and market environment, a company's ability to quickly identify external changes and adjust its strategy in a timely manner is a key factor in the success of its innovation efforts. According to dynamic capabilities theory,

organizations must continuously adjust their resource allocation structures through “sensing, capturing, and reconfiguring” capabilities in order to adapt to complex and ever-changing environments. Strategic agility is a key manifestation of an organization’s dynamic capabilities, reflecting its ability to rapidly adjust its strategic direction and resource allocation in an uncertain environment [37]. When a company possesses a high degree of strategic agility, executive AI adoption efforts can be more quickly translated into organizational-level technological applications and innovation initiatives.

From the perspective of technology adoption mechanisms, strategic agility can enhance the positive impact of AI adoption on sustained green innovation [36,38]. On the one hand, companies with high strategic agility are better able to identify innovation opportunities presented by AI technology and adjust their R&D strategies in a timely manner; on the other hand, strategic agility enhances a company’s ability to reallocate resources, enabling it to rapidly apply AI technology to green R&D activities. In addition, agile enterprises are better positioned to establish mechanisms for continuous innovation, thereby ensuring the long-term and stable implementation of green innovation activities. Based on this, Hypothesis 3 is formulated:

Hypothesis 3. *Strategic agility positively moderates the promotional effect of executive AI adoption on corporate persistent green innovation.*

Whether technological resources can be transformed into innovative outcomes depends not only on the resources themselves, but also on a company’s ability to integrate and utilize them. From the perspective of integrating the resource-based view with dynamic capabilities theory, the data factor allocation capability plays a key mediating role between executive AI adoption and the firm’s sustained green innovation, while strategic agility determines whether the firm can fully unlock the innovative value of its data resources. When a company possesses a high degree of strategic agility, the data resources generated following executive AI adoption can be integrated and applied to innovation activities more quickly, thereby enhancing the data factor allocation capability in promoting green innovation [2,36,39].

Furthermore, in companies with high strategic agility, data-driven innovation mechanisms are more likely to translate into green innovation performance [40,41]. On the one hand, agile enterprises can quickly identify market changes and adjust resource allocation, thereby improving the efficiency of data resource utilization; on the other hand, strategic agility helps enterprises establish continuous learning mechanisms, enabling data resources to be continuously transformed into new knowledge of green technologies. In organizations with high strategic agility, the mediating role of data factor allocation between executive AI adoption and sustained green innovation will be more pronounced. Based on this, Hypothesis 4 is formulated as follows:

Hypothesis 4. *Strategic agility positively moderates the mediating effect of data factor allocation on the relationship between executive AI adoption and corporate persistent green innovation; that is, the higher the strategic agility, the stronger the mediating effect of data factor allocation, and vice versa.*

In summary, the research hypotheses of this paper are shown in Figure 1.

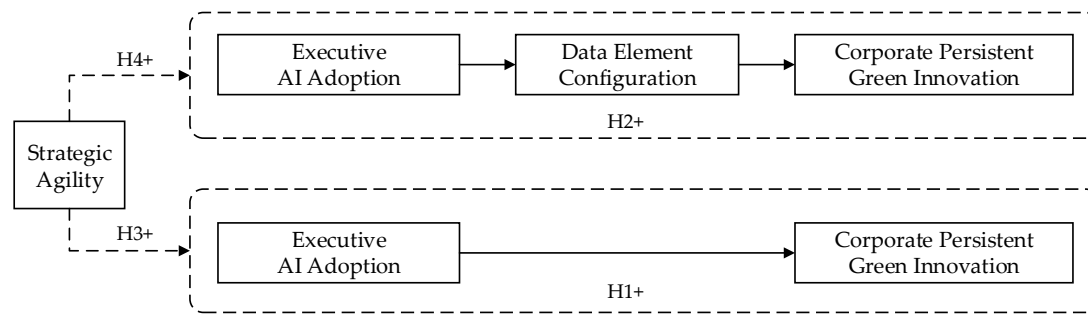


Figure 1. Research Hypothesis Diagram.

3. Research Design

3.1. Model Specifications

To test Hypothesis 1, the study constructed the following basic regression model:

$$\ln CSI_{i,t} = \alpha_0 + \alpha_1 AIPS_{i,t} + \alpha_2 Controls_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

In Model (1), $\ln CSI_{i,t}$ represents the corporate persistent green innovation of firm i in year t , and $AIPS_{i,t}$ represents the executive AI adoption in year t , $Controls_{i,t}$ are control variables. μ_i represents the industry fixed effect, γ_t represents the year fixed effect, and $\varepsilon_{i,t}$ is the random error term, with standard errors clustered at the firm level.

To test Hypothesis 2, the study employed a stepwise regression approach to examine the mediating effect, with the testing procedure consisting of three steps: Model (2), Model (3), and Model (1) (which examines the main effect). Regression Models (2) and (3) are as follows:

$$dig_{i,t} = \beta_0 + \beta_1 AIPS_{i,t} + \beta_2 Controls_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (2)$$

$$\ln CSI_{i,t} = \delta_0 + \delta_1 AIPS_{i,t} + \delta_2 dig_{i,t} + \delta_3 Controls_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (3)$$

In Models (2) and (3), $dig_{i,t}$ is a mediating variable representing a firm's data factor allocation capability.

To test Hypothesis 3, this study builds on Model (1) by introducing strategic agility and an interaction term between executive AI adoption and strategic agility to construct Model (4), thereby examining the moderating role of corporate strategic agility in the relationship between executive AI adoption and corporate persistent green innovation.

$$\ln CSI_{i,t} = \epsilon_0 + \epsilon_1 AIPS_{i,t} + \epsilon_2 CSA_{i,t} + \epsilon_3 AIPS_CSA_{i,t} + \epsilon_4 Controls_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (4)$$

In Model (4), $CSA_{i,t}$ is the moderating variable, representing corporate strategic agility, while $AIPS_CSA_{i,t}$ is the interaction term constructed after standardizing executive AI adoption and strategic agility.

To test Hypothesis 4, we follow the approach of Huang, Wei et al. (2024) [15] to construct Models (5) and (6) and examine the specific mechanism through which the moderating effect of corporate strategic agility operates.

$$dig_{i,t} = \theta_0 + \theta_1 AIPS_{i,t} + \theta_2 CSA_{i,t} + \theta_3 AIPS_CSA_{i,t} + \theta_4 Controls_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (5)$$

$$\ln CSI_{i,t} = \rho_0 + \rho_1 AIPS_{i,t} + \rho_2 CSA_{i,t} + \rho_3 AIPS_CSA_{i,t} + \rho_4 dig_{i,t} + \rho_5 Controls_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (6)$$

3.2. Sample Selection and Data Sources

Based on the research focus and the availability of data, this study uses Chinese A-share listed companies from 2010 to 2023 as the research sample. The data on firm characteristics and executive backgrounds used in this study were sourced from the China Stock Market & Accounting Research Database (CSMAR); patent data were collected from the China Research Data Services Platform (CNRDS); and annual report data were sourced from the Juchao Information Network, the companies' official websites, and the stock exchanges where the companies are listed. All of the above public data sources are freely available to the public; commercial databases can be accessed through institutional subscriptions. This study is reproducible.

The data filtering process is as follows: (1) Exclude companies subject to risk warnings, including listed companies designated as ST (other risk warnings) and *ST (delisting risk warnings). In accordance with the regulatory requirements of the Shanghai Stock Exchange and the Shenzhen Stock Exchange, these two categories of companies are typically flagged due to persistent losses or abnormal financial conditions and face a higher risk of delisting. Their business decisions may deviate from normal corporate behavior, thereby affecting the reliability of research findings; therefore, they have been excluded from the analysis. (2) Exclude listed financial companies. The balance sheet structures and business models of financial firms differ significantly from those of non-financial firms; therefore, in accordance with standard research practice, they are excluded. (3) Exclude firms with missing values for key variables during the sample period. (4) To mitigate the potential impact of outliers on the regression results and address the issue of fat-tailed distributions commonly found in firm-level variables, all continuous variables are winsorized at the 1st and 99th percentiles. This method helps reduce the influence of outliers on the estimates while preserving the information in the sample. After cleaning and preprocessing the raw data through the steps described above, we ultimately obtained 19,136 valid observations for Chinese A-share listed companies.

3.3. Variable Measure

3.3.1. Dependent Variable

Corporate Persistent Green Innovation (*lnCSI*). First, this paper uses the total number of green patents independently filed by companies as a measure of green innovation levels. Building on this foundation, and drawing further on the research approach outlined in [2,3], we measure the sustainability of a firm's innovation activities by examining changes in the number of green patent applications (*CGP*) over time, thereby constructing an indicator of corporate persistent green innovation. The specific formula is as follows:

$$CSI_t = \frac{GGP_t + GGP_{t-1}}{GGP_{t-1} + GGP_{t-2}} \times (GGP_t + GGP_{t-1}) \quad (7)$$

In the equation, CSI_t represents the firm's level of persistent green innovation in year t , while GGP_t , GGP_{t-1} , and GGP_{t-2} represent the number of green patent applications filed by the firm in years t , $t - 1$, and $t - 2$, respectively.

Theoretically, the core of persistent green innovation lies in the cumulative and dynamic nature of innovation [36,37]. Accordingly, the first component of this indicator $\frac{GGP_t + GGP_{t-1}}{GGP_{t-1} + GGP_{t-2}}$ measures the growth rate of a company's green innovation output over the past two periods relative to the preceding two periods, reflecting the dynamic trends in innovation activity. The second component $(GGP_t + GGP_{t-1})$ reflects the current stock of green innovation. Multiplying these two components avoids the abnormal fluctuations caused by using only growth rates in years with a small base, while also addressing the shortcoming of relying solely on stock levels—which overlooks the sustainability of in-

novation (such as a surge in a given year followed by a sharp decline). Therefore, this indicator comprehensively captures information regarding green innovation across the dimensions of intensity and sustainability, aligning with the theoretical essence of persistent green innovation.

It should be noted that the *CSI* index primarily reflects the temporal continuity of green patent output, but cannot fully capture the actual environmental performance of green innovation. However, given that this indicator effectively captures the dynamic and sustained nature of green innovation activities and has been widely used in relevant research, this paper continues to employ it to measure the level of corporate persistent green innovation. To reduce the skewness of the variable's distribution, this paper takes the natural logarithm of *CSI*, using $\ln CSI$ as a proxy for a firm's corporate persistent green innovation capability.

To mitigate the skewness in the distribution of the variables, the natural logarithm of the *CSI* index is taken here to obtain $\ln CSI$ as a proxy for the firm's corporate persistent green innovation capability.

3.3.2. Explanatory Variable

Executive AI Adoption (*AIPS*). Existing research on measuring corporate adoption of AI technology has largely relied on text-based word frequency analysis, which involves counting the frequency of AI-related keywords in listed companies' annual reports to assess the extent of their adoption of AI technology. However, simple keyword-based statistical methods may be subject to certain biases: on the one hand, keyword dictionaries cannot fully cover all relevant expressions, which may result in some relevant information going unrecognized; on the other hand, the presence of AI-related keywords in a text does not necessarily imply that company management has made a clear decision to adopt the technology, as some statements may simply be used to describe industry trends or technical background. Therefore, this study employs a text recognition method based on pre-trained language models to measure executives' level of AI adoption.

Step 1: Text data acquisition and preprocessing. Drawing on relevant research [4,21,42], we selected the "Management's Discussion and Analysis (MD&A)" section from the annual reports of A-share listed companies as our text corpus. The MD&A provides a comprehensive overview of management's assessment of the company's operational performance and strategic direction regarding technology adoption, offering valuable insights into senior management's stance on and implementation of AI. Based on this, we collected and organized MD&A reports from A-share listed companies for the period 2010–2023, ultimately obtaining 48,324 samples from 5535 companies.

Step 2: Build the dataset to be annotated (DTBA). The purpose of building this dataset is to filter out sentences that meet one of the criteria for executive AI adoption, thereby improving the efficiency of manual annotation. Following the approach of Liang et al. (2024) [43], we first segment the MD&A text into sentences using periods, semicolons, and exclamation marks as delimiters. Then, tokenization and data cleaning are performed with the Jieba tokenizer (version 0.42.1) based on Python 3.10. Building on this foundation, and drawing on the research by Yao et al. (2024) [4] and Qiao et al. (2025) [44] regarding AI metrics, we combined manual revisions with standardized concept mapping to construct a relatively comprehensive dictionary of AI-related keywords (see Table 1). Next, based on keyword matching principles, sentences containing at least one AI keyword are extracted from the MD&A text as candidate samples. To improve the effectiveness and accuracy of text analysis, this study further preprocessed the candidate sentences: (1) Exclude sentences whose length falls at extreme percentiles. Specifically, remove sentences whose length is above the 95th percentile or below the 5th percentile to minimize the impact of

outlier text on subsequent recognition results. (2) Remove noise text. Due to the format of annual reports, they inevitably contain some noise text—such as header text and page numbers—that interferes with model training and classification. Therefore, this text is manually removed. (3) Remove sentences that are difficult to read. This includes sentences that are too long or too short, as well as text containing garbled characters or obvious formatting errors. Following the above processing, we ultimately obtained 174,965 data points containing management-level statements related to AI, which form the foundational dataset for subsequent text recognition and variable construction.

Table 1. AI Keyword Glossary.

Dimension	Category Description	Keyword
Conceptual Foundations	Including general AI concepts, generative AI paradigms, foundation models, etc.	Artificial Intelligence (AI), AIGC, Generative Artificial Intelligence (Generative AI), Large AI, Large model, Large Language Model (LLM); AI Foundation Model, Pre-trained Model, Pretrained Model, Intelligent Agent, Augmented Intelligence
Core Technologies & Models	Including algorithms, model architectures, deep learning methods, development frameworks, and computing infrastructure, etc.	Machine Learning, Deep Learning, Reinforcement Learning, Support Vector Machine (SVM), Neural Network, Deep Neural Network (DNN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Capsule Network, Variational Autoencoders (VAE), Generative Adversarial Network (GAN), Diffusion Model, Flow-based Models, Autoregressive Model, Feature Extraction, Feature Recognition, Pattern Recognition, Transformer Architecture, transformers, BERT, GPT, ChatGPT, Cross-lingual Language Model (XLM), Text-to-Text Transfer Transformer (T5), OPT, LLaMA, MPT, Pythia, General Language Model (GLM), BLOOM, CTRL, CPM, CPT, ERNIE, Vision Transformer (ViT), AlexNet, Residual Networks (ResNet), MobileNet, EfficientNet, LeNet, DALL-E, Detection Transformer (DETR), KOSMOS-2, ImageBind, OpenFlamingo, mPLUG-Owl, TensorFlow, PyTorch, Torch, Keras, Caffe, Caffe2, MXNet, PaddlePaddle, TensorFlow Extended (TFX), Horovod, Catalyst, Deep Graph Library (DGL), Natural Language Processing (NLP), Computer Vision, Knowledge Graph, Knowledge Representation, Data Mining, Big Data Analytics, Big Data Processing, Big Data Management, Big Data Platform, Big Data Operations, Big Data Marketing, Big Data Risk Control, Distributed Computing, Cloud Computing, Edge Computing, Multimodal Generative Architecture, Internet of Things (IoT)
Applications & Industrial Use	Covering the manifestations of AI in industries, products, and specific applications	AI product, AI chip, smart chip, smart sensor, wearable product, Business Intelligence (BI), Human–Computer Interaction (HCI), Human–Machine Collaboration, Human–Machine Dialogue, Image Recognition, Face Recognition, Voiceprint Recognition, Biometric Recognition, Speech Recognition, Speech Synthesis, Speech Interaction, Question Answering System, Machine Translation, Intelligent Speech, Intelligent Search, Intelligent Customer Service, Smart Home, Smart Healthcare, Smart Agriculture, Smart Education, Smart Government, Smart Environmental Protection, Smart Finance, Intelligent Finance, Smart Banking, Smart Insurance, Robo-advisor, Smart Retail, Smart Transportation, Unmanned Driving, Autonomous Driving, Robotic Process, Automation, Intelligent Computing, Augmented Reality (AR), Virtual Reality (VR), ERNIE Bot, Tongyi Qianwen (Qwen), Spark Model, Pangu Model, Hunyuan Model, Baichuan Model, Luminous Model

Notes: This glossary is constructed for the purpose of keyword-based text analysis in this study. All terms listed in the table, including software, frameworks, and model names, are included as terminology entries to capture comprehensive AI-related expressions in corporate disclosures.

Step 3: Manually code the sentences in the DTBA to construct a labeled dataset. The purpose of manual annotation is to manually determine from the text whether a company

has actually adopted AI technology, thereby laying the groundwork for model training. Drawing on the research by Cai et al. (2025) [45] and Zhou et al. (2025) [21], we have further developed manual coding rules to classify AI-related statements into two categories: (1) Application-oriented AI statements, assigned a value of 1. These primarily highlight instances where enterprises have actually applied, deployed, or promoted AI technology within specific business processes, management practices, or technical systems. (2) For AI sentences that are not application-oriented, assign a value of 0. This includes two scenarios: first, when the AI sentence indicates that the meaning of the AI keyword in that context is unrelated to AI; second, when the AI sentence provides only conceptual explanations of AI technology, descriptions of the industry background, introductions to technical features, or forward-looking statements. To ensure annotation quality, this study employed a double-blind, independent annotation method, in which two researchers who had undergone systematic training independently annotated all sentences. The Cohen's kappa coefficient for the annotation results was 0.8149, indicating a level of agreement that was nearly perfect [46]. For sentences where there was a discrepancy in the annotations, a third senior researcher served as the final arbiter to ensure the objectivity and accuracy of the results. After manual coding, each data point is stored in a text document using text content, tab delimiters, and tags to construct a labeled dataset suitable for model training.

Step 4: Train the BERT model. Following the research by Zhang et al. (2025) [42], we conducted deep learning training using Google's open-source BERT-Base (Chinese) pre-trained model in a PyTorch and CUDA environment. The version of PyTorch used in this paper is 2.2.1, and the version of CUDA is 12.1. Sentences were randomly selected from the annotated dataset to serve as training samples, comprising 19,928 application-oriented AI sentences and 15,992 non-application-oriented AI sentences. Based on this, the training samples are merged. Following common practices in the field of machine learning [47], a 8:2 split is used to divide the data into training and validation sets in order to strike a reasonable balance between the size of the training dataset and the reliability of the validation results. Specify a GPU for local training in the training set. The training device configuration is as follows: GPU is an RTX 3070 Ti, CPU is a Core i7-12700H, and RAM is 16GB. The model is then saved. Ultimately, the model's recognition results on the training and validation sets showed that the prediction accuracy was 94% and 92%, respectively, the precision was 95% and 93%, respectively, and the recall was 94% and 92%, respectively. The model performed well.

Step 5: Develop metrics for executive AI adoption. A pre-trained BERT model is used to analyze AI-related sentences, determine whether a company has adopted AI technology, and generate a continuous score to construct a continuous executive AI adoption index. The specific calculation method is as follows.

$$AIPS_{i,t} = \ln \left(\sum_{j=1}^{N_{i,t}} P_{i,t,j} + 1 \right) \quad (8)$$

In the equation, $AIPS_{i,t}$ represents the degree of executive AI adoption at firm i in year t ; $N_{i,t}$ represents the number of AI-related statements identified in the firm's MD&A text for that year; $P_{i,t,j}$ denotes the probability that the BERT model predicts the j th statement to be an "application-oriented AI sentence"; this index ranges from [0, 1], with higher values indicating a higher degree of executive AI adoption. Compared to traditional approaches, this method can identify differences in semantic expression within the text, thereby providing a more accurate picture of executives' level of AI adoption.

To test the robustness of the measures of the aforementioned variables, this paper further employs the natural logarithm of the number of AI-related sentences in MD&A reports plus one (*AIC*), the number of executives with an information technology background (*ITB*), and the natural logarithm of the number of AI patent applications plus one (*Alpat*) as proxy indicators of executive AI adoption. Details are provided in subsequent sections and will not be elaborated upon here.

3.3.3. Mediating Variable

Data Factor Allocation (*dig*). Drawing on relevant research [48], we processed corporate annual financial reports using text analysis methods to count the frequency of disclosures of keywords related to data factor technologies—such as AI, blockchain, cloud computing, and big data—and aggregated their occurrence counts to characterize the extent of corporate investment in and utilization of data factors. Specific technical keywords related to data factor are shown in Table 2. Generally speaking, the higher the frequency with which the above keywords appear in annual reports, the stronger the company’s capabilities in data resource integration and technology application, thereby reflecting the company’s level of data factor allocation. To minimize differences in the dimensions of the variables, the statistical results were scaled.

Table 2. Data Factor Related Technical Keywords.

Dimension	Keyword
AI Technology	Artificial Intelligence, Business Intelligence, Image Understanding, Investment Decision Support System, Intelligent Data Analysis, Intelligent Robot, Machine Learning, Deep Learning, Semantic Search, Biometric Technology, Face Recognition, Speech Recognition, Identity Verification, Autonomous Driving, Natural Language Processing
Blockchain Technology	Blockchain, Digital Currency, Distributed Computing, Differential Privacy Technology, Smart Financial Contract
Cloud Computing Technology	Cloud Computing, Stream Computing, Graph Computing, In-memory Computing, Multi-party Secure Computing, Brain-inspired Computing, Green Computing, Cognitive Computing, Converged Architecture, Hundred-million-level Concurrency, Exabyte-level Storage, Internet of Things (IoT), Cyber-Physical Systems
Big Data Technology	Big Data, Data Mining, Text Mining, Data Visualization, Heterogeneous Data, Credit Reference, Augmented Reality, Mixed Reality, Virtual Reality
Application of Digital Technology	Mobile Internet, Industrial Internet, Mobile Interconnection, Internet Healthcare, E-commerce, Mobile Payment, Third-party Payment, NFC Payment, Smart Energy, B2B, B2C, C2B, C2C, O2O, Internet of Vehicles, Smart Wearables, Smart Agriculture, Intelligent Transportation, Smart Healthcare, Intelligent Customer Service, Smart Home, Robo-advisor, Smart Cultural Tourism, Smart Environmental Protection, Smart Grid, Smart Marketing, Digital Marketing, Unmanned Retail, Internet Finance, Digital Finance, Fintech, Financial Technology, Quantitative Finance, Open Banking

3.3.4. Moderating Variable

Strategic Agility (CSA). Existing research has primarily measured this concept from an organizational behavior perspective, falling into two main categories: one involves measurement methods derived from similar concepts and existing scales; the other involves the development of new measurement indicators specifically for strategic agility.

Sambamurthy et al. (2003) developed an analytical framework for organizational agility based on three dimensions—customer responsiveness, collaborative agility, and operational agility—laying the groundwork for subsequent research [49]. Based on this framework, Tallon and Pinsonneault (2011) developed an eight-item scale that measures a firm’s ability to respond to scenarios such as changes in demand, adjustments to the

supplier network, and the launch of new products by competitors [50]. Meanwhile, Doz and Kosonen (2008) propose, from a capability-based perspective, that strategic agility consists of three meta-capabilities: strategic sensitivity, leadership coherence, and resource fluidity [51]. Junni et al. (2015) operationalized the measurement of these three metacognitive abilities in the context of corporate mergers and acquisitions and developed a six-item indicator system [52]. Furthermore, Arokodare and Asikhia (2020) refined strategic agility into five dimensions—strategic insight, internal responsiveness, external responsiveness, human resource capabilities, and information technology capabilities—from a capability structure perspective [53].

In recent years, the academic community has increasingly sought to use publicly available corporate data to construct proxy indicators in order to enhance the objectivity of strategic agility measurements. Li et al. (2022) used text analysis to measure strategic agility based on the time interval between the occurrence of an environmental incident and the company's first strategic response action [54]; Fan and Pan (2024) used the frequency of board meetings to characterize a firm's ability to respond to environmental changes [39]; Wang and Liu (2024) combine business operational data with organizational metrics to characterize a firm's adaptability and strategic adjustment capabilities [55]. Overall, the existing dimensions and metrics of strategic agility are diverse, and no unified standard has yet been established.

Given that existing questionnaire scales still have certain limitations in defining strategic agility, and that it is difficult to obtain questionnaire data from listed companies, this study utilizes publicly available data to measure strategic agility through a construct comprising three dimensions: responsiveness, competence, and flexibility. The specific indicator system is shown in Table 3. Regarding the composite index methodology, the Critic-entropy weighting method was employed to determine the weights of each indicator. By comprehensively considering the dispersion and correlation structure of the indicators, this method fully utilizes sample information, reduces biases resulting from subjective weighting, and, to a certain extent, mitigates the impact of multicollinearity on weight allocation, thereby enhancing the objectivity and robustness of the composite index construction [56].

Table 3. Strategic Agility Metrics Framework.

Indicator	Sub-Indicator	Measurement Item	Description	Direction
Responsiveness	Agile Responsiveness	Board Meeting Frequency	Number of board meetings held in the year	Positive (+)
	Technological Adaptability	Number of Invention Patent Applications	Ln (Number of Invention Patent Applications + 1)	Positive (+)
Competence	Human Resource Skills	R&D Personnel Ratio	Number of R&D personnel/Total number of employees	Positive (+)
	Human Resource Quality	Highly Educated Employee Ratio	Number of employees with a master's degree or above/Total number of employees	Positive (+)
	Information Processing Efficiency	Internal Control Index	DIB Internal Control Index	Positive (+)
Flexibility	Operational Flexibility	Asset Turnover Ratio	Operating revenue/Average total assets	Positive (+)

Notes: Technological adaptability is measured by taking the natural logarithm of the number of a firm's invention patent applications plus one. To avoid overlap with the dependent variable (green patents), this indicator excludes the number of green invention patent applications. The DIB Internal Control Index, developed by DIB Enterprise Risk Management Technology Co., Ltd. (Shenzhen, China) in collaboration with Xiamen University (Xiamen, China), Sun Yat-sen University (Guangzhou, China), and other universities, is an authoritative indicator for measuring the internal control quality of Chinese enterprises. A higher value of the index indicates higher internal control quality.

3.3.5. Control Variable

Drawing on previous research, we select the following variables as control variables: ownership type (*SOE*), firm age (*FA*), debt-to-equity ratio (*Lev*), return on assets (*ROA*), proportion of independent (non-executive) directors on the board of directors (*Indep*), whether executives have an overseas background (*OB*), whether executives have a financial background (*FB*), management expense ratio (*Mfee*), and total executive compensation (*Pay*). The specific definitions of these variables are shown in Table 4. The descriptive statistics for the variables (Table 5) show that the standard deviations of all variables are within an acceptable range, and the data exhibit low dispersion.

Table 4. Variable Definitions.

Variable Type	Variable Name	Symbol	Measurement
Dependent Variable	Corporate Persistent Green Innovation	<i>lnCSI</i>	Change in the number of green patent applications from the previous period
Explanatory Variable	Executive AI Adoption	<i>AIPS</i>	As defined above
Mediating Variable	Data Factor Allocation	<i>dig</i>	Number of keywords related to data factors
Moderating Variable	Strategic Agility	<i>CSA</i>	Composite index constructed using the Critic-Entropy weight method
Control Variable	Ownership Type	<i>SOE</i>	Dummy variable equal to 1 for state-owned enterprises, and 0 otherwise
	Firm Age	<i>FA</i>	Ln (Current year—Year of incorporation + 1)
	Debt to Asset Ratio	<i>Lev</i>	Total liabilities/Total assets
	Return on Assets	<i>ROA</i>	Net income/Average total assets
	Proportion of Independent Directors	<i>Indep</i>	Number of independent directors/Total number of directors
	Executives' Overseas Background	<i>OB</i>	Dummy variable equal to 1 if executives have overseas background, and 0 otherwise
	Executives' Financial Background	<i>FB</i>	Dummy variable equal to 1 if executives have financial background, and 0 otherwise
	Administrative Expense Ratio	<i>Mfee</i>	Administrative expenses/Operating revenue
	Executive Compensation	<i>Pay</i>	Ln (Total compensation of the top three executives)

Table 5. Descriptive Statistics. (N = 19,136).

Variable Name	Mean	Std. Dev.	Min	Max
<i>lnCSI</i>	2.014	1.445	0	8.329
<i>AIPS</i>	0.609	0.767	0	4.192
<i>dig</i>	0.138	0.306	0	1.87
<i>CSA</i>	0.306	0.085	0.023	0.68
<i>SOE</i>	0.375	0.484	0	1
<i>FA</i>	2.932	0.33	1.792	3.611
<i>Lev</i>	0.419	0.189	0.051	0.888
<i>ROA</i>	0.04	0.056	−0.234	0.193
<i>Indep</i>	0.375	0.054	0.3	0.571
<i>OB</i>	0.609	0.488	0	1
<i>FB</i>	0.688	0.463	0	1
<i>Mfee</i>	0.084	0.062	0.008	0.41
<i>Pay</i>	14.63	0.714	12.528	16.573

4. Empirical Results Analysis

4.1. Benchmark Regression Analysis

Table 6 presents the results of the baseline regression analyzing the relationship between executive AI adoption (*AIPS*) and corporate persistent green innovation (*lnCSI*). Overall, the regression coefficients for *AIPS* are significantly positive across all model specifications, indicating that executive AI adoption significantly promotes an increase in the level of corporate persistent green innovation. These results provide preliminary support for the research hypothesis.

Table 6. Baseline regression results.

	(1)	(2)	(3)
Variable	<i>lnCSI</i>	<i>lnCSI</i>	<i>lnCSI</i>
<i>AIPS</i>	0.1621 *** (5.84)	0.1248 *** (3.98)	0.1254 *** (4.50)
<i>_cons</i>	1.9154 *** (60.40)	1.9381 *** (58.31)	−3.3238 *** (−5.86)
<i>N</i>	19,136	19,136	19,136
<i>adj. R²</i>	0.177	0.188	0.273
<i>Controls</i>	NO	NO	YES
<i>Ind</i>	YES	YES	YES
<i>Year</i>	NO	YES	YES

Notes: t-statistics based on clustered robust standard errors are presented in parentheses. Significance levels are indicated by *** ($p < 0.01$). *Ind* / *Year* represent industry fixed effects and year fixed effects, respectively. YES indicates that the corresponding dimension has been controlled; NO indicates the opposite.

Specifically, in Column (1), which includes only industry fixed effects without controlling for other variables or annual fixed effects, the regression coefficient for *AIPS* is 0.1621 and is significant at the 1% level.

Column (2) further controls for annual fixed effects based on Column (1). The results show that the regression coefficient for *AIPS* is 0.1248, which remains significant at the 1% level. Although the coefficient has decreased slightly compared to Model (1), the overall direction and significance remain stable, indicating that the promotional effect of executive AI adoption on corporate persistent green innovation remains robust even after controlling for time-based external shocks.

In Column (3), control variables are further incorporated, and a dual fixed-effects model (fixed for both industry and year) is employed; the regression coefficient for *AIPS* is 0.1254, which remains significant at the 1% level.

As fixed effects and control variables were progressively introduced, the regression coefficient for *AIPS* consistently remained significantly positive, indicating that the study's findings possess a high degree of stability and reliability. Executive AI strategies can significantly promote corporate persistent green innovation in firms, thereby confirming Hypothesis 1. It follows that executive AI adoption can enhance companies' strategic understanding of cutting-edge digital technologies, drive sustained investment in green technology R&D and green innovation activities, and thereby foster persistent green innovation by companies.

4.2. Endogeneity and Robustness Tests

4.2.1. Instrument Variables Method

There may be a reciprocal relationship between executive AI adoption and corporate persistent green innovation; that is, companies that are active in persistent green innovation may be more inclined to focus on cutting-edge technologies, and certain unobservable

confounding variables may simultaneously influence changes in both. To address the endogeneity issues mentioned above, we select the mean executive AI adoption rate at other firms in the same industry and region—lagged by three periods—as an instrumental variable. We then perform the estimation using two-stage least squares (2SLS). Second, given that executive AI adoption at peer firms may indirectly influence the firm’s persistent green innovation through competitive pressure, this study further includes market competition as a control variable in the regression analysis (see Section 4.4.2 for specific definitions and measurements), thereby isolating this potential influence channel as much as possible. In terms of relevance, due to the in-group effect, past AI decisions within the same industry significantly influence the executive AI adoption at the firm under study. Regarding exclusivity, a three-period lag allows for the avoidance of direct impacts from current competitive pressures. Furthermore, this study controls for the degree of market competition and isolates the transmission channels of innovation competition among peers, ensuring that green innovation is influenced solely by the firm’s executive AI adoption, thereby satisfying the exclusivity constraint.

The regression results are shown in columns (1) and (2) of Table 7. In the first-stage regression, the coefficient for *L3.IV* was 0.9156, which was significant at the 1% level; in the second stage, the coefficient for *AIPS* was 0.2977, which was significant at the 1% level. This indicates that there is a strong correlation between the instrumental variable and the endogenous dependent variable, and that, even after controlling for endogeneity, the positive effect of executive AI adoption on persistent green innovation remains significant.

Table 7. Endogeneity test results.

	(1)	(2)	(3)
	First Stage	Second Stage	PSM
Variable	<i>AIPS</i>	<i>lnCSI</i>	<i>lnCSI</i>
<i>L3.IV</i>	0.9156 *** (30.70)		
<i>AIPS</i>		0.2977 *** (3.82)	0.0935 *** (2.65) −2.6999 *** (−3.87)
Kleibergen-Paap rk LM (<i>p</i> -value)		223.829 (0.000)	
Kleibergen-Paap rk Wald F		942.340	
S-Y Weak ID Test:10%		(16.38)	
<i>N</i>	14254	14254	7953
<i>adj. R</i> ²	0.222	0.122	0.227
<i>Controls</i>	YES	YES	YES
<i>Ind</i>	YES	YES	YES
<i>Year</i>	YES	YES	YES

Notes: t-statistics based on clustered robust standard errors are presented in parentheses. Significance levels are indicated by *** ($p < 0.01$). *Ind* / *Year* represent industry fixed effects and year fixed effects, respectively. YES indicates that the corresponding dimension has been controlled.

The Kleibergen-Paap rk LM [57] statistic is 223.829, with a *p*-value of 0.000, which significantly rejects the null hypothesis of “insufficient instrumental variable identification” at the 1% significance level. The Kleibergen-Paap rk Wald F [57] statistic is 942.340, which is significantly higher than the critical value of 16.38 for the weak instrumental variable test at the 10% significance level; therefore, we can reject the null hypothesis regarding the weak instrumental variable. The results above indicate that the selected instrumental variables are not only highly correlated with the endogenous dependent variable but also pass the identification deficiency test and the weak instrumental variable test, suggesting that the instrumental variables are appropriately specified and effective. The estimates

obtained on this basis exhibit good robustness, indicating that the core conclusions remain valid even after addressing potential endogeneity issues.

4.2.2. Propensity Score Matching

We use propensity score matching (PSM) to address the endogeneity issues that may arise from self-selection in the sample. First, we construct a dummy variable based on the median level of executive AI adoption. Second, we select all control variables as matching covariates and perform sample matching using 1:1 nearest-neighbor propensity score matching with a threshold of 0.01. After conducting balance tests to ensure there are no significant differences in characteristics between groups, we re-run the regression estimates using the matched samples. The empirical results are shown in column (3) of Table 7; the PSM test results are consistent with those presented earlier.

4.2.3. Lagged Explanatory Variable

Executive AI adoption is a strategic corporate decision; however, its role in enabling persistent green innovation involves a time lag between decision-making and implementation, R&D investment, technology commercialization, and the iteration of results. Consequently, there is an inherent time lag between these two processes. The baseline model uses a regression of current variables and is designed to identify the overall average effect. To account for the temporal logic in which AI-driven decision-making by senior executives precedes the emergence of corporate green innovation, and to further mitigate endogeneity issues arising from bidirectional causality, this paper conducts a robustness test using the core explanatory variable *L2.AIPS*, which is lagged by two periods. The results in Table 8, Column (1), show that *L2.AIPS* continues to have a significant positive impact on corporate persistent green innovation. The signs and significance of the coefficients are highly consistent with those in the baseline regression, which not only confirms the validity of the temporal transmission logic between the two variables but also indicates that the conclusions of the baseline study are robust.

Table 8. Robustness test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	<i>lnCSI</i>	<i>lnCSI</i>	<i>lnCSI</i>	<i>lnCSI</i>	<i>lnBCSI</i>	<i>lnACSI</i>	<i>lnCSI</i>	<i>lnCSI</i>
<i>L2.AIPS</i>	0.1161 *** (3.76)							
<i>AIPS</i>					0.1152 *** (7.88)	0.0306 ** (2.28)	0.1232 *** (7.31)	0.1336 *** (8.55)
<i>AIC</i>		0.1129 *** (4.05)						
<i>ITB</i>			0.0990 *** (3.89)					
<i>AIpat</i>				0.3987 *** (21.17)				
<i>_cons</i>	−3.8568 *** (−6.46)	−3.3261 *** (−5.86)	−3.1996 *** (−5.65)	−1.9590 *** (−3.88)	−3.7944 *** (−15.71)	−2.2746 *** (−10.69)	−3.5948 *** (−13.14)	−3.4992 *** (−13.89)
<i>N</i>	16074	19136	18687	19136	17689	17668	15272	19043
<i>adj. R²</i>	0.289	0.272	0.273	0.339	0.233	0.272	0.256	0.262
<i>Controls</i>	YES	YES	YES	YES	YES	YES	YES	YES
<i>Ind</i>	YES	YES	YES	YES	YES	YES	YES	YES
<i>Year</i>	YES	YES	YES	YES	YES	YES	YES	YES
<i>Ind_Year</i>	NO	NO	NO	NO	NO	NO	NO	YES

Note: Values in parentheses indicate t-statistics. Columns (1)–(8) show clustered standard errors. Significance levels are denoted as *** ($p < 0.01$), and ** ($p < 0.05$). *Ind/Year/Ind_Year* represent industry fixed effects, year fixed effects, and industry_year joint fixed effects, respectively. YES indicates that the corresponding dimension has been controlled; NO indicates the opposite.

4.2.4. Replace the Explanatory Variable

In the benchmark regression, executive AI adoption (*AIPS*) is measured using a continuous probability score. To avoid measurement bias that might arise from relying on a single indicator, proxy variables were reconstructed based on three dimensions: strategic articulation, management capability foundation, and technological innovation practices. First, we re-measure executive AI adoption using the natural logarithm of the number of applied AI sentences in the MD&A section of corporate annual reports plus one (*AIC*) [21]. Second, the stronger the IT background of senior executives, the more likely they are to increase management's focus on and investment in AI strategies. Here, based on the characteristics of executives' AI backgrounds, we use the number of executives with an IT background (*ITB*) to measure executive AI adoption [15]. Finally, from the perspective of a company's technological output in the field of AI, we re-measure executive AI adoption using the logarithm of the number of AI patent applications plus one (*Aipat*) [4]. The regression results in columns (2) through (4) of Table 8 show that the regression coefficients for *AIC*, *ITB*, and *Aipat* are 0.1129, 0.0990, and 0.3987, respectively, all of which are significantly positive at the 1% level. This indicates that, even after changing the measurement method of the explanatory variable, the positive impact of executive AI adoption on corporate persistent green innovation remains significant, and the research findings are robust.

4.2.5. Replace the Dependent Variable

To further test the robustness of the research findings, we replaced the measurement method for the dependent variable. We selected the number of green invention patent applications and the number of green utility model patent applications as proxy indicators of enterprises' corporate persistent green innovation, and constructed indicators of the changes in the number of these two types of patent applications over time using the calculation method in Equation (7), denoted as *lnBCSI* and *lnACSI*, respectively. Based on this, we conducted a new regression analysis. The results in columns (5) and (6) of Table 8 show that the regression coefficient for executive AI adoption remains significantly positive, indicating that the core conclusion remains robust even after changing the measurement method of the dependent variable.

4.2.6. Exclude Data from Municipalities Directly Under the Central Government

Because the four municipalities of Beijing, Shanghai, Tianjin, and Chongqing significantly outperform other regions in terms of policy support, allocation of innovation resources, and levels of digital development—and possess unique policy advantages and a concentration of innovation resources—this may have a reinforcing effect on executives' AI adoption and green innovation behavior, thereby confounding the results of the baseline regression. Therefore, this study excludes the samples from these four municipalities and conducts the regression analysis anew. As shown in column (7) of Table 8, after excluding samples from municipalities directly under the central government, the regression coefficient for executive AI adoption remains significantly positive, indicating that the study's conclusions are robust.

Since municipalities directly under the central government significantly outperform other regions in terms of policy support, allocation of innovation resources, and levels of digital development, this may have a reinforcing effect on enterprises' adoption of AI technologies and green innovation activities, thereby influencing the results of the benchmark regression. After excluding the four municipalities of Beijing, Shanghai, Tianjin, and Chongqing from the sample and rerunning the regression, we found that the regression coefficient for executive AI adoption in Table 8, column (7), remained significantly positive, indicating that the study's conclusions are robust.

4.2.7. Further Adjust the Fixed Effects

To control for unobservable shocks at the industry level over time, this study estimates the model by introducing industry-year joint fixed effects in addition to the baseline regression with industry and year fixed effects. As shown in the results in column (8) of Table 8, even under a more stringent fixed-effects specification, the coefficient for executive AI adoption remains significantly positive, and the study's conclusions remain robust.

It should be noted that due to data constraints, such as lagged variables, proxy variables, the exclusion of city-level data, and the use of stricter fixed effects, the number of observations varies across the models in Table 8. Such variations in sample size are common in robustness analyses and do not affect the interpretation of the overall conclusions.

4.3. Analysis of the Mechanism of Influence

4.3.1. Data Factor Allocation

Columns (1) through (3) in Table 9 examine the mediating role of data factor allocation in executive AI adoption and persistent green innovation. Column (1) indicates that executive AI adoption has a significant positive effect on corporate persistent green innovation; Column (2) shows that the coefficient for executive AI adoption on data factor allocation is positive at the 1% significance level; Column (3) shows that the coefficients for both executive AI adoption and data factor allocation on corporate persistent green innovation are significantly positive. This suggests that the data factor allocation plays a mediating role in the process by which executive AI adoption promotes corporate persistent green innovation; specifically, executive AI adoption enhances the data factor allocation capability, thereby resolving challenges related to information, efficiency, and risk, and helping enterprises achieve corporate persistent green innovation. Hypothesis H2 is thus supported. To further verify the mediating effect, the study employed the Sobel test [58] and the bootstrap method. The results indicate that both testing methods support the conclusion that a mediating effect exists.

Table 9. Results of the mediated effect test.

	(1)	(2)	(3)
Variable	<i>lnCSI</i>	<i>dig</i>	<i>lnCSI</i>
<i>AIPS</i>	0.1254 *** (4.50)	0.1683 *** (16.79)	0.0613 ** (2.07)
<i>dig</i>			0.3807 *** (4.66)
<i>_cons</i>	−3.3238 *** (−5.86)	0.0219 (0.24)	−3.3321 *** (−5.90)
<i>N</i>	19136	19136	19136
<i>adj. R²</i>	0.273	0.547	0.276
<i>Controls</i>	YES	YES	YES
<i>Ind</i>	YES	YES	YES
<i>Year</i>	YES	YES	YES
Sobel test			$p = 3.691 \times 10^{-7}$
Bootstrap test (total effect)			(0.0976, 0.1549) (significant)
Bootstrap test (indirect effect)			(0.0493, 0.0799) (significant)
Bootstrap test (direct effect)			(0.0302, 0.0950) (significant)

Notes: t-statistics based on clustered robust standard errors are presented in parentheses. Significance levels are denoted as *** ($p < 0.01$), and ** ($p < 0.05$). *Ind*/*Year* represent industry fixed effects and year fixed effects, respectively. YES indicates that the corresponding dimension has been controlled.

4.3.2. Strategic Agility

Column (1) of Table 10 examines the moderating effect of strategic agility on executive AI adoption and persistent green innovation. The results show that the coefficient for the interaction term between executive AI adoption and strategic agility (*AIPS_CSA*) is 1.0181 and is significant at the 1% level. This indicates that the higher the strategic agility, the more significant the role of executive AI adoption in promoting corporate persistent green innovation, thereby confirming Hypothesis H3. It should be noted that the *AIPS* coefficient in Column (1) represents the marginal effect when a firm's strategic agility is at the sample mean [59], which is precisely the baseline relationship tested by H1. The fact that the main effect is not significant at the mean level does not conflict with the significance of the interaction effect; the former describes the baseline effect at the sample mean, while the latter reveals the heterogeneity of the effect. Both can hold simultaneously and are complementary to one another.

Table 10. Results of the moderated effect test.

	(1)	(2)	(3)
Variable	<i>lnCSI</i>	<i>dig</i>	<i>lnCSI</i>
<i>AIPS</i>	0.0407 (1.54)	0.1562 *** (15.63)	0.0090 (0.33)
<i>CSA</i>	4.7217 *** (17.51)	0.2145 *** (4.94)	4.6782 *** (17.37)
<i>AIPS_CSA</i>	1.0181 *** (4.39)	0.4104 *** (4.71)	0.9349 *** (3.95)
<i>dig</i>			0.2029 *** (2.67)
<i>_cons</i>	−2.9104 *** (−5.67)	0.0624 (0.70)	−2.9231 *** (−5.69)
<i>N</i>	19136	19136	19136
<i>adj. R²</i>	0.330	0.558	0.331
<i>Controls</i>	YES	YES	YES
<i>Ind</i>	YES	YES	YES
<i>Year</i>	YES	YES	YES

Notes: t-statistics based on clustered robust standard errors are presented in parentheses. Significance levels are denoted as *** ($p < 0.01$). *Ind/Year* represent industry fixed effects and year fixed effects, respectively. YES indicates that the corresponding dimension has been controlled.

Based on the mean (M) and standard deviation (SD) of the moderator variable, this study categorizes strategic agility into three levels: values below M−1SD are classified as the Low CSA group; values equal to M are classified as the Medium CSA group; and values above M + 1SD are classified as the High CSA group. The moderating effects of strategic agility across these three levels are shown in Figure 2. It can be observed that the trend line for the Low CSA group is significantly negative, indicating that, in this case, executive AI adoption inhibits corporate persistent green innovation; the trend line for the Medium CSA group is flat, with a weak effect; and the trend line for the High CSA group is significantly positive and has the steepest slope, indicating that, in this case, executive AI adoption significantly drives green innovation. The fact that the slopes of the three lines turned positive and gradually increased confirms the positive moderating effect of strategic agility. This suggests that strategic agility is a key enabling factor for executive AI adoption to drive persistent green innovation. Only when companies possess sufficient strategic agility can AI be transformed into green innovation capabilities; otherwise, it may have a stifling effect due to factors such as misallocation of resources.

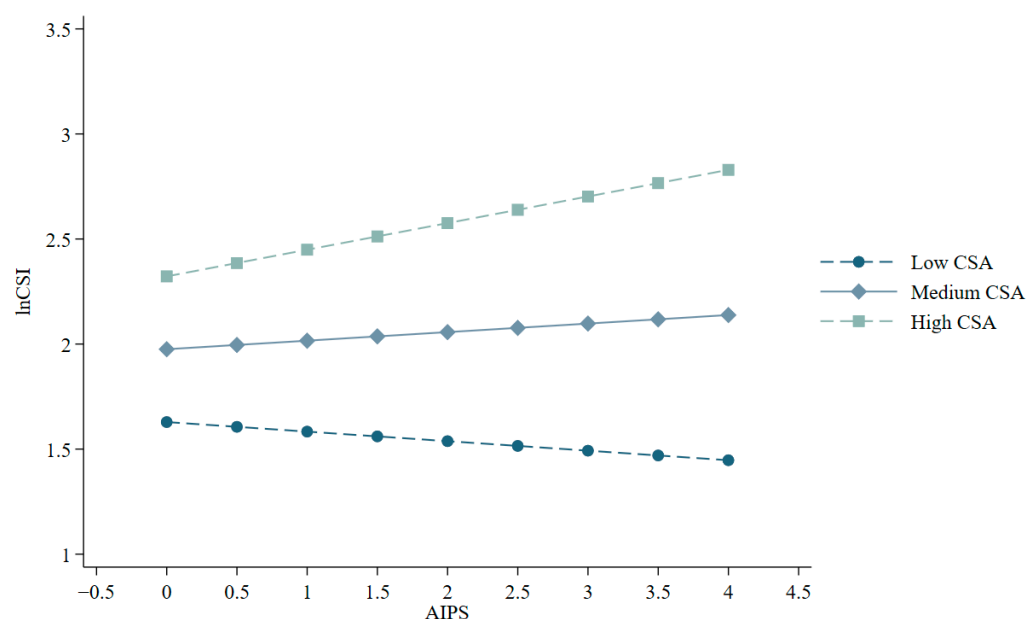


Figure 2. Moderating Effect of CSA on AIPS-InCSI Relationship.

Based on the acceptance of Hypotheses H2 and H3, and using the stepwise regression method of the mediation model, Table 10 Columns (2)–(3) examine the specific mechanisms through which strategic agility influences executive AI adoption and the firm’s corporate persistent green innovation. First, the results in Column (2) show that strategic agility significantly amplifies the positive impact of executive AI adoption on data factor allocation, indicating that strategic agility plays a positive moderating role at the level of decision-making behavior. Furthermore, the results in Column (3) indicate that strategic agility positively moderates the mediating effect: when a firm’s level of strategic agility is high, the mediating effect of data factor allocation between AI technology adoption and persistent green innovation becomes more pronounced, thereby more effectively driving the sustained realization of corporate persistent green innovation in the firm, confirming Hypothesis H4.

4.4. Heterogeneity Analysis

4.4.1. Total Factor Productivity

Total factor productivity reflects a company’s core ability to integrate resources, absorb technology, and translate these into innovation capabilities; differences in a company’s production efficiency may influence the effectiveness of executive AI adoption in driving persistent green innovation. Here, the LP method [60] is used to calculate the results, and the sample is divided into high and low groups based on the median. As shown in columns (1) and (2) of Table 11, the regression coefficients for AIPS in the high-TFP group and the low-TFP group are 0.1801 and 0.0839, respectively, and are significant at the 1% and 5% levels, respectively. This suggests that in firms with higher total factor productivity, executive AI adoption plays a more significant role in promoting persistent green innovation. Enterprises with high total factor productivity possess stronger technological absorption capabilities and greater efficiency in resource allocation, enabling executive AI adoption to be more effectively integrated into production and innovation systems, thereby significantly enhancing their role in promoting persistent green innovation.

Table 11. Heterogeneity analysis results.

	(1)	(2)	(3)	(4)
	High TFP	Low TFP	Strong Market Competition	Weak Market Competition
Variable	<i>lnCSI</i>	<i>lnCSI</i>	<i>lnCSI</i>	<i>lnCSI</i>
<i>AIPS</i>	0.1801 *** (4.63)	0.0839 ** (2.56)	0.1615 *** (4.40)	0.1161 *** (3.30)
<i>_cons</i>	−3.0874 *** (−4.10)	−0.8422 (−1.25)	−3.3366 *** (−4.36)	−3.3920 *** (−4.52)
<i>N</i>	9565	9567	9701	9435
<i>adj. R²</i>	0.324	0.166	0.296	0.259
<i>Controls</i>	YES	YES	YES	YES
<i>Ind</i>	YES	YES	YES	YES
<i>Year</i>	YES	YES	YES	YES

Notes: t-statistics based on clustered robust standard errors are presented in parentheses. Significance levels are denoted as *** ($p < 0.01$), and ** ($p < 0.05$). *Ind*/*Year* represent industry fixed effects and year fixed effects, respectively. YES indicates that the corresponding dimension has been controlled.

4.4.2. Market Competition

In highly competitive markets, intense competition intensifies the pressure on companies to survive and the need for differentiation, prompting them to rely more heavily on technological innovation to gain a competitive edge, thereby amplifying the enabling role of AI technology in green innovation. Based on the existing literature [61], the Herfindahl–Hirschman Index (*HHI*) is used here to measure industry concentration, defined as the sum of the squares of the ratios of each company’s revenue to the industry’s total revenue. It should be noted that the smaller the value of *HHI*, the more fragmented the industry and the more intense the market competition. It should be noted that the smaller the value of *HHI*, the more fragmented the industry and the more intense the market competition. Therefore, to facilitate the interpretation of results, this study measures the degree of market competition by calculating the 1-*HHI* and further divides the sample into two categories—“strong market competition” and “weak market competition”—based on the median for further analysis. As shown in columns (3) and (4) of Table 11, the regression coefficients for *AIPS* were both significantly positive at the 1% level in both the high-competition and low-competition groups, with coefficients of 0.1615 and 0.1161, respectively. This indicates that in firms facing stronger market competition, executive AI adoption more significantly promotes corporate persistent green innovation.

5. Discussion and Implications

5.1. Discussion

This paper integrates executive AI adoption with corporate persistent green innovation into a single theoretical framework to examine whether executive AI adoption influences corporate persistent green innovation and to identify the specific mechanisms through which this influence operates. Using data from Chinese A-share listed companies from 2010 to 2023, we conducted an empirical analysis and reached the following conclusions.

First, executive AI adoption significantly promotes corporate persistent green innovation. Existing research has largely examined the impact of AI on green innovation from the perspective of digital transformation or AI investment at the organizational level, generally overlooking the critical role that executive AI adoption—as the core decision-makers in technology adoption—plays in the sustainability of corporate persistent green innovation. This study addresses the gap in existing research regarding the insufficient focus on the behavior of micro-level actors and enhances the explanatory power of the High-Tier Theory in the intersection of digital and green transitions.

Second, executive AI adoption can promote corporate persistent green innovation by enhancing a company's data factor allocation capability. While existing literature acknowledges that data is a core factor of production in the digital economy, there is still no clear understanding of the underlying logic by which executive AI adoption translates into corporate persistent green innovation value through optimized data factor allocation. This study explicitly reveals the transmission pathway of "executive AI adoption—data factor allocation capability—corporate persistent green innovation."

Third, strategic agility positively moderates the impact of executive AI adoption on corporate persistent green innovation, serving as a key boundary condition for AI technology to empower corporate persistent green innovation. Furthermore, when a firm's level of strategic agility is high, the mediating effect of data factor allocation between AI technology adoption and persistent green innovation becomes more pronounced, thereby more effectively driving the sustained realization of green innovation. Existing research has rarely explored the moderating role of strategic agility in the relationship between digital technology and green innovation; this study explains why identical levels of AI technology adoption yield differentiated green innovation outcomes.

Fourth, the impact of executive AI adoption on corporate persistent green innovation varies across firms; in firms with higher total factor productivity and stronger market competition, executive AI adoption has a more significant positive effect on corporate persistent green innovation.

5.2. Theoretical and Practical Significance

The specific theoretical contributions of this study are as follows: First, it addresses the limitations of existing measurement methods in the fields of AI and strategic agility. Most existing studies measure corporate AI proficiency by counting the number of keywords. This paper constructs an executive AI adoption index based on the BERT pre-trained model, enabling a refined and continuous quantification of executives' strategic technology decisions. Additionally, it employs the Critic-entropy weighting method to develop a comprehensive strategic agility index, thereby effectively enhancing the objectivity and scientific rigor of this variable's measurement. Second, it has expanded the scope of research on the relationship between AI and green innovation. While existing literature has largely focused on the impact of AI on individual green innovation initiatives within firms, this study is the first to systematically examine the long-term effects of executive AI adoption on corporate persistent green innovation. It also reveals the moderating role of strategic agility as a key boundary condition, thereby providing a more dynamic theoretical perspective for understanding the relationship between the two. Third, it provides a deeper analysis of the underlying mechanisms through which AI drives green innovation. This study identifies the data factor allocation capability as the core mediating pathway through which executive AI adoption influences corporate persistent green innovation. It further finds that strategic agility has a significant reinforcing effect on this mediating pathway. Additionally, the study analyzes the heterogeneous effects from the perspectives of total factor productivity and market competition, thereby providing a new analytical framework for future research.

The practical significance of this study lies in the fact that it provides important empirical evidence and decision-making references for corporate green transformation and targeted government policies. For businesses, this study has established that executive AI adoption is a core strategic lever for driving persistent green innovation. It highlights the pivotal role of strategic agility as a precursor and identifies the key pathways through which data factors are allocated. By challenging the linear assumption that "AI inevitably promotes green innovation," the study provides theoretical guidance for companies to rationally assess the value of AI investments and avoid the pitfalls of blind digitalization.

For the government, the study has demonstrated the heterogeneous nature of AI-driven green innovation, providing empirical support for the formulation of differentiated and targeted industrial support policies.

5.3. Recommendation

In light of the research findings, this paper proposes the following recommendations:

Companies should optimize long-term incentive plans for senior executives by incorporating performance metrics related to AI transformation and green innovation into compensation and equity incentive schemes. At the same time, they should establish robust error-tolerance mechanisms that fully acknowledge the inherent risks associated with senior executives' decisions regarding executive AI adoption and persistent green innovation—risks characterized by high investment, long time horizons, and significant uncertainty regarding technological pathways. Specifically, the error tolerance mechanism applies only to bona fide errors resulting from compliance with procedures, legitimate motives, and the fulfillment of due diligence obligations—that is, errors that stem from thorough deliberation prior to decision-making, are free from personal gain, involve adequate risk mitigation measures, and are followed by proactive corrective actions after failure. Errors arising from violations of laws and regulations or dereliction of duty are not subject to error tolerance. Companies should establish data-driven decision-making systems, leveraging AI technology to enhance capabilities in data collection, integration, and analysis, and unblock the value conversion pathway linking “data—technology—innovation”; Companies should establish a dynamic strategic management system to enhance monitoring and responsiveness to the external environment, thereby strengthening the positive moderating effect of strategic agility on AI adoption and green innovation, and achieving a deep integration of technology and strategy.

The government should refine its policy framework for AI-driven green innovation, incorporate the green application of AI into key evaluation criteria for high-tech enterprise certification and green factory selection, and expand channels for green financial support; at the same time, it should improve the error-tolerance system for state-owned enterprises to alleviate concerns among senior executives regarding decision-making. For enterprises with high total factor productivity, the government should strengthen exemplary leadership and provide targeted support; for enterprises facing intense market competition, the government should improve market regulation and green standards to leverage the driving force of competition; for enterprises with low productivity and weak competitiveness, the government should provide targeted assistance, using industry–academia–research platforms to address capacity gaps and narrow the gap in green transformation.

5.4. Limitations and Future Directions

Limitations: First, the accuracy of the measurement of data factor allocation capabilities needs to be further improved. This paper uses the frequency of keywords in text to characterize the data factor allocation within enterprises. While this method primarily reflects enterprises' willingness to disclose information regarding data technologies and their superficial investments, it struggles to accurately capture the actual efficiency of data factor allocation and the effectiveness of value transformation throughout the entire green innovation process. Second, this study uses Chinese A-share listed companies from 2010 to 2023 as its sample and does not include unlisted small and medium-sized enterprises (SMEs) or overseas companies. A-share listed companies generally possess stronger financial resources and technological foundations; consequently, their decision-making regarding AI adoption and their capacity for green innovation investment differ systematically from those of SMEs, which face tighter resource constraints. The generalizability of the study's

findings to unlisted enterprises and companies operating under different institutional environments requires further verification.

Outlook: First, in the future, we can further refine the methods used to measure data factor allocation capabilities. By integrating information from multiple sources—such as corporate financial data, patent data, and supply chain data—we can establish a comprehensive indicator system to enhance the accuracy and comprehensiveness of core variable measurements. Second, the scope of the research sample could be expanded in the future. This could include unlisted small and medium-sized enterprises, companies listed on the National Equities Exchange and Quotations (NEEQ), and overseas enterprises operating under different institutional environments, in order to test the external validity of the research findings and provide more targeted theoretical support and practical guidance for the green digital transformation of various types of enterprises.

6. Conclusions

Previous studies have identified that corporate governance and the external environment influence persistent green innovation, and have confirmed the positive impact of AI on corporate green innovation; however, there remains a lack of discussion regarding the underlying mechanisms through which executive AI adoption affects corporate persistent green innovation. This study integrates the hierarchical team theory, the resource-based view, and the dynamic capabilities theory to examine whether and how executive AI adoption influences corporate persistent green innovation. The results reveal that executive AI adoption significantly promotes corporate persistent green innovation in firms, with data factor allocation serving as a mediating variable in this relationship. Furthermore, strategic agility positively moderates the relationship between executive AI adoption and corporate persistent green innovation, while also strengthening the mediating role of data factor allocation. Heterogeneity analysis indicates that the promotional effect of executive AI adoption is more pronounced in firms with higher total factor productivity and stronger market competition. These findings shift the research focus from firm-level AI investment to the individual decision-making behavior of executives, offering a new approach to understanding the microfoundations of persistent green innovation, while also providing highly actionable guidance for optimizing government policies and implementing corporate strategies.

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