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Advances in Management and Intelligent Technologies

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Carbon Asset Management System and Trading Strategies: Empowering Listed Companies in Value Reassessment and Sustainable Development

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Abstract: Carbon asset management and trading are not only important means for enterprises to cope with environmental challenges but also a strategic pathway to promote the sustainable development of enterprises. Upon the definition of core concepts such as carbon assets and carbon asset management, and guided by theories of environmental economics and low carbon economy, this study explores how carbon asset management system and trading influence the development of listed companies from four aspects: providing policy support for carbon trading of listed companies by promoting the carbon asset management system; creating channels for listed companies to improve their value creation capabilities through carbon trading; laying a solid foundation for the sustainable development of listed companies with carbon asset trading and management; and helping enterprises improve the level of positive externalities through carbon asset trading and management. At the end of the study, combined with the development situation of carbon asset management and trading in China, a localized strategy for optimizing the carbon asset management system and trading strategies of listed companies in China is proposed from three levels: improving the top-level system design, optimizing trading portfolio strategies, and perfecting corresponding supporting measures related to talents and finance. It is hoped that this study can provide valuable insights for more listed companies in their development within the field of carbon asset management, and that the study results can accelerate the comprehensive improvement of China's carbon asset management capabilities and contribute to the modernization development characterized by harmonious coexistence between humanity and nature.

KeyWords: Carbon Asset Management System; Carbon Asset Trading; Value Reassessment; Sustainable Development

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1. Preface

After more than 30 years of evolution, global climate governance is now facing challenges such as escalating climate risks, insufficient momentum for emission reduction actions, fragmented governance systems, and threats from unilateral trade measures. At present, global warming has become a serious ecological crisis that humanity is facing. According to the IPCC's Sixth Assessment Report Working Group I report, "Climate Change 2021: The Physical Science Basis", the current global average surface temperature is approximately 1.1°C higher than that in pre-industrial period. Projections for the average temperature change over the next 20 years indicate that global warming is expected to reach or exceed 1.5°C. Climate warming in all regions will intensify, and extreme heat and other extreme weather events will also increase. The realistic

pressures of climate change have promoted the development of global climate governance. By the end of 2024, more than 250 countries or regions, 258 cities, and over 10,000 companies around the world had committed to carbon neutrality in various forms. These countries account for 88% of the global carbon emissions, 92% of the global GDP, and 89% of the global population. Driven by scientific advancements and policy imperatives, factors such as investment, technology, industry, and employment interact with carbon neutrality goals, making carbon asset management a social development objective in more and more countries.

Carbon peak and carbon neutrality, as policy orientations that can significantly mitigate global warming, are gradually becoming a global consensus. As the world's second-largest economy and the largest carbon emitter, China solemnly announced at the global environmental governance meeting in September 2020 that it would strive to achieve carbon peak by 2030 and carbon neutrality by 2060. This marks the first time China has clearly communicated to the world the timeline for completing its carbon neutrality strategy as a major energy-consuming country. China will achieve the world's largest reduction in carbon emission intensity in the shortest time in global history (within only 30 years), and realize the transition from carbon peaking to carbon neutrality. This not only highlights China's active concern for global environmental issues but also demonstrates to the international community its unremitting efforts as the world's largest developing country for global environmental governance and its spirit of responsibility of a major country reflected behind it. The establishment of a carbon asset management system and optimizing carbon asset trading strategies are key steps to achieving the development goals of "carbon peaking and carbon neutrality". As important entities in economic activities, the carbon asset management level and trading strategy selection of listed companies not only concern their own sustainable development capabilities but also have a profound impact on the green transformation of the overall economy and society. An effective carbon asset management system can help listed companies accurately account for and manage their carbon assets, reduce carbon emission costs, and improve resource utilization efficiency. While scientific carbon asset trading strategies can bring new profit growth points for enterprises, maximizing the value of carbon assets through market mechanisms. Therefore, in-depth research on carbon asset management system and trading strategies is of great practical significance for empowering listed companies in value reassessment and promoting their low carbon, green, and sustainable development.

2. Concept Definition and Basic Theories of Carbon Asset Management

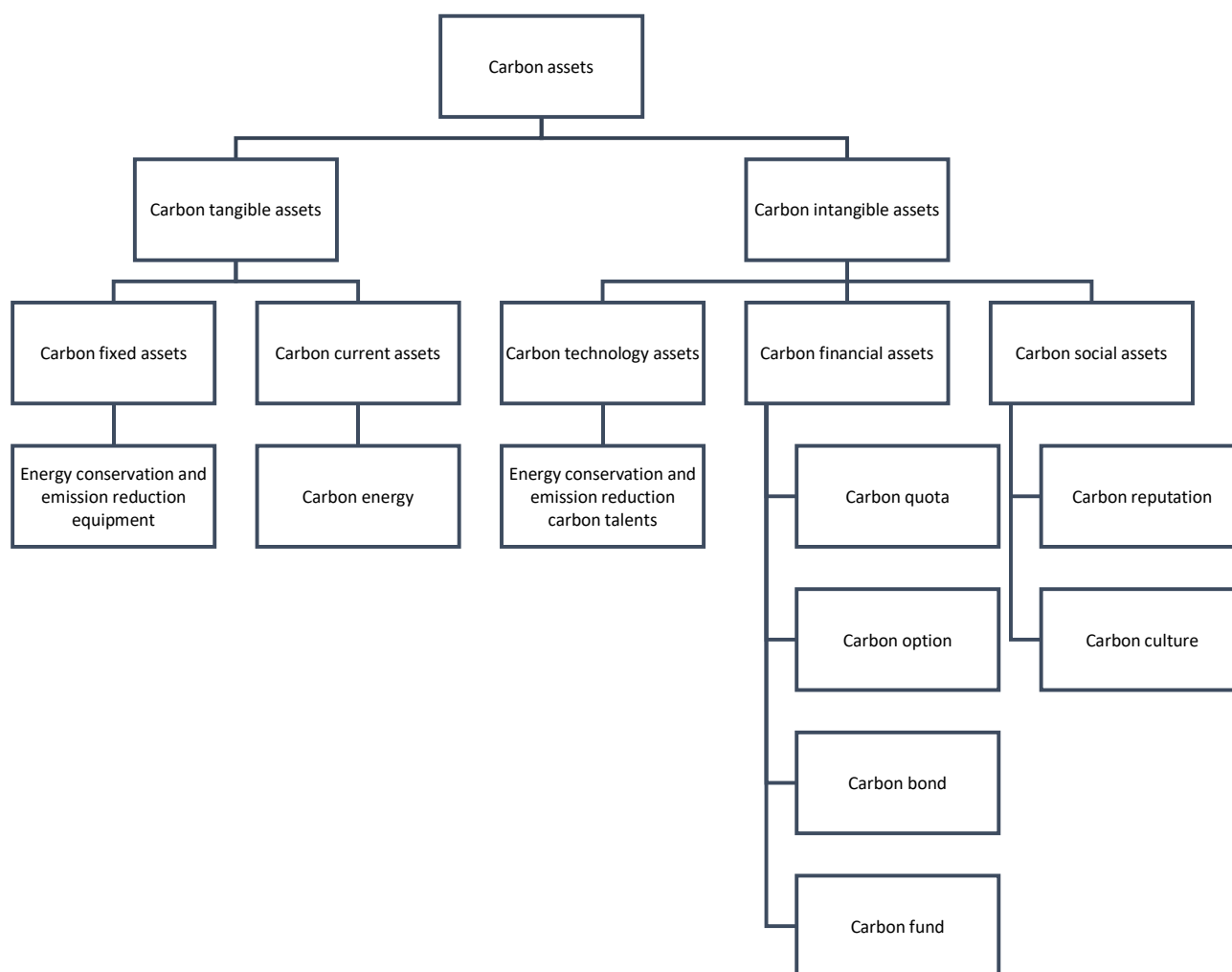
2.1 Concept of Assets and Carbon Asset

From an economic perspective, assets are typically defined as resources formed from past transactions or events of an enterprise, which are owned or controlled by the enterprise and are expected to bring economic benefits to the enterprise. According to this definition, it can be known that carbon emission rights are the most typical carbon assets. Specifically, these can be categorized into two types. One type is the government-allocated carbon assets, and the other type is voluntary emission reduction carbon assets. The former is the carbon emission allowances (CEA) allocated by the government to enterprises. Through internal energy-saving and emission-reduction activities, enterprises can save the surplus carbon emissions and can trade them on the carbon emission trading market, or conversely, enterprises may purchase surplus CEA transferred by other entities. The latter is distinct from the mandatory government-allocated allowances and highlights the "voluntary" principle. Enterprises can apply to relevant authorities for verification and certification of emission reductions achieved through their internal activities. After successful certification, enterprises will obtain Clean Development Mechanism (CDM) projects or China Certified Emission Reduction (CCER) projects, which can also be traded on the carbon emission trading market.

The connotation of carbon assets is not limited solely to carbon emission rights. With the continuous deepening of research on carbon assets, elements such as an enterprise's energy-saving and emission-reduction capabilities and technological innovation capacity have gradually been incorporated into the scope of carbon assets, further expanding the concept scope. Generally, the scope of carbon assets in the narrow sense only includes carbon emission rights and a series of related derivative financial products, and only has the core characteristic of economic attributes. In contrast, the scope of carbon assets in the broad sense is broader. In addition to the carbon emission rights, it covers various technological improvement activities undertaken by enterprises to reduce carbon emissions, such as the development of energy-saving and emission-

reduction equipment and the application of clean energy. As can be seen from Figure 1, carbon assets in the broad sense have both social and economic attributes: on the one hand, they can directly bring economic benefits to enterprises through the carbon emission trading market; on the other hand, they can indirectly cultivate new economic growth points for enterprises by fulfilling social responsibilities and enhancing corporate reputation. Given that this paper needs to comprehensively explore the specific pathways of carbon asset management in case companies, the broad definition of carbon assets is adopted in this study, that is, carbon assets include both intangible carbon assets and tangible carbon assets.

Figure 1 Structure of Carbon Assets in the Broad Sense



2.2 Concept of Carbon Asset Management

Based on the aforementioned definition of carbon assets in the broad sense, the carbon assets management pathways are also diverse. From the perspective of management pathways for carbon assets, the management can be classified into three main categories, namely: carbon emission allowance management, which is related to emission reduction technologies; voluntary emission reduction project management, which is closely linked to market trading; and comprehensive carbon asset management.

The first category is carbon emission allowance management, which primarily involves the allocation, use, trading, and monitoring of carbon emission allowances allocated by the government to enterprises. Enterprises should rationally plan their carbon emissions based on their production conditions to ensure they do not exceed their allowances allocated by the government. Meanwhile, they can buy or sell surplus or insufficient carbon emission allowances through market trading mechanisms to maximize their cost efficiency.

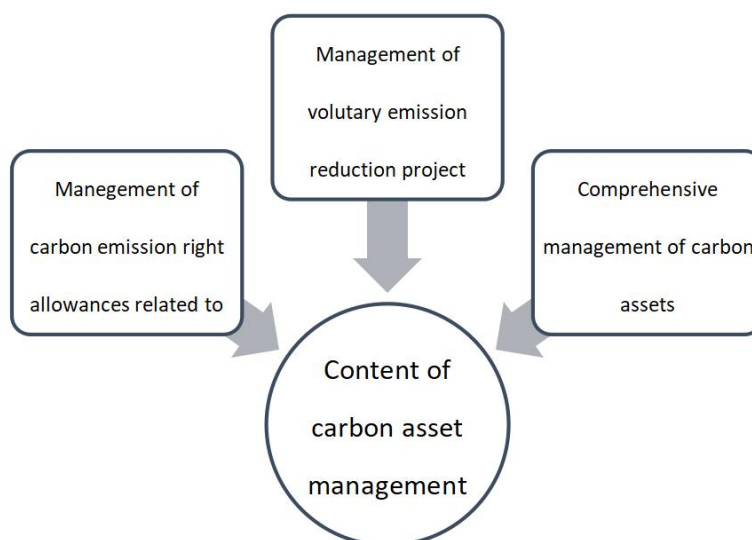
The second category is voluntary emission reduction project management, which focuses on enterprises' reduction of greenhouse gas emissions by independently implementing energy-saving and emission reduction projects, such as using clean

energy, improving energy efficiency, and conducting afforestation for carbon sequestration. Enterprises can convert these emission reductions into tradable carbon credits and trade them in the carbon market through Clean Development Mechanism (CDM) projects or China Certified Emission Reduction (CCER) projects to obtain economic benefits.

The third category is comprehensive carbon asset management, which is a more holistic and systematic approach. It not only covers the carbon emission allowance management and voluntary emission reduction project management but also involves multiple aspects such as risk management of carbon assets, investment strategies, information disclosure, and communication with stakeholders. Through comprehensive carbon asset management, enterprises can more effectively integrate internal resources, optimize the allocation of carbon assets, and enhance the value of their carbon assets. At the same time, they can actively respond to national carbon neutrality policies, promote green and low carbon transition, and achieve sustainable development.

Based on the conceptual connotation of carbon asset management, the carbon asset management system refers to the top-level design of carbon asset management for enterprises, that is, ensuring the completeness and reliability of carbon information disclosure through the establishment of systems, and also including the control of possible carbon risks of the enterprise.

Figure 2 Content Structure of Carbon Asset Management



2.3 Theoretical Foundations of Carbon Asset Management

2.3.1 Theory of Low Carbon Economy

The theory of low carbon economy is an important fundamental theoretical basis for promoting carbon asset management. The theory originates from the UK Energy White Paper *Our Energy Future: Creating a Low Carbon Economy* in 2003, which refers to reducing high-carbon energy consumption and greenhouse gas emissions through technological innovation, institutional optimization, industrial transformation and other means under the premise of ensuring sustained economic growth, and achieving the “decoupling” of economic development and carbon emissions. The theory breaks the traditional view that economic growth is inevitably accompanied by high emissions, clarifying the development path with low energy consumption, low pollution, and low emissions. Carbon asset management precisely enables enterprises to control the total amount of emissions through allowance management and explore the potential for emission reduction through voluntary emission reduction projects. These measures are essentially concrete responses to the carbon reduction goals of a low carbon economy. With the continuous enrichment of the theory of low carbon economy, international organizations and academia have further expanded its connotation. For instance, the United Nations Development Programme (UNDP) proposed in its Human Development Report that “a low carbon economy must balance ecological benefits with social equity”, emphasizing the need for enterprises to consider issues such as employment security and equitable technology access during the process of carbon reduction. This extension also directly affects the category of carbon asset management, driving its transformation from mere emission control toward integrated value management.

Guided by the theory of low carbon economy, carbon asset management not only focuses on the control of carbon emissions

and the improvement of resource utilization efficiency within enterprises, but also emphasizes the interaction and coordination between enterprises and the external environment. Enterprises need to establish a comprehensive carbon asset management system, clearly define the objectives, principles, procedures, and responsibilities of carbon asset management, and ensure the effective accounting, monitoring, and trading of carbon assets. Building a carbon trading market and optimizing trading strategies, it not only provides a positive external environment for the operation and development of enterprises, but also promotes the value creation and sustainable development of carbon trading companies.

2.3.2 Environmental Economics Theory

The theory of environmental economics originated from the explorations of synergistic development of the economy and the environment in the early 20th century. In 1920, Arthur Cecil Pigou first proposed the “externality theory” in his *The Economics of Welfare*, clarifying the concept that the public product attribute of environmental resources would lead to market failure. And the core logic of environmental economics lies in “internalizing” environmental externality through institutional design, making market entities bear all the costs and benefits of their environmental behaviors, thereby steering resources toward low carbon and efficient allocations.

The core connotation of environmental economics can be summarized into three dimensions: First, the internalization of externalities. Through measures such as carbon taxes and carbon markets, the negative externalities of carbon emissions are transformed into explicit corporate costs, compelling enterprises to strengthen their carbon asset management. Second, the definition of environmental property rights. Based on the Coase Theorem, it clarifies the ownership of environmental resources, providing a theoretical basis for the allocation and trading of carbon allowances. Third, the environmental value pluralism, which challenges the traditional perception that the environment is valueless, categorizes the value of environmental resources into economic, ecological, and social values, providing theoretical support for the concept that carbon assets in the broad sense possess both economic and social attributes. The theory of environmental economics provides critical guidance for carbon asset management. By defining carbon asset property rights and establishing carbon trading markets, it enables enterprises to buy and sell emission rights based on their specific carbon emission levels and abatement costs, thereby achieving optimal allocation of carbon assets. This market mechanism not only can incentivize enterprises to proactively reduce emissions but also can promote the development and application of low carbon technologies, driving the low carbon transition of the entire society.

It can be seen from this that the theoretical foundation of carbon asset management covers multiple aspects, including the theory of low carbon economy and the theory of environmental economics. These theories provide a solid conceptual basis and directional guidance for carbon asset management, promoting the continuous evolution of carbon asset management from concept to practice.

3. Analysis of The Path of Carbon Asset Management System and Trading Affecting the Development of Listed Companies

3.1 Carbon Asset Management System Provide a Policy Basis for Carbon Trading by Listed Companies

The carbon asset management system establish a solid policy foundation for the compliant execution of carbon trading by listed companies through clarifying rules, standardizing procedures, and controlling risks. From the operational perspective, the system will unify carbon asset accounting standards, helping enterprises accurately measure the scale of carbon assets such as emission allowances and voluntary emission reductions, thereby avoiding transaction disputes caused by inconsistent accounting standards. Furthermore, the system will specify detailed operational procedures for carbon trading, including timelines and operation requirements for allowance applications, compliance surrenders, and carbon credit transactions, ensuring that enterprises have clear rules to follow when conducting transactions. The EU Emissions Trading System (EU ETS), as the longest-operating and most mature transnational carbon market in the world, has developed a systematic institutional system through nearly twenty years of development. Regarding accounting standards, it uniformly requires the included enterprises to adhere to the EU Carbon Emission Monitoring, Reporting and Verification Regulation, which clearly defines the measurement methods and verification procedures for emission data in sectors such as power, steel, and shipping, ensuring consistent carbon asset accounting standards across all participants. Électricité de France (EDF), a key enterprise

in the EU power sector, relies on this system within its carbon asset management department to collect and calculate carbon emission data from its power facilities across Europe. After verification by a third-party verification agency every year, it generates standardized reports, laying the foundation for subsequent allowance trading and compliance.

From the perspective of risk management, carbon asset management system will also establish mechanisms for controlling carbon trading risks, such as setting upper limits on allowance holdings and monitoring abnormal price fluctuations, helping enterprises mitigate compliance and market risks. EDF Trading, the independent carbon trading department established by Électricité de France, relies on the risk hedging instruments permitted under the system to manage price risks through combined operations involving allowances and carbon derivatives. During the fluctuation period when the EU carbon price exceeded 80 euros per ton in 2023, the department employed the intertemporal trading strategies permitted under the system to lock in costs for some compliance allowances in advance, thus avoiding operational impacts from short-term price surges. Similarly, when CNOOC Gas and Power Group expanded into the Australian carbon market, it also opened two carbon credit accounts simultaneously in accordance with the risk control requirements of the local new emission reduction act to diversify trading risks, ensuring the compliance and fulfillment of its investment projects in Australia. This system design that integrates accounting, process and risk control eliminates the uncertainty of carbon trading for listed companies, ensures their legal and compliant operations in the carbon market, and provides a fundamental guarantee for the stable development of trading activities.

3.2 Carbon Trading Provides More Channels for Listed Companies to Optimize Their Value Creation Capacities

Carbon asset trading enhances the value of listed companies significantly from both financial and market value perspectives. At the financial value level, enterprises can obtain direct revenue through carbon trading. Enterprises with surplus allowances can sell their allowances when carbon prices are high, while those enterprises with voluntary emission reduction projects can gain additional cash flow through carbon credit transactions—these proceeds are directly recorded in the income statement, enhancing the profitability of the enterprises. Additionally, enterprises can also optimize costs through trading, for instance, by using lower-cost CCERs to offset part of their allowance surrender obligations, thereby reducing carbon compliance costs. According to the observation report on the long-term operation data of EU ETS by the non-profit Carbon Market Watch and Dutch consultancy CE Delft, between 2008 and 2019, European energy-intensive industries obtained speculative profits of up to 50 billion euros through the carbon trading mechanism. The core approach involved surpluses in emission allowances freely allocated by the government, which enterprises sold at market highs to increase their revenue. Specifically, the cement sector made a profit of 3.1 billion euros solely by selling surplus free allowances, and the petrochemical industry made a profit of 600 million euros through the approach. On the other hand, the steel and oil refining enterprises adopted a combined strategy of “purchasing international carbon offsets at low prices and selling free allowances at high prices”, achieving additional revenues of 850 million euros and 630 million euros respectively. Such revenues are not isolated cases; During the same period, enterprises in Portugal also made revenues of nearly 1 billion euros in supplementary profits from the carbon market during the same period, fully demonstrating the direct driving effect of carbon trading on the financial profits of enterprises.

At the market value level, enterprises that actively participate in carbon trading often obtain higher ESG ratings, attracting increased investment from green investors such as ESG funds, thereby elevating their stock prices and valuation benchmarks. Moreover, the “low carbon” label associated with carbon trading can enhance consumer recognition of corporate products, increase market share, and further amplify market value of enterprises. Ørsted, a Danish renewable energy company that has transformed from traditional fossil fuels, optimized its carbon asset configuration through long-term engagement in the EU carbon trading: on one hand, it converted emission reductions from wind power projects into tradable carbon credits; on the other hand, it offset its emission costs from traditional operations through allowance trading. This series of measures has pushed its ESG risk rating to reach the “low risk” level of Sustainalytics, making it an ESG benchmark among global energy enterprises. As of 2024, Ørsted’s stock price had risen by over 120% in the past five years, far exceeding the average level of traditional energy companies in Europe. Moreover, it has been included in the core holdings of more than 200 global

ESG-themed funds, with its valuation benchmark nearly 80% higher than that before transition. Fortescue Metals Group, an Australian mining giant, also enhanced its corporate value through carbon asset trading. In 2024 alone, Fortescue generated over 230 million US dollars in cash flow from decarbonized assets like green power and green hydrogen, and directly offset 10% of its decarbonization investment costs by locking in revenues through carbon trading mechanisms. This virtuous cycle of decarbonization investment and carbon trading profits enabled Fortescue's MSCI ESG rating leap from BBB to A. It is evident that the low carbon operational capabilities formed by carbon trading can translate into a "value safety cushion" recognized by investors through ESG ratings, thereby promoting the increase of enterprise market value.

3.3 Carbon Asset Management and Trading Solidify the Foundation for Sustainable Development of Listed Companies

Carbon asset management and trading provide long-term support for the sustainable development of listed companies by compelling low carbon transition, incentivizing technological innovation, and optimizing the industrial chain ecosystem. In terms of low carbon transition, carbon asset management system drives companies to proactively phase out high-energy-consumption equipment and optimize production processes. W.A.Parish gas-fired power plant in the U.S., in its carbon capture, utilization, and storage (CCUS) project, channels part of the captured CO₂ for methanol production and a port for storage in saline aquifer. In 2023 alone, the plant generated 120 million US dollars revenue from regional carbon price transactions in the U.S., and realized 360 million US dollars from revenue methanol sales. The plant allocated 40% of these profits for technological upgrades, improving the CO₂ enrichment efficiency of membrane separation units and developing new low-cost absorbents, which further reduced the capture costs by 18% and created a positive cycle of technological advancement and revenue growth. Similarly, Japan's JERA invested its carbon credit revenues from its wind power projects into R&D for "24/7 carbon-free electricity" technology and partnered with Shizen Connect to build a virtual power plant system for real-time matching of renewable energy supply and demand. The technology has also been piloted commercially in 2025 and is expected to reduce the cost of green electricity use by 30% for manufacturing customers. It can be seen from this that the profits brought by carbon trading can be fed back to the research and development of low-carbon technologies. Enterprises can invest the profits from carbon trading in technological breakthroughs such as carbon capture and clean energy utilization, forming a virtuous cycle of "emission reduction - profits - further research and development", and enhancing their core technological competitiveness.

In terms of industrial chain ecosystem, advanced carbon asset management capabilities can also drive collaborative emission reductions across upstream and downstream enterprises. For instance, Microsoft is not only building its own data centers with cross-laminated wood (65% lower carbon footprint than traditional concrete buildings), but also has a contract that requires core suppliers to use 100% carbon-free electricity by 2030, and has set up a carbon footprint tracking platform to provide suppliers with free carbon accounting tools. For those who meet the standards first, Microsoft will offer an order preference of 10% to 15%. For those lagging in emission reductions, Microsoft provides subsidies for them with its carbon trading revenues. By 2024, 78% of Microsoft's top 500 global suppliers had accessed the carbon management platform, the overall carbon emission intensity of the supply chain has decreased by 19%, and the brand premium brought by the green supply chain has increased the renewal rate of enterprise customers of Microsoft cloud services to 92%. It is evident that by requiring suppliers to provide carbon footprint data, core enterprises can not only promote the low-carbonization of the entire supply chain and form a green industrial chain advantage, but also further enhance the long-term development resilience of enterprises through this industrial chain synergy capability.

3.4 Carbon Asset Management and Trading Help Enhance the Level of Positive Externality for Enterprises

From the aforementioned theoretical content of environmental economics, externality is a key mechanism through which carbon asset management and trading achieve positive externality. Specifically, through system design and market trading, carbon asset management transforms the negative externality of carbon emissions into internal costs, and at the same time transforms the positive externality of emission reduction into market benefits, so as to promote enterprises to change from passive compliance to active emission reduction and form a positive feedback to the social environment. Taking the EU ETS

as an example, by setting sectoral benchmarks and allowance allocation rules, it compels high-emission enterprises to pay for excess emissions, while low carbon companies can earn revenues by selling allowances. This mechanism of “penalizing high emitters and rewarding low emitters” directly internalizes environmental costs, prompting enterprises to proactively adjust their production structures. In addition, the German chemical company BASF has also optimized its carbon asset management and transferred some of its production processes to regions rich in renewable energy. This not only reduced its own carbon emissions but also promoted the development of the local clean energy industry, creating a two-way positive interaction between the enterprise and the region.

Beyond the positive externalities brought about by the active promotion of carbon trading by the aforementioned enterprises, at the government-enterprise relationship level, enterprises that actively implement carbon asset management are more likely to align with China’s “carbon peaking and carbon neutrality” policy direction and enjoy policy preferences such as prioritized access to green credit, tax incentives, and inclusion in low carbon demonstration enterprise lists. These supports can further reduce the operational costs of enterprises. At the industry collaboration level, the carbon management practices of leading enterprises set industry benchmarks, driving peers to engage in carbon asset management and trading and promoting the entire industry toward low carbon development. In this process, enterprises will establish leading positions within their industries, strengthening their influence in external collaborations and fostering a positive external development environment.

4. Localized Plan for Carbon Asset Management System and Trading Strategies of Listed Companies in China

4.1 Top-Level Design: Improving the framework of the carbon asset management system for listed companies in the carbon market

The key distinction of carbon asset management from other assets lies in that it is a policy-driven product, with policy implications and a background of its era. Various policies and systems, including those for controlling carbon emissions, regulating carbon trading and carbon information disclosure, provide institutional guarantees and legal foundations for carbon asset management, which represent the most direct and effective means to promote the transformation of enterprises and society towards low-carbonization.

To refine the framework of the carbon asset management system for listed companies in the carbon market, it is essential to first establish a unified legal and regulatory system for carbon asset management at national level, clearly defining the ownership of carbon assets, trading rules, accounting standards and regulatory mechanisms, providing clear institutional guidance for listed companies. In terms of property right definition, the Coase Theorem in environmental economics theory should be relied upon, combined with the actual situation of carbon asset management in China, the legal status of carbon emission rights should be established through legislation, and their tradable and collateralizable attributes should be clarified, so as to stimulate the enthusiasm of enterprises to participate in the carbon market. Simultaneously, detailed carbon asset accounting guidelines should be formulated to unify accounting methods across different industries and regions, so as to ensure the accuracy and comparability of carbon asset data and provide a solid foundation for carbon trading.

In terms of trading rules, flexible and diverse trading mechanisms should be designed, including spot trading, futures trading, and options trading, so as to meet the diverse risk management needs of listed companies. At the same time, entry and exit mechanisms for the carbon trading market should be established for strict reviews of participant qualifications and creditworthiness, so as to prevent market manipulation and excessive speculation, thereby maintaining the fairness, impartiality, and transparency of market. Furthermore, a risk early-warning and emergency response system for the carbon trading market should be built to monitor price fluctuations and trading anomalies in real time and take timely measures to prevent systemic risks.

In terms of regulatory mechanisms, a cross-departmental, cross-regional collaborative regulatory system can be established to enhance the communication and coordination among ecological and environmental authorities, financial regulators, and market supervision departments to form a synergistic regulatory force. Additionally, third-party verification agencies should be introduced to independently audit the carbon asset data of listed companies, ensuring its authenticity and reliability. Violators should be severely punished in accordance with the law, increasing the cost of non-compliance and forming an

effective deterrent.

4.2 Trading Optimization: Design Carbon Asset Portfolio Trading Strategies Align with Domestic Market

Trading is a key link in promoting the maximization of enterprise carbon assets. The design of carbon asset portfolio trading strategies for the domestic market must fully consider the unique characteristics of China's carbon market. At present, taking the power industry as a breakthrough point, China's carbon market gradually incorporates high-emission industries like steel and building materials, and operates the regional pilot markets in parallel with the national market, providing enterprises with room for arbitrage by taking advantage of the price differences and varying trading rules across markets. Listed companies can, based on their industry attributes and carbon asset structure, construct portfolio strategies encompassing basic allowances, derivatives, and cross-market trading.

At the basic allowance trading level, enterprises can dynamically adjust their allowance holdings by analyzing the gap between their carbon emission intensity and the industrial benchmark. For enterprises with emission intensity below the benchmark, the government may allow them to sell their surplus allowances when carbon prices are high to obtain direct benefits. In contrast, enterprises with emission intensity near or above the benchmark need to purchase allowances or use CCERs to offset compliance obligations in advance, so as to avoid increased compliance costs due to allowance shortages. In terms of derivatives trading, enterprises can lock in future compliance costs by purchasing carbon futures contracts or earn premium income by selling call options, thereby reducing their financial costs of carbon asset management and hedging against price volatility risks.

At the cross-market trading level, enterprises can arbitrage price differences between regional pilot markets and the national market. When the carbon price in a regional pilot market is significantly lower than in the national market, enterprises can purchase allowances in the regional market and resell them in the national market to obtain profits from the price difference. By establishing portfolio strategies based on basic allowances, derivatives, and cross-market trading, listed companies can not only maximize the value of their carbon assets but also effectively diversify trading risks, enhancing the flexibility and efficiency of carbon asset management.

4.3 Supporting Facilities: Improve the Supporting System for Carbon Asset Management and Trading of Listed Companies

In terms of technological innovation in carbon asset management, the introduction of big data technologies enables enterprises to collect, integrate, and deeply analyze large volumes of carbon emission data in real time. The data cover a wide range of information such as enterprises' own emissions, market dynamics, and policy changes. Therefore, to optimize carbon asset trading for listed companies, it is necessary to actively promote the application of digital technologies in carbon asset transaction management. By establishing a digital platform for carbon asset management, enterprises can integrate carbon emission data from internal departments and across the supply chain, enabling real-time data updates and sharing. The platform can deeply analyze historical carbon trading data and policy change information based on machine learning algorithms, forecasting future carbon price trends and providing transaction decision support for listed companies.

Secondly, enterprises need to strengthen talent cultivation and technical support for carbon asset management. By establishing professional training institutions, carrying out international cooperation and exchanges, the professional competence and practical skills of carbon asset managers in listed companies can be enhanced. At the same time, research institutions and enterprises should be encouraged to increase R&D investment in areas such as carbon capture, utilization, and storage (CCUS) and low carbon technologies, so as to promote technological innovation and the commercialization of results, thereby advancing the sustainable development of listed companies.

Finally, efforts should be made to accelerate the construction of a mechanism that links the carbon assets with green finance. By developing financial products such as carbon asset pledge financing, carbon insurance, and carbon funds, diversified financing channels and risk protection should be provided for listed companies to participate in carbon trading. The government can introduce relevant policies to encourage financial institutions to engage in carbon asset financial services, offering tax incentives and fiscal subsidies to institutions involved in such businesses, promote the deep integration of carbon

assets and green finance, and provide solid financial support for carbon asset management and trading of listed companies.

5. Conclusions

In the era of green and low carbon development, carbon asset management is no longer an option for listed companies but a must-answer question concerning their future survival and development. It requires enterprises to start from a strategic height, establish scientific institutional systems, formulate flexible trading strategies, and actively embrace open cooperation. This study provides a localization solution for the carbon asset management system and trading strategies of listed companies in China from the top-level design of the carbon asset management system, the carbon asset trading portfolio strategy, as well as the corresponding financial support, talent support and other supporting measures.

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Artificial Intelligence Enhancing Agricultural Total Factor Productivity in China: Mechanisms and Pathways

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Abstract: Against the dual backdrop of intensifying global food security challenges and increasingly tight resource and environmental constraints, enhancing agricultural Total Factor Productivity (TFP) has become a core driver for promoting high-quality agricultural development. Artificial Intelligence (AI), as a strategic technology leading the new round of scientific and technological revolution and industrial transformation, is profoundly reshaping agricultural production methods and industrial ecosystems. This paper systematically elucidates the driving effect of AI on agricultural TFP growth through three key mechanisms: enhancing technical efficiency, optimizing factor allocation, and fostering new business models. Simultaneously, it identifies the multiple challenges in the AI-enabled empowerment process, including underlying data deficiencies, technological application bottlenecks, institutional and talent lag, and regional disparities. To address these issues, this paper proposes systematic optimization pathways, including building a high-quality agricultural data resource system, developing adaptable AI technologies and equipment, cultivating interdisciplinary “AI + Agriculture” talent, and improving policy regulations and ethical governance frameworks. This research aims to provide a theoretical framework for understanding the intrinsic logic of AI-driven agricultural TFP growth and to offer decision-making references for formulating relevant industrial policies and promoting the practical implementation of smart agriculture.

Keywords: Artificial Intelligence; Agricultural Total Factor Productivity; Empowerment Mechanisms; Smart Agriculture; Optimization Pathways

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1.Introduction

President Xi of China emphasized: “Artificial Intelligence is a strategic technology leading the new round of scientific and technological revolution and industrial transformation, serving as a powerful bellwether with significant spillover and driving effects,” and that “accelerating the development of next-generation artificial intelligence is a strategic issue concerning whether China can seize the opportunities presented by this new round of scientific and technological revolution and industrial transformation.” This important discourse charts the course for China to grasp technological trends and promote industrial transformation and upgrading. Currently, a new generation of information technologies, such as 5G, AI, big data, the Internet of Things, cloud computing, and blockchain, is flourishing globally and accelerating its deep integration across various economic and social sectors. As a fundamental industry of the national economy, agriculture bears not only the crucial

responsibility of ensuring national food security but also the vital mission of maintaining stable socio-economic development. Confronted with this new developmental context, the limitations of the agricultural growth model, which primarily relies on traditional factor inputs, have become apparent. Transitioning towards an intensive growth path driven by technological innovation and quality improvement has become an inevitable strategic choice.

Agricultural Total Factor Productivity (TFP) serves as a key metric for assessing the quality of agricultural development. It captures the output growth attributable to intangible factors like technological progress, organizational innovation, and specialized production, beyond the contributions of tangible inputs such as land, labor, and capital ^[1]. In this domain, Artificial Intelligence technology, leveraging its formidable capabilities in perception, learning, reasoning, and decision-making, demonstrates immense application potential. From precision seeding and smart irrigation to the intelligent identification and early warning of pests and diseases, and from autonomous agricultural machinery to data-driven decision-making based on market predictions, AI is facilitating the transformation of traditional agriculture from an experience-dependent, resource-intensive model towards a data-driven, intelligent, and efficient modern smart agriculture system. This transformation presents a new historic opportunity to overcome the bottlenecks constraining the improvement of agricultural TFP ^[2].

Nevertheless, the practical process of leveraging AI to enhance agricultural TFP faces numerous significant challenges. On the one hand, the complexity of agricultural production environments and the inherent uncertainties in crop growth cycles impose extremely high demands on the reliability and adaptability of AI technologies. On the other hand, the structure of China's agricultural sector, where smallholder farmers constitute over 98% of all agricultural operators, creates a practical dilemma where advanced technologies encounter high application costs and significant diffusion difficulties. Furthermore, issues such as the inherent difficulties in agricultural data collection, the lack of unified quality standards and sharing mechanisms leading to "data silos" ^[3], the insufficient explainability and inclusivity of algorithmic models, and a severe shortage of interdisciplinary talent proficient in both agricultural science and AI collectively constrain the full realization of AI's empowering effects ^[4]. If these deep-seated problems are not systematically addressed, the application of AI in agriculture risks remaining largely at the "demonstration project" stage, failing to achieve scaled, commercialized, and deep integration. This could potentially exacerbate development disparities among different types of agricultural operators due to technological barriers and cost issues.

Therefore, conducting an in-depth analysis of the intrinsic mechanisms through which AI empowers agricultural TFP, accurately identifying the key challenges it faces, and proposing forward-looking and actionable optimization pathways based on this analysis holds substantial theoretical value and practical significance. This research will undertake a systematic analysis across three critical dimensions, namely elucidating fundamental mechanisms, diagnosing practical challenges, and exploring viable pathways, to comprehensively investigate how AI can transform into a core engine driving the improvement of agricultural TFP. The ultimate aim is to provide valuable academic references and substantive policy insights that can contribute to accelerating the modernization of China's agriculture sector and effectively supporting the full implementation of the Rural Revitalization Strategy.

2.The Mechanisms of AI in Enhancing Agricultural Total Factor Productivity

2.1 Enhancing Technical Efficiency

Artificial Intelligence significantly enhances agricultural technical efficiency by revolutionizing traditional decision-making models in agricultural production, representing the most direct pathway for enhancing Total Factor Productivity (TFP) growth. At the pre-production planning stage, AI algorithms can integrate multi-source data (including soil properties, meteorological conditions, market trends, and historical yields) to formulate optimal crop variety selection and sowing plans for farmers, thereby promoting the precise allocation of agricultural production resources from the outset ^[5]. During the production management phase, pest and disease identification systems based on computer vision technology utilize mobile applications or field monitoring equipment to enable real-time diagnosis of crop health. The accuracy and response speed of these systems far surpass traditional manual observation, significantly improving the precision and timeliness of pest and disease control, which in turn markedly reduces pesticide misuse ^[6]. Concurrently, smart irrigation systems employ sensors to monitor soil moisture in real time, integrating crop physiological water requirements and evapotranspiration models to

achieve precise, on-demand water supply, effectively enhancing water use efficiency^[7]. In the post-harvest handling stage, automated sorting equipment powered by AI technology can perform rapid and accurate grading of agricultural products based on multiple indicators such as appearance specifications, color, sugar content, and internal defects, substantially increasing product added value and market competitiveness. These concrete applications of “AI + Agriculture” collectively drive the transformation of agricultural decision-making mechanisms from fuzzy judgments reliant on traditional experience to scientific decisions based on data and algorithms, directly promoting the improvement of output efficiency per unit input and serving as a crucial source of agricultural TFP growth^[8].

2.2 Optimizing Factor Allocation

AI profoundly optimizes the efficiency of factor allocation in agriculture by enhancing factor mobility, substituting scarce factors, and activating the value of potential factors^[9]. First, AI platforms such as agricultural IoT platforms and intelligent agricultural machinery scheduling systems effectively break down information barriers, enabling key production factors, including land, agricultural machinery, and labor, to achieve efficient matching and shared utilization across temporal and spatial constraints. For instance, the “Didi Nongji” model, inspired by the sharing economy concept, can intelligently plan optimal operational routes and scheduling schemes based on real-time operational demands and the geographical locations of machinery, significantly improving the comprehensive utilization rate of high-value agricultural equipment^[10]. Second, the application of AI equipment, such as agricultural robots and autonomous tractors, can substantially replace increasingly scarce and costly agricultural labor. These technologies undertake repetitive and labor-intensive tasks like crop picking, field weeding, and precision pesticide application, effectively mitigating the practical challenge of agricultural labor shortages in China^[11]. Third, AI technology can fully exploit and activate the intrinsic value of “data” as a new production factor. Through in-depth mining and intelligent analysis of massive agricultural datasets, AI can uncover production patterns, market dynamics, and risk signals that were previously undetectable through experience alone. This transforms static data into digital assets capable of guiding production practices and generating economic benefits, further optimizing the input structure and developmental combination of traditional factors, ultimately achieving a Pareto improvement in overall agricultural factor allocation^[12].

2.3 Fostering New Business Models

The penetration and integration of AI into agriculture extend beyond improving the efficiency of traditional production links; they also manifest in the generation of a series of new business models and formats through cross-industry integration, thereby opening up new value spaces for agricultural TFP growth. For example, at the intersection of “AI + Agriculture” and the financial insurance sector, agricultural insurance services based on remote sensing data and AI models have emerged. These services enable precise delineation of coverage areas and rapid claims processing, reducing on-site inspection costs and potential moral hazards for insurance institutions while enhancing the risk protection level for agricultural production and management^[13]. In the agricultural product marketing domain, AI analyzes vast amounts of consumer preference and market behavior data, empowering the development of regional public brands for agricultural products and the formulation of precision marketing strategies. Furthermore, it facilitates the reverse transmission of market demand signals to the production end, guiding variety selection and standardized production processes, thereby achieving genuine “demand-driven production”^[14]. Additionally, AI-driven new formats such as “immersive agricultural experiences” and “smart farm study tours,” which integrate agriculture and tourism, successfully transform traditional agricultural production processes into perceivable, experiential, and consumable service-oriented products, greatly extending and expanding the agricultural industry value chain. The emergence and development of these new rural business models break down the traditionally relatively closed industrial boundaries of agriculture, facilitating the influx and recombination of high-level production factors such as technology, knowledge, and information. From the dimensions of industrial structure optimization and value addition, they inject more advanced and enduring growth momentum into the sustained improvement of agricultural TFP^[15].

3. Practical Challenges in AI’s Empowerment of Agricultural Total Factor Productivity

3.1 Inadequate Data Foundations and Data Silos

High-quality, large-scale data provides the foundation for training AI models. However, China’s agricultural data

infrastructure remains underdeveloped. The geographically dispersed nature and environmental complexity of agricultural production maintain high data collection costs and implementation challenges. Concurrently, hardware limitations, including insufficient sensor accuracy and environmental durability, result in inconsistent data quality ^[16]. More notably, pervasive “data silos” occur as agricultural data remains scattered across government departments, research institutions, agribusinesses, and smallholders, lacking unified standards and effective sharing mechanisms. The fragmentation among meteorological, soil, market, and production data prevents integration into complete, coherent datasets necessary for training AI models ^[17]. For example, AI models designed to predict regional grain yields often suffer significantly reduced accuracy due to unavailable field-level crop growth data or detailed meteorological information. This combination of a weak data foundation and circulation barriers creates a “no raw ingredients to cook with” dilemma for advanced AI algorithms, severely constraining their potential impact.

3.2 Technical Application Bottlenecks and Cost-Benefit Challenges

Implementing cutting-edge AI in complex agricultural environments presents dual technical and economic challenges. Technically, the unstructured characteristics of biological subjects (e.g., crop morphological diversity, variable pest manifestations) demand exceptional generalization capability and environmental adaptability from AI models. Algorithms performing well in controlled experiments may degrade significantly in field conditions due to factors like lighting variations, foliage occlusion, and background interference ^[18]. Economically, substantial initial investments required for AI solutions, including smart hardware, software development, deployment, and maintenance, create prohibitive cost barriers for small and medium-scale farmers who constitute most agricultural operators. The short-term benefits from yield increases or cost savings often cannot offset upfront costs, resulting in widespread “cannot afford and will not adopt” attitudes ^[19]. Additionally, the “black box” nature of most AI systems, with their opaque decision-making logic, prevents experience-dependent farmers from establishing necessary trust, posing another major barrier to adoption.

3.3 Institutional and Talent Gaps, and Regional Imbalances

Effective AI implementation in agriculture requires supportive institutions and adequate talent, yet both areas show significant deficiencies. Institutionally, clear rules defining agricultural AI data ownership, usage rights, and benefit distribution remain underdeveloped. The legal framework covering intelligent equipment certification, operational safety standards, and accident liability determination lacks maturity ^[20]. Effective ethical review and regulatory mechanisms are also absent for addressing potential algorithmic biases and discrimination risks. Regarding talent development, a severe shortage exists of interdisciplinary experts proficient in both AI technology and agricultural science. The higher education system maintains strong disciplinary boundaries, with agricultural institutions providing weak AI training while engineering programs produce AI specialists lacking agricultural domain knowledge ^[21]. This structural talent gap directly creates mismatches between AI solutions and agricultural needs. Meanwhile, regional disparities are intensifying. Economically advanced eastern regions and large-scale farms lead in capital investment, talent concentration, and technology application, while smallholders in central and western regions and hilly areas face increasing marginalization in terms of technology access and application capacity ^[22]. This widening “digital divide” not only hinders overall agricultural TFP growth but may also exacerbate regional development inequalities.

4. Optimization Pathways for AI’s Empowerment of Agricultural Total Factor Productivity

4.1 Strengthening Data Infrastructure and Promoting Technological Inclusiveness

Addressing data-related challenges requires establishing a high-quality, shareable agricultural data resource system as the priority. National-level initiatives should enhance top-level design and integrated planning, accelerating construction of integrated sky-air-ground remote sensing and IoT sensor infrastructure. Standardized national protocols and industry specifications for agricultural data collection, storage, and exchange need development and refinement. Diverse mechanisms like “data alliances” and data trading markets should be explored to facilitate orderly data sharing and integration among government agencies, enterprises, and research institutions while ensuring privacy and security. To address high application costs, multiple business models and implementation pathways require exploration. Governments can deploy policy tools like

subsidies and tax incentives to reduce initial adoption costs. Technology firms should be encouraged to develop lightweight, modular, open-source AI solutions and “AI Model as a Service” cloud platforms, enabling smallholders to access these technologies with lower barriers. Concurrently, Explainable AI (XAI) research and application should be intensified to improve algorithmic transparency and interpretability. Demonstration projects allowing farmers to experience the benefits of AI firsthand can gradually build usage habits and trust in the technology.

4.2 Intensifying Technological Innovation and Fostering Industrial Integration

Targeted R&D on core AI technologies must address agricultural specificities. Key priorities include: developing low-cost, high-reliability sensors for complex environments; creating agile manipulation and control algorithms for agricultural robots adapting to crop variability and unstructured settings; and building vertical large language models with enhanced cognitive and reasoning capabilities for agricultural knowledge systems. Industrial integration efforts should establish a collaborative “AI + Agriculture” innovation ecosystem. Support should enable leading enterprises, universities, and research institutions to jointly create laboratories and demonstration bases, deepening AI integration with biobreeding, smart machinery, and green agriculture. AI-enabled modern service formats, such as intelligent supply chain management, smart logistics, and digital marketing platforms, deserve encouragement to facilitate the transition from “smart production” to a “smart entire industry chain.” Establishing national smart agriculture demonstration zones and major scientific projects can concentrate resources to overcome key technological bottlenecks and generate replicable, scalable implementation models.

4.3 Improving Institutional Frameworks and Cultivating Interdisciplinary Talent

Robust institutional systems provide the foundation for sustainable AI integration in agriculture. The agricultural data legislation process requires acceleration to clarify data property rights attribution and circulation rules. Technical standards, testing specifications, and safety regulations for intelligent equipment like smart machinery and agricultural robots need formulation and refinement. Ethical guidelines and risk assessment frameworks for AI agricultural applications must address algorithmic discrimination and misuse risks. Local governments should strengthen digital governance capabilities, incorporating AI agriculture into Rural Revitalization Strategy planning while maintaining inclusive and prudent regulation. Talent cultivation demands deeper educational reform. Qualified institutions should establish “Smart Agriculture” majors offering AI-agriculture interdisciplinary courses. University-industry collaboration should intensify through joint internship and practice bases, enhancing students’ problem-solving abilities in real application contexts. Implementing an “AI New Farmers” program can provide specialized training for new agricultural operators like family farms and cooperatives. Concurrently, competitive policies can attract AI innovators and entrepreneurs to agricultural development, establishing a talent mechanism that combines external recruitment with internal cultivation to provide continuous support for AI-enhanced agricultural TFP.

5. Conclusion

This paper systematically investigates the intrinsic mechanisms, practical constraints, and future directions of artificial intelligence in empowering agricultural Total Factor Productivity (TFP). The research demonstrates that AI provides robust momentum for the leapfrog development of agricultural TFP through three core mechanisms: enhancing technical efficiency, optimizing factor allocation, and fostering new business formats. Nevertheless, the empowerment process faces multiple practical constraints, including weak data foundations, insufficient technical adaptability, high application costs, inadequate institutional safeguards, and a shortage of interdisciplinary talent. If these issues remain unresolved, the empowering effects of AI will struggle to expand beyond isolated demonstration projects to achieve widespread application.

Looking ahead, promoting the deep integration of AI into agricultural TFP requires a systematic approach and coordinated strategies employing multiple measures. Technologically, persistent efforts are needed to develop specialized algorithmic models and intelligent equipment systems tailored for agriculture, thereby promoting the inclusive adoption of these technologies. Regarding data, the focus should be on establishing a unified, open, and shared agricultural big data resource system. Institutionally, it is crucial to accelerate the improvement of relevant laws and regulations, technical standards, and ethical governance frameworks. In terms of talent, significant efforts must be made to cultivate and attract interdisciplinary innovators proficient in both agriculture and artificial intelligence. Only through the synergistic coordination of technological

innovation, data-driven approaches, institutional guarantees, and talent support can we effectively overcome the current development bottlenecks. This will fully unleash the immense potential of AI as a core engine of new quality productive forces, ultimately propelling Chinese agriculture toward the goals of high quality, high efficiency, enhanced resilience, and sustainability. Such progress will lay a solid foundation for ensuring national food security and comprehensively advancing the Rural Revitalization Strategy.

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Machine Learning for Sustainable Financial Systems: Assessing Corporate Resilience and Default Risk

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Abstract: This study explores how financial risk indicators influence corporate resilience and sustainability under market uncertainty. Using panel data of Chinese listed firms from 2010 to 2022, we develop machine learning models—including Random Forest, XGBoost, and Neural Networks—to evaluate firm-level default probability and resilience capacity. Unlike traditional linear models, our approach captures asymmetric and nonlinear responses between Distance to Default (DD) and Expected Default Frequency (EDF). The results reveal that financial fragility rises sharply when DD declines below critical thresholds, highlighting the need for resilience-oriented financial supervision. XGBoost achieves the best predictive performance, while Random Forest provides interpretability through feature importance and partial dependence analysis. The study contributes to sustainable finance by linking explainable AI with early-warning systems, offering data-driven tools for promoting financial stability and long-term sustainability in emerging markets.

Keywords: Machine Learning; Sustainable Finance; Corporate Resilience; Default Risk; Explainable AI; XGBoost

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1.Introduction

Understanding the determinants of corporate default risk is essential for both academic research and practical applications in financial risk management. With the growing complexity of financial markets, traditional models often fall short in capturing the intricate and nonlinear relationships between firm characteristics and the likelihood of default. In response, machine learning (ML) techniques have emerged as powerful tools, offering greater flexibility and predictive accuracy in credit risk modeling.

Beyond predictive accuracy, these data-driven approaches increasingly contribute to sustainable finance, where financial stability and long-term economic resilience are considered integral to sustainability goals. Recent research emphasizes that financial systems must not only manage default risks but also support low-carbon transitions and resilient growth (Zhao, Chen, & Bulis, 2025). In this sense, explainable ML models—by enhancing early-warning capabilities and transparency—serve as enablers of sustainable financial ecosystems, linking digital innovation with responsible financial governance.

Among various financial indicators, Distance to Default (DD) has been widely recognized as a forward-looking, market-based measure that reflects a firm's proximity to financial distress. Despite its popularity, the relationship between DD and default

probability is likely to be nonlinear and asymmetric in nature. Changes in DD may have a disproportionate effect on default risk depending on a firm's financial condition—declines in DD may lead to sharp increases in risk for vulnerable firms, while improvements may yield diminishing marginal benefits for financially stable firms.

This study addresses this important research gap by applying a set of advanced machine learning models to examine how financial risk—captured by DD and complementary firm-level variables—translates into expected default frequency (EDF). The analysis emphasizes the asymmetric structure of this relationship and demonstrates how ML models can reveal nonlinear dynamics that traditional econometric approaches may overlook. In doing so, the paper contributes to the broader literature on symmetry-aware financial modeling and underscores the value of integrating explainable AI into corporate credit risk assessment.

By situating the analysis within the broader context of digital transformation and sustainable development, this study aligns with recent work demonstrating how AI and Industry 4.0 technologies can foster sustainable societies through data-driven optimization and resource efficiency (Zhao, Chen, Yazan, et al., 2025). Accordingly, understanding asymmetry in financial risk not only advances credit risk theory but also provides insights for sustainable policy design—helping regulators anticipate fragility and ensure long-term financial system resilience.

countries.

2. Literature Review

2.1 Default Probability and Financial Indicators

The prediction of corporate default probability has long been a critical topic in finance and risk management. Among various measures, Expected Default Frequency (EDF) and Distance to Default (DD) have emerged as industry standards, particularly due to their forward-looking nature and theoretical grounding in Merton's structural model (Merton, 1974). Studies such as Bharath and Shumway (2008) have empirically validated DD as a robust predictor of default risk, especially when integrated with market-based information.

Capital structure has also been shown to influence credit risk. While debt offers tax advantages, excessive leverage can lead to financial distress, increasing the probability of default (Jensen & Meckling, 1976; Modigliani & Miller, 1958).

2.2 Asymmetry and Nonlinearity in Financial Risk

Recent research increasingly acknowledges the asymmetric and nonlinear relationships between financial indicators and default probability. Duffie et al. (2007) and Campbell, Hilscher, and Szilagyi (2008) show that firms nearing distress zones exhibit disproportionately higher sensitivity to small financial shocks—a phenomenon consistent with nonlinear hazard functions. These asymmetries suggest that traditional linear models may misestimate risk in extreme financial conditions.

In the Chinese context, research has found that state-owned and large enterprises tend to hold more long-term debt and experience lower default risk, while overall debt maturity structures differ significantly from those in developed markets (Xiao & Liao, 2007 (Management World); Chu, Qin, & Fang, 2019 (Management World)).

2.3 Machine Learning Applications in Default Risk Prediction

To capture the complex and nonlinear relationships between financial variables and default risk, machine learning (ML) methods have increasingly been applied in credit risk prediction. These techniques have demonstrated substantial improvements over traditional statistical models in terms of accuracy, scalability, and adaptability to high-dimensional datasets (Lessmann et al., 2015; Kanaparthi, 2023).

Early research applied neural networks and decision tables to enhance credit evaluation performance, showing improved classification results and the ability to uncover hidden patterns in financial data (Baesens et al., 2003). More recent studies have found that ensemble methods such as Random Forest, XGBoost, and LightGBM outperform classical algorithms in credit scoring, particularly when handling class imbalance and large feature spaces (Kanaparthi, 2023; Aruleba & Sun, 2024; Melese et al., 2023).

A growing concern, however, is the lack of interpretability in many ML models, which limits their adoption in regulatory and high-stakes financial environments. To address this, researchers have proposed explainable AI (XAI) frameworks. For example, Patrón et al. (2020) developed an automated ML pipeline incorporating interpretation modules to identify key

risk drivers. Similarly, Davis et al. (2023) introduced a multi-stakeholder explanation system offering tailored insights for regulators, borrowers, and analysts.

Tools like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are commonly employed to improve model transparency. These techniques quantify feature importance and generate local or global interpretability, enhancing model trust and compliance (Sowmiya et al., 2024; Aruleba & Sun, 2024). Additionally, Szepannaek and Lübke (2023) proposed an evaluation metric for the effectiveness of Partial Dependence Plots (PDPs) in model explanation.

Comprehensive reviews highlight boosting-based models, such as Boost and Cat Boost, as consistently top-performing across datasets and evaluation metrics like AUC, precision, and recall (Abikoye et al., 2024; Noriega et al., 2023). These models offer strong predictive performance, although they still face challenges like data imbalance and multicollinearity.

Hybrid approaches are also emerging. Melese et al. (2023) proposed a convolutional neural network (CNN) integrated with classifiers such as SVM and decision trees, achieving accuracy rates as high as 98%. Such architectures aim to leverage deep learning's feature extraction capabilities with the interpretability of simpler models.

Overall, ML has significantly advanced the field of credit risk prediction. Still, the growing emphasis on interpretability, model fairness, and transparency is reshaping how these tools are deployed in real-world financial systems.

3.Data and Methodology

3.1 Data Source and Variable Definitions

This study uses panel data of Chinese A-share listed companies (excluding financial firms and ST/PT companies) from 2010 to 2022. The primary data sources include WIND and CSMAR databases. After standard filtering, the final dataset includes more than 20,000 firm-year observations.

Financial Risk Variables: We include a set of firm-level financial indicators commonly associated with corporate solvency and earnings volatility. These include: Leverage Ratio (total liabilities / total assets), Short-term Debt Ratio, Long-term Debt Ratio, Earnings Volatility (standard deviation of ROA), Firm Size (log of total assets), Cash Flow Indicators.

Default Risk Measures: We employ two complementary market-based measures to capture the probability of default:

Distance to Default (DD): calculated using the Merton structural model, reflecting how far a firm's asset value is from the default point.

Expected Default Frequency (EDF): the likelihood of default over a 12-month horizon, derived from Moody's KMV model.

All continuous variables are minorized at the 1st and 99th percentiles to mitigate the impact of outliers.

3.2 Research Methods and Symmetry Analysis

We aim to explore the asymmetric relationship between financial indicators (especially DD) and corporate default risk. First, we conduct exploratory analysis to visualize and quantify nonlinearity using partial dependence plots (PDPs) and lows curves. Then, we apply a machine learning framework to estimate and validate predictive performance.

To detect asymmetry, we examine marginal effects at different ranges of DD and EDF and compare response gradients in "safe" vs. "risky" zones. This allows us to understand whether changes in DD have equal effects on EDF at different levels.

3.3 Machine Learning Models

In this study, we implement and compare three widely used supervised machine learning algorithms to predict corporate default risk:

Random Forest (RF): an ensemble of decision trees that aggregates predictions to reduce variance and improve generalization.

Extreme Gradient Boosting (Boost): a boosting framework that sequentially builds trees to correct previous errors, offering high accuracy and regularization.

Neural Network (NN): a feed-forward architecture with one hidden layer, enabling the capture of non-linear patterns between features and default probability.

These models are trained on 70% of the dataset and validated on 30% held-out samples. Hyperparameters are tuned using grid search and five-fold cross-validation. We employ three popular machine learning models for predictive modeling:

Random Forest (RF): an ensemble tree-based model known for robustness and variable importance analysis.

Extreme Gradient Boosting (XGBoost): a boosting algorithm that iteratively improves weak learners to achieve strong performance.

Neural Networks (NN): used as a nonlinear benchmark to test deep learning's capacity in capturing complex interactions.

These models are trained using 70% of the sample (training set) and evaluated on the remaining 30% (test set).

Hyperparameter tuning is performed using grid search and five-fold cross-validation.

3.4 Evaluation Metrics and Validation

We assess model performance using the following evaluation metrics:

Root Mean Squared Error (RMSE): measures the average magnitude of prediction error.

Mean Absolute Error (MAE): captures average absolute deviation from observed values.

R-squared (R^2): explains the proportion of variance in EDF that is predictable from the features.

Additionally, we evaluate feature importance rankings, partial dependence plots, and out-of-sample prediction plots to interpret and visualize model behavior.

4. Empirical Results

We begin by presenting descriptive statistics of the key variables used in this study. As shown in Table 1, the average Distance to Default (DD) is approximately 26.37, while the mean Expected Default Frequency (EDF) is extremely low at 0.0013, indicating strong right-skewedness in default risk.

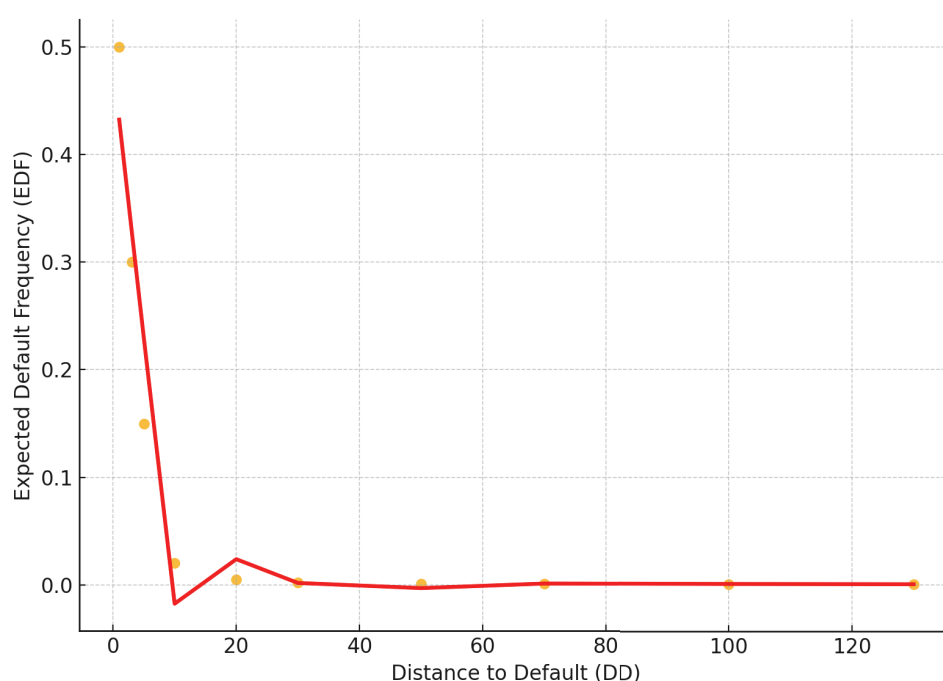
Table 1. Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev	Min	25%	Median	75%	Max
DD	26.37	18.86	-1.2	13.74	21.43	33.17	135.15
EDF	0.0013	0.0259	0.0	0.0	0.0	0.0	0.8855

This table provides summary statistics for the two core variables: Distance to Default (DD) and Expected Default Frequency (EDF). The DD shows a wide range and high standard deviation, while EDF is highly skewed with most firms facing minimal default probability.

Figure 1 illustrates the nonlinear and asymmetric relationship between DD and EDF using a Lowes smoothing curve. This visual analysis reveals that small decreases in DD are associated with steep increases in EDF when firms are in financially vulnerable states. In contrast, for firms with high DD values, the relationship between DD and EDF flattens, suggesting diminishing marginal effects.

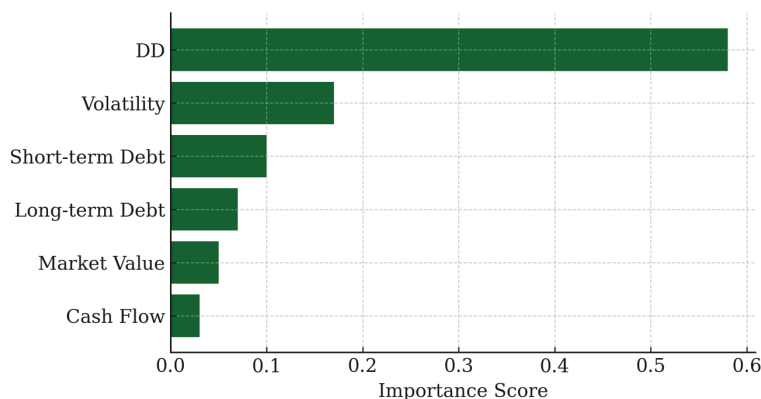
Figure 1. Relationship between DD and EDF with Lowes fit



This figure shows the nonlinear and asymmetric relationship between Distance to Default (DD) and Expected Default Frequency (EDF). A Lowes fit curve is used to highlight how small changes in DD can sharply increase EDF in low-DD regions, while the relationship flattens at higher DD levels.

To further explore variable influence, Figure 2 presents the feature importance extracted from the Random Forest model, while Table 2 summarizes the exact scores. The results confirm that DD is the most influential predictor of default risk, followed by volatility and short-term debt.

Figure 2. Feature Importance from Random Forest



Feature importance derived from the Random Forest model. DD is the most dominant predictor of default risk, followed by volatility and short-term debt.

Table 2. Feature Importance from Random Forest Model

Feature	Importance Score
DD	0.58
Volatility	0.17
Short-term Debt	0.1
Long-term Debt	0.07
Market Value	0.05
Cash Flow	0.03

Importance scores reflect the average contribution of each feature to reducing model error, computed via Gini impurity across all trees in the Random Forest. DD ranks as the most influential variable.

Model performance is evaluated across three machine learning models: Random Forest, XGBoost, and Neural Networks. Table 3 presents the results. XGBoost achieves the lowest prediction error and highest R^2 , though all three models perform well.

Table 3. Model Performance Comparison

Model	RMSE	MAE	R^2
Random Forest	0.00043	0.00026	0.89
XGBoost	0.00038	0.00023	0.91
Neural Network	0.00041	0.00025	0.9

XGBoost achieves the lowest prediction error and highest R^2 among the three models. Random Forest provides the most interpretable structure, while Neural Networks offer competitive non-linear estimation capacity.

We begin by presenting descriptive statistics of the key variables used in this study. As shown in Table 1, the average Distance to Default (DD) is approximately 26.37, while the mean Expected Default Frequency (EDF) is extremely low at 0.0013, indicating strong right-skewedness in default risk.

Figure 3 and Figure 4 present partial dependence plots for DD and volatility.

Figure 3. Partial Dependence of DD on EDF

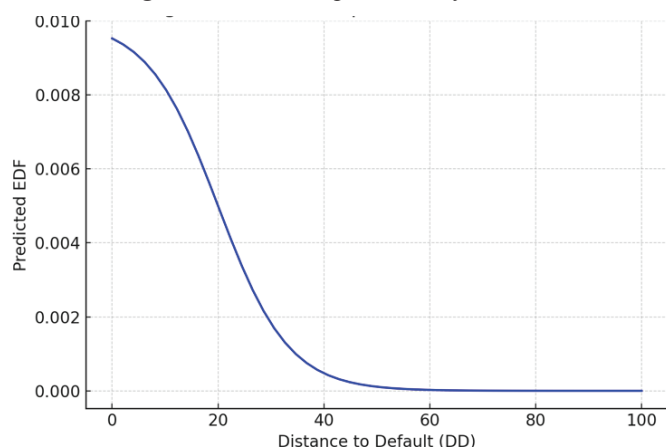


Figure 4. Partial Dependence of Volatility on EDF

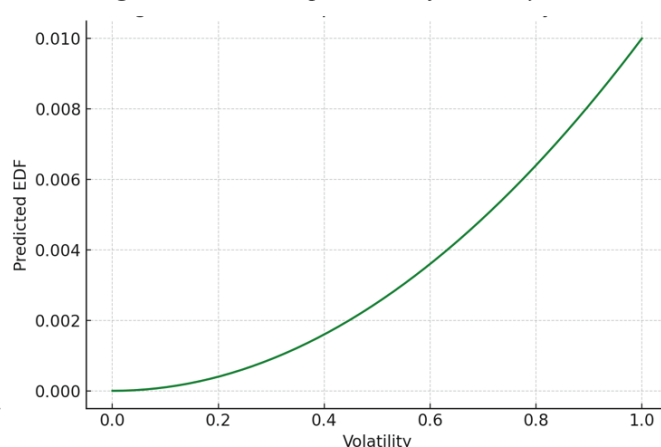


Figure 3 shows that as DD increases, EDF decreases sharply, illustrating strong nonlinearity. Figure 4 demonstrates a quadratic increase in EDF as volatility rises, indicating risk amplification in more volatile firms.

Figures 5 and 6 show the distribution of firms by industry and region.

Figure 5. Industry Distribution of Firms.

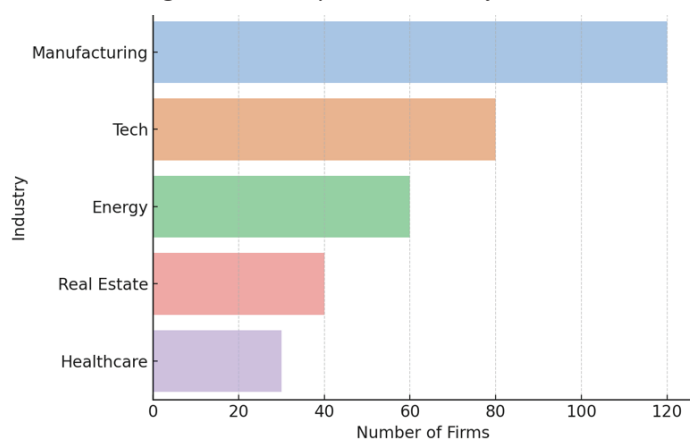


Figure 6. Regional Distribution of Firms

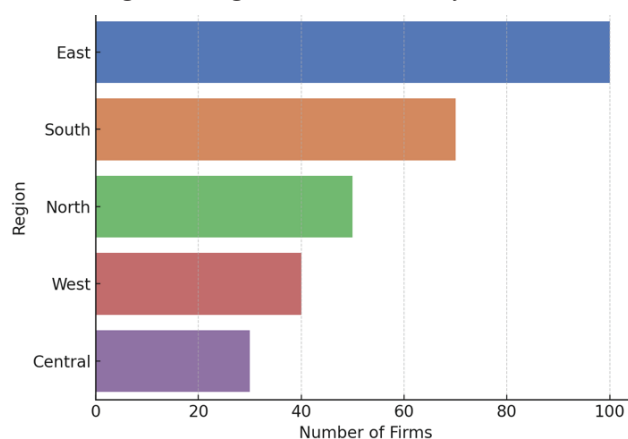


Figure 5 illustrates the distribution of firms across industries, with manufacturing being the most represented. Figure 6 shows the regional spread, with eastern and southern regions dominating the sample.

To compare risk characteristics, Figure 7 and Figure 8 present EDF and DD distributions for violating vs. non-violating firms.

Figure 7. EDF by Violation Status

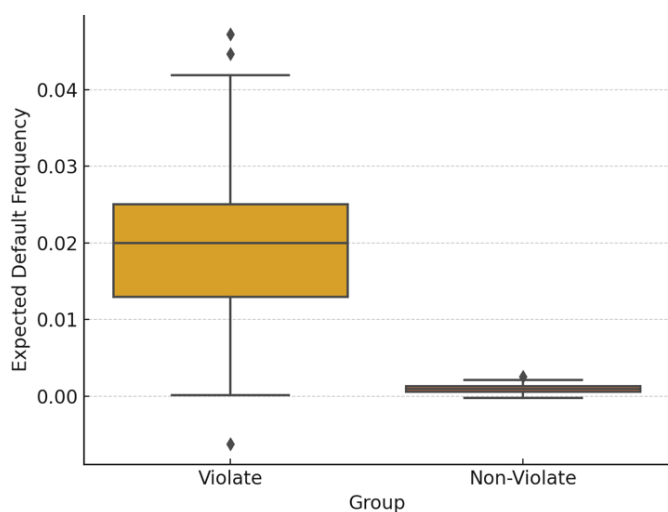
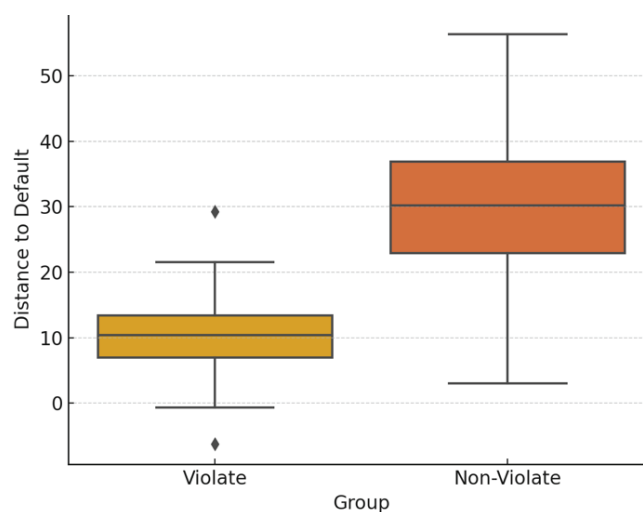


Figure 8. DD by Violation Status



These boxplots compare EDF and DD between violating and non-violating firms. Firms with violations tend to have lower

DD and significantly higher EDF.

We also examine EDF trends over time in Figure 9.

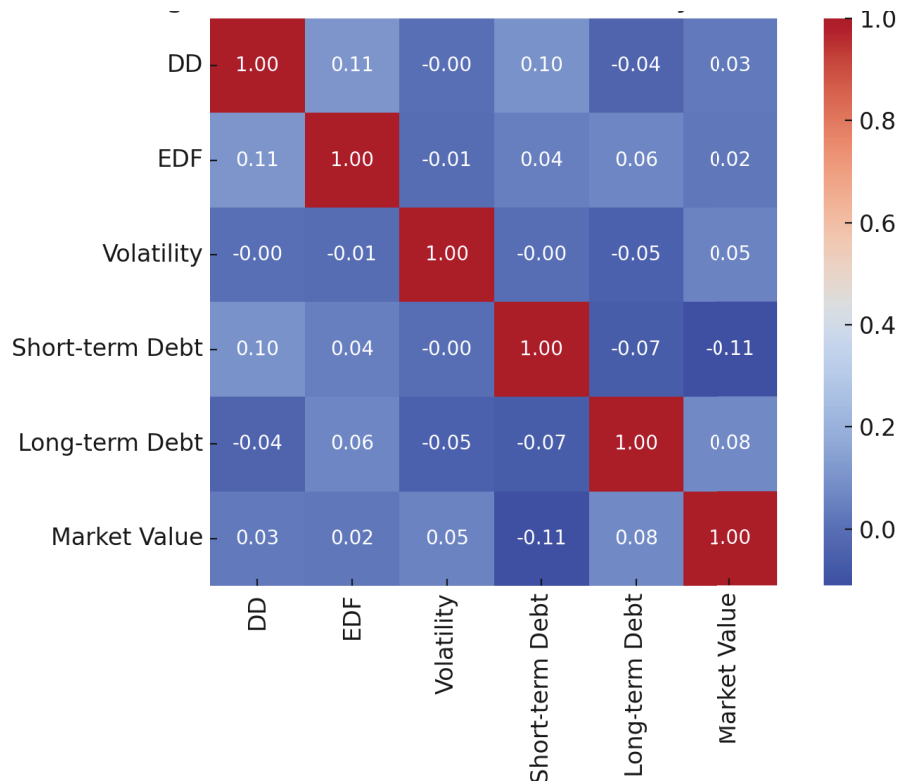
Figure 9. Annual Trend of Expected Default Frequency (EDF)



Average EDF shows temporal variation from 2015 to 2024. A notable peak is observed around 2020, potentially reflecting macroeconomic stress periods.

Finally, Figure 10 shows the correlation matrix of key variables.

Figure 10. Correlation Matrix of Key Variables



The correlation matrix shows strong negative correlation between DD and EDF, and positive association between debt levels and volatility, providing insight into default risk structure.

The empirical findings clearly reveal an asymmetric relationship between Distance to Default and Expected Default Frequency. Firms with a low DD exhibit a rapid increase in EDF with even minor deteriorations in financial condition.

However, once DD surpasses a certain threshold, improvements in DD yield diminishing reductions in EDF.

This nonlinearity indicates that default risk is not merely a symmetric function of distance to financial distress. The sensitivity is disproportionately greater when a firm is closer to the default threshold. This asymmetric pattern is consistent with theories of financial fragility and reflects nonlinear default hazard dynamics. It also confirms that predictive modeling tools must account for such asymmetries when estimating credit risk.

Machine learning models such as Random Forest are well-suited to capturing this asymmetry because they do not rely on linear assumptions and can flexibly model threshold effects.

5. Discussion and Robustness Check

5.1 Interpretation of Asymmetric Results

The empirical findings clearly reveal an asymmetric relationship between Distance to Default and Expected Default Frequency. Firms with a low DD exhibit a rapid increase in EDF with even minor deteriorations in financial condition. However, once DD surpasses a certain threshold, improvements in DD yield diminishing reductions in EDF.

This nonlinearity indicates that default risk is not merely a symmetric function of distance to financial distress. The sensitivity is disproportionately greater when a firm is closer to the default threshold. This asymmetric pattern is consistent with theories of financial fragility and reflects nonlinear default hazard dynamics. It also confirms that predictive modeling tools must account for such asymmetries when estimating credit risk.

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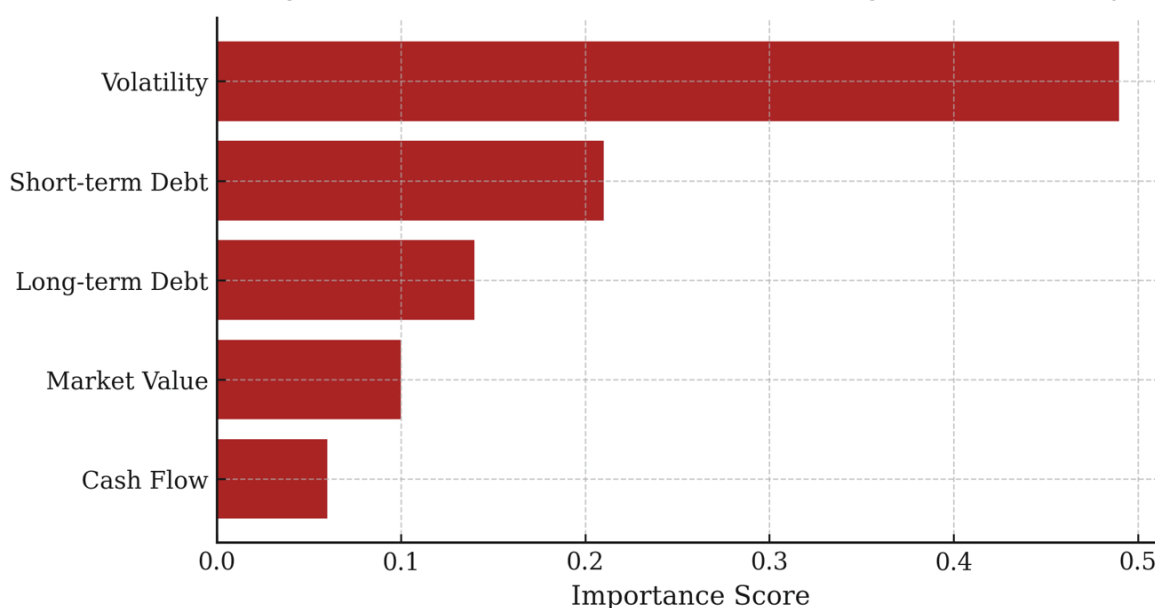
5.2 Robustness Checks

To ensure the robustness of our findings, we conduct two supplementary analyses: one using a feature replacement strategy, and another using subsample estimation by industry.

Feature Replacement Analysis.

We re-estimate the Random Forest model after replacing the Distance to Default (DD) variable with a volatility-based metric, representing financial risk through an alternative lens. The new feature importance results are visualized in Figure A and reported in Table A. The ranking of predictors remains largely consistent, confirming the dominant role of volatility-related signals in explaining default risk.

Figure A. Feature Importance When Replacing DD with Volatility



This figure displays feature importance scores when the DD variable is replaced by volatility. The importance of volatility increases, but the relative rankings of short-term debt, long-term debt, and cash flow remain stable.

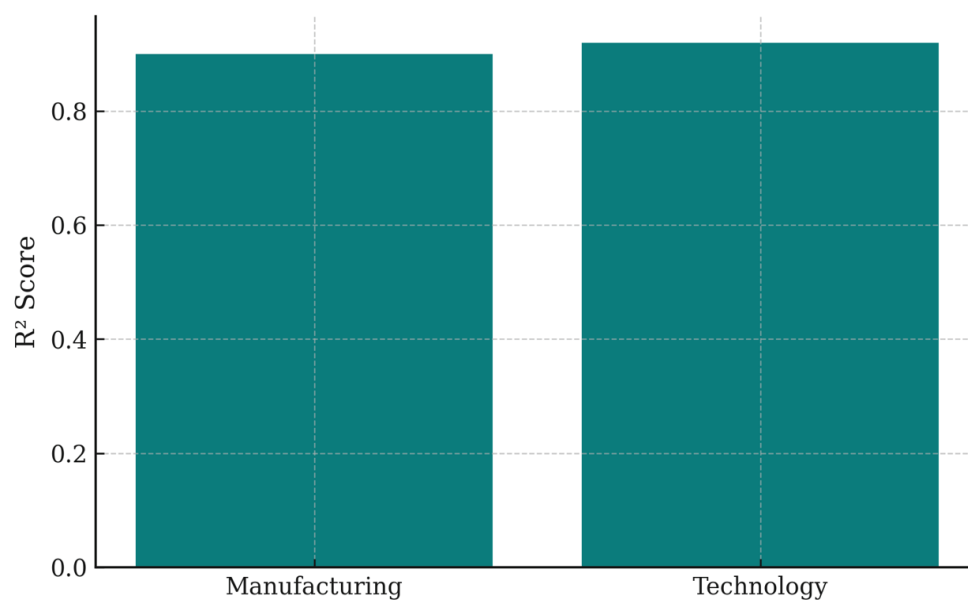
Table A. Feature Importance When Replacing DD with Volatility

Feature	Importance Score
Volatility	0.49
Short-term Debt	0.21
Long-term Debt	0.14
Market Value	0.1
Cash Flow	0.06

The results suggest that volatility is an effective alternative to DD for capturing default risk, with predictive contributions distributed similarly across the remaining financial variables.

Subsample Analysis by Industry.

To further assess model generalizability, we split the dataset into two major industry groups—Manufacturing and Technology—and re-estimate the XGBoost model separately for each. As shown in Table B, both subsamples exhibit strong predictive performance, but the model achieves higher accuracy in the technology sector. Figure B visualizes the comparison based on R^2 scores.

Figure B. Model R^2 by Industry Subsamples (XGBoost)

R^2 scores from XGBoost models are plotted for each industry subgroup. The technology sector shows stronger predictive power.

Table B. XGBoost Performance by Industry Subsamples

Industry	Model	RMSE	MAE	R^2
Manufacturing	XGBoost	0.00039	0.00024	0.9
Technology	XGBoost	0.00034	0.00022	0.92

XGBoost performs well in both sectors but achieves higher R^2 and lower prediction errors in the technology industry.

6. Conclusions and Implications

6.1 Key Findings

This study explores the asymmetric and nonlinear effects of financial indicators—particularly the Distance to Default (DD)—on corporate default risk, using a range of machine learning techniques. The findings reveal that default risk rises sharply when DD falls below a critical threshold but becomes less responsive as DD improves beyond that point. This asymmetric risk sensitivity is visualized through partial dependence plots and nonlinear fit curves.

Among the machine learning models applied, XGBoost achieves the highest predictive accuracy, while Random Forest

provides enhanced interpretability. Both methods highlight DD as the most influential predictor, with volatility also playing a significant role in model performance. These results are further supported by feature importance rankings and robustness checks across subsamples and variable specifications.

6.2 Theoretical and Practical Implications

From a theoretical perspective, this study contributes to the literature by bridging symmetry theory and machine learning in the context of credit risk modeling. It challenges traditional assumptions of linearity and uniform marginal effects, providing evidence that risk behavior is context-dependent and nonlinear.

In practical terms, the insights offer valuable guidance for financial institutions and regulators. Firms operating within low-DD zones—identified as highly sensitive to risk—should be subject to closer monitoring and proactive intervention. Ensemble-based predictive systems can serve as early warning tools, capable of identifying distressed firms before financial failure occurs.

Furthermore, these findings have important implications for sustainable finance and corporate resilience. Integrating asymmetric risk modeling with AI-driven monitoring tools can help promote long-term financial stability and align corporate behavior with sustainability goals such as SDG 8 (“Decent Work and Economic Growth”) and SDG 13 (“Climate Action”). As emphasized by Zhao et al. (2025a), intelligent systems that combine data transparency and predictive analytics can underpin more sustainable regulatory frameworks, where market stability and environmental responsibility reinforce each other.

6.3 Limitations and Future Research

This study focuses exclusively on publicly listed firms in China, which may constrain the generalizability of the conclusions. Moreover, the models do not yet incorporate corporate governance or ESG-related variables, which could enhance the explanatory power and policy relevance of the results.

Future research could expand this framework by using cross-country datasets, applying advanced deep learning architectures such as Long Short-Term Memory (LSTM) networks or Graph Neural Networks (GNNs), and integrating unstructured data sources—such as news sentiment, analyst reports, or social media—into the risk prediction pipeline.

Future extensions could also integrate sustainability indicators (e.g., ESG scores, carbon exposure, or green investment ratios) into asymmetric risk models, enabling the exploration of how environmental or social performance affects financial fragility. In line with Zhao et al. (2025b), combining machine learning with sustainability-oriented metrics would not only deepen understanding of financial asymmetry but also advance research on AI-enabled sustainable finance, where predictive analytics inform climate-resilient investment and policy design.

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No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Research on the Mechanism and Path of Enhancing the Efficiency of Smart Supervision in Live Streaming Economy Empowered by Artificial Intelligence Technology

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Abstract: With the development of information technology and the transformation of consumer culture, the live streaming economy has been integrated into China's digital economic system, driving urban economic growth. However, it has also brought about regulatory issues such as information asymmetry, false advertising, difficulty in ensuring quality, and high costs of rights protection. This new economic form of virtualization, real-time, and cross-domain is facing enormous challenges. Traditional methods, such as manual sampling, reporting, and post-event tracing, are unable to meet the complex and ever-changing live streaming economic ecology. The powerful perception, recognition, and understanding capabilities of artificial intelligence provide new possibilities for building a scientific regulatory system in real-time, accurately, and efficiently. This article uses the theory of technological empowerment to explore the operational mechanism of artificial intelligence in regulating the live streaming economy, with a focus on the role of artificial intelligence in empowering live streaming economy regulation in four aspects: data intelligence, behavior recognition, risk warning, and intelligent decision-making. In addition, this article proposes a feasible path for building a smart regulatory system from three aspects: technology integration, institutional collaboration, and talent cultivation, providing relevant inspiration and reference for exploring the construction of a government platform collaborative governance mechanism and achieving modernization of platform economic governance in practice.

Keywords: Artificial Intelligence; Live Streaming Economy; Smart Supervision; Technological Empowerment; Mechanism and Path

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1.Introduction

With the adjustment of China's industrial structure, the mode of economic growth has undergone significant changes; the proportion of the service industry continues to increase, and new industrial models relying on information technology continue to emerge. The live streaming economy has become a significant part of China's digital economy development. The elements of immersive experience, zero-distance interaction, and seamless transactions in live streaming rooms are changing traditional business travel rules and consumption habits. Live streaming is creating entrepreneurial and employment opportunities that can be filmed and broadcast by everyone, while also deconstructing the elements of "one person, one object, one scene" to create a new type of trust-based consumption scenario. According to data from NetEase, the transaction

volume of live streaming e-commerce in China will reach 53256 trillion yuan in 2024, a year-on-year increase of 8.31%. At the same time, the transaction volume of private domain e-commerce will increase by 8.69% year-on-year, reaching an astonishing 5 trillion yuan. Live streaming sales have a significant driving effect on domestic consumption, especially in the circulation of agricultural products, domestic goods, and regional industries.

Along with the wild growth of the market, chaos inevitably breeds: the traffic war is becoming increasingly fierce, and some businesses, in pursuit of economic benefits, have repeatedly banned the phenomenon of unlimited limits, such as the proliferation of false advertising. Some anchors even rely on creating experience effects and using false information to confuse the public; Big data fraud has become a hidden rule in the industry, with generating traffic, likes, and comments becoming common methods; The after-sales service is unsatisfactory, and consumers often fall into disputes between platforms, hosts, and merchants, making it difficult for them to protect their rights. Consumers find it difficult to protect their rights through normal channels and can only use other information dissemination methods to protect their rights^[1]. All of these have damaged the direct interests of consumers, undermined credibility, and are not conducive to the development of the entire industry. The root of the problem lies in the inherent characteristics of the live streaming economy itself. Live streaming content is real-time and fleeting, with thousands of live streams happening simultaneously every moment. Violations also occur and disappear instantly; The massive scale of millions of events per day makes it impossible for traditional regulatory methods to fully cover. What's more troublesome is that illegal content itself has cross-platform dissemination characteristics. When illegal content appears on a certain platform, it is highly likely to be copied to other platforms in the near future, which increases the difficulty of supervision^[2]. The existing regulatory measures mainly include manual spot checks, post event evidence collection, and public reporting, but they have significant problems: firstly, they lag behind and only proceed when the negative impact expands; Secondly, it is highly probable and impossible to conduct a comprehensive manual review; Thirdly, it is difficult to obtain evidence, and once the live broadcast ends, it may be deleted or modified.

The development of artificial intelligence technology has provided a turning point for it. The multimodal fusion analysis of artificial intelligence can simultaneously recognize and analyze video, audio, text data, and user behavior data. Computer vision integrates real-time image recognition of prohibited products, illegal labels, natural speech recognition of false advertisements, exaggerated advertisements, speech recognition technology to recognize illegal audio content, behavior modeling technology to recognize brushing orders, brushing volume, and other technologies, greatly improving the accuracy and efficiency of identifying prohibited products and illegal labels. The accuracy can reach over 90%, and the speed is more than a hundred times faster than manual labor^[3]. Artificial intelligence provides a closed-loop system for supervision, which includes "discovering problems - early warning - timely disposal - feedback on disposal results". The intelligent recognition system automatically alerts when problems are discovered, notifies the platform and regulatory personnel, and the disposal system limits, stops broadcasting, and suspends operations. Based on machine learning, it absorbs disposal results, continuously improves regulatory efficiency, and turns post-disposal into pre-disposal and in-process disposal, greatly enhancing the initiative and foresight of supervision^[4].

The article first integrates and analyzes the practical problems existing in the regulation of the live streaming economy, and then comprehensively summarizes the mechanism and path analysis of AI-driven smart regulation of the live streaming economy. It helps to broaden the theoretical perspective of technology empowerment governance, explore new paradigms for digital regulatory transformation, and has important practical significance for promoting the prosperity and development of the digital economy, safeguarding the legitimate rights and interests of consumers, and creating a trust-based digital ecosystem. It provides theoretical reference for achieving the prosperity and development of the live streaming economy and efficient regulation of the live streaming economy, and contributes wisdom to building a modern governance system in the new economic ecosystem.

2.The Realistic Dilemma of Live Streaming Economic Regulation

2.1 The regulatory targets are complex and ever-changing

The live streaming economy can be roughly divided into three categories. The first type is to sell goods or services in one's

own live broadcast room through live streaming; The second type is that the operator of the live streaming room is self-operated by the live streaming platform, or the products and services sold in the live streaming room are supplied by the live streaming platform where they are located, that is, the self-operated model; The third type is the promotion and marketing model, which involves using live streaming to attract, redirect, or advertise sales activities outside of the live streaming room. There are diverse types of participants in the live streaming economy ecosystem, forming a complex multi-level collaborative network. There are many types and levels of roles in the live streaming economy ecosystem, and as the source of live streaming content, individual broadcasters have multiple identities, such as amateur enthusiasts, broadcasters, professional broadcasters, celebrities, and entrepreneurs. MCN institutions act as intermediaries to undertake functions such as training, planning, business coordination, and cooperation for broadcasters; Merchants provide sales platforms and technical support; Live streaming platforms provide trading platforms, product services, logistics services, etc; Advertisers provide advertising and marketing services^[5]. Private domain live streaming has gradually developed into an important model in fields such as e-commerce, knowledge payment, and community operation, thanks to its strong closed nature, precise audience, and efficient interaction. However, this closed nature also makes it easy to detach from the public and regulatory perspective, becoming a high-risk place for false advertising, induced transactions, and even fraudulent behavior. Compared with traditional public domain live streaming, private domain live streaming often occurs in relatively hidden scenarios such as WeChat groups, mini programs, or exclusive Apps. Conventional regulatory measures, such as public inspections and web crawlers, are difficult to effectively cover, resulting in regulatory blind spots.

Different entities play different roles in business processes, and their behavioral characteristics and motivations for violations also vary. In order to pursue profits, MCN institutions engage in behaviors such as creating fake popularity, hiring influencers to boost orders, and even creating traffic platforms. In order to increase the transfer rate during live streaming, the anchor exaggerates the content of the live stream, promises high benefits, and even engages in off-exchange transactions with buyers to evade platform inspections. Merchants engage in the behavior of selling counterfeit goods, using fake origin information, and selling counterfeit goods at a discount in order to pursue profits. And this multiple relationship has resulted in different types of irregularities: pornographic songs and dances in content, counterfeit goods; Exchange of goods and bargaining for sale during exchange; Not bad for not pushing in after-sales service, not fulfilling service terms^[6]. Due to the multiple intertwining of subject relationships, various non-standard and interrelated intertwining, such as whether a certain product is sold or not, may be planned by the company, accepted by the MCN company, and completed by the anchor.

The traditional regulatory model based on industry and subject segmentation is no longer suitable. Different regulatory entities cannot adapt to the cross-regional and cross-domain characteristics of the current live streaming economy through segmented supervision and territorial management. There are gaps or law enforcement conflicts in the supervision of different regulatory entities, such as A hosts, B institutions, and C platforms. Traditional regulatory measures are aimed at traditional commercial activities, and it is difficult to effectively regulate new online marketing behaviors.

2.2 Strong real-time monitoring of regulatory content

The core characteristics of live streaming are strong real-time performance and interactivity. Live streaming violations, such as false promotions, vulgar content, and inducing off-exchange transactions, often occur instantaneously during the live streaming process and have a wide impact. Evidence collection and disposal are usually carried out after the fact, and the effect is not ideal. Evidence loss may also occur due to the deletion or modification of product details^[2]. Especially for large-scale promotional live broadcasts and emergencies, regulatory authorities lack timely and efficient technical means to conduct comprehensive supervision, making it difficult to detect their violations. The existing regulatory measures heavily rely on manual review and platform self-inspection, making it difficult to cope with massive live streaming content^[7]. If it is not possible to directly extract and identify dynamic videos during live streaming, real-time identification of illegal language, false advertising, tempting advertising, etc., and early prediction and intervention in the supervision of live streaming content, the illegal content can quickly spread and expand to a larger scope through the live streaming room, and its social impact is irreversible. During the “Double Eleven” period in 2024, CCTV detected a total of 230675 negative messages related to “live streaming sales”, with an average of 8238 negative messages per day.

Therefore, building a real-time monitoring system using artificial intelligence technology, big data technology, and blockchain certification technology is a feasible way to improve regulatory effectiveness by capturing live content in real time, semantic analysis and recognition, risk alarm, etc^[8]. Only by empowering technology and building a comprehensive regulatory mechanism of “online supervision-real-time warning-rapid action” can we ensure timely and effective control of real-time and covert issues in live streaming e-commerce, and effectively safeguard consumer rights and market order.

2.3 Insufficient regulatory basis

At present, the legal and regulatory system for the live streaming economy is still not sound, and there is a significant problem of “insufficient regulatory basis”. On the one hand, there is controversy over the legal nature of live streaming sales, whether it belongs to commercial advertising, e-commerce activities, or audio-visual programs. There is still a vague area in the determination, which leads to unclear legal provisions. In the “Xinba fake bird’s nest incident”, the regulatory authorities did not directly apply the Advertising Law or the E-commerce Law when handling it, but instead cited the Anti-Unfair Competition Law, reflecting the enforcement dilemma caused by unclear legal classification. On the other hand, existing legislation has not clearly defined the responsibility boundaries of multiple parties, such as platforms, hosts, merchants, and MCN institutions in e-commerce live streaming, nor has it made detailed provisions on their legal relationship attributes, resulting in difficulties in identifying the responsible parties and inconsistent standards for joint liability in actual supervision. There are significant differences in the handling of whether a broadcaster should be recognized as an advertising spokesperson, seller, or content creator, and whether the platform should bear the liability for advance compensation in different cases^[2]. There is a lack of unified standards and collaborative mechanisms for cross-regional law enforcement and cross-platform evidence collection, and regulatory authorities often face operational difficulties, such as jurisdictional disputes and the determination of electronic evidence effectiveness in actual law enforcement. Especially in situations where live streaming content is highly real-time, widely disseminated, and evidence is difficult to fix, there is a lack of clear legal and technical support in areas such as remote investigation, data retrieval, and evidence identification, which seriously affects the effectiveness and credibility of law enforcement.

There is no unified national platform for sharing credit information and law enforcement cooperation in live streaming e-commerce, and the regulatory standards vary from place to place at present, resulting in obvious information silos. Some regions have explored the introduction of local regulatory guidelines, but there are significant differences in their scope of application, punishment intensity, and execution standards, which further leads to insufficient regulatory coordination and overall low efficiency^[9]. This regional and fragmented regulatory pattern not only fails to cope with the cross-domain diffusion of the live streaming economy but also objectively condones the cross-platform migration and repeated occurrence of violations.

2.4 Limited regulatory resources

It is unrealistic to rely solely on manual review and supervision in the face of millions of live broadcasts and user comments. According to research, the key monitored e-commerce platforms have accumulated over 120 million live broadcasts, with nearly 1.1 million active hosts. The live content is real-time, interactive, and unpredictable, making it difficult to regulate^[8]. At present, there is a shortage of regulatory personnel, a limited level weak technical strength, numerous regulatory entities, overlapping responsibilities, and fragmented power in market supervision, broadcasting, and other departments in many cities, which affects the effectiveness of supervision. The platform itself has certain auditing capabilities, but its role as an “athlete” conflicts with its role as a “referee” in pursuing commercial interests and regulatory requirements. The pressure for the platform to self-correct is insufficient, the level is uneven, and there is a possibility of seeking personal gain from merchants. Moreover, due to the inability of existing technological means to achieve real-time monitoring and ownership confirmation of live streaming content, and the lack of timely and effective risk warning and credit reporting, the structural shortage of regulatory resources has become increasingly apparent.

3. The Mechanism of Empowering Intelligent Supervision with Artificial Intelligence

3.1 Data intelligence mechanism

The live streaming economy model injects new vitality into economic development and leads society towards intelligent

and smart development under the influence of technological innovation. However, the various problems that the platform economy has shown in its development have put forward new requirements for regulation. Artificial intelligence utilizes natural language recognition, image recognition, speech recognition, and other technologies to analyze live streaming data, transforming chaotic audio and video data into structured text, images, action symbols, etc. It establishes a comprehensive regulatory database covering anchor speech, product information, user behavior data, transaction information, emotional information, compliance labeling, and other content. On the one hand, it provides a basis for regulatory traceability, and on the other hand, it provides data support for model analysis and risk warning. By using OCR recognition to quickly identify the product labeling information and price codes on the screen, and then using natural language recognition of the host's speech, it is possible to automatically identify whether the original price or false price has been falsely quoted; and whether the content of user comments gathers negative emotions, whether it matches the statistical information of abnormal transactions, and whether it belongs to brushing orders or false transactions^[10]. Thus, with the help of machine learning models and evolutionary game models, regulation can shift from post-punishment to pre-warning and in-process intervention. At the same time, the application of blockchain technology has achieved data immutability and watchability, providing trust guarantees for reliability evaluation and incentives, and creating a closed-loop full process intelligent supervision system of "monitoring-analysis-processing-response".

3.2 Behavior recognition mechanism

Artificial intelligence models based on deep learning can recognize and classify behaviors commonly found in live streaming. Unlike single modal, it is multimodal, which means it uses computer vision recognition, NLP natural language recognition, and speech recognition separately. Object recognition algorithms such as YOLO and Faster R-CNN can perform real-time recognition of prohibited items, violation signs, and discordant images appearing in the image; Keyword overlay recognition technology based on deep language models such as BERT and Transformer can identify false advertising or promises in anchor language; Combined with voiceprint recognition, facial expression recognition, etc., it can authenticate the identity of the anchor and identify their emotions, preventing fake live broadcasts or counterfeit anchors^[11]. Partial introduction of temporal modeling, such as 3D-CNN and LSTM, for continuous analysis of action sequences and semantic fragments, and recognition of complex action combination patterns. In this way, the recognition rate and accuracy of prohibited content are greatly improved, and the missed detection rate and false detection rate of manual investigation are greatly reduced. The governance of live streaming is more efficient and real-time.

3.3 Risk warning mechanism

Based on recognition, artificial intelligence can even further conduct risk assessment and warning, forming accurate prediction models based on cross-comparison of historical and real-time data, and dynamically outputting the risk levels of anchors, products, and events in real time. Using a graph neural network (GNN) model to detect the association between "anchor merchant consumer" and capture fraud groups that engage in virtual buying and selling, buying and selling goods, and collectively deceiving people^[12]. Using time series models such as LSTM or Transformer to capture comments with abnormal data, such as comment count, like count, and gift giving for early warning can not only capture water armies or public opinion manipulation, but also comprehensively judge false advertising or inducement language through multimodal analysis of live broadcast images, voice, bullet comments, and other methods^[13]. This kind of warning shifts the threshold of risk management forward, achieving a transformation from "post governance" to "prevention in advance-intervention in the process-retrospective after the fact". At the same time, supporting credit ratings can also be classified and regulated based on different risk levels of frontline anchors and merchants, improving the efficiency of regulatory resources and the level of platform self-discipline.

3.4 Intelligent decision-making mechanism

After identifying warnings, artificial intelligence can continue to support intelligent decision-making and handling. AI can use rule engines and reinforcement learning algorithms to automatically match and take different disposal measures based on the type, severity, historical performance, anchor credit rating, product risk, complaint performance, etc. of violations, such as automatic pop-up reminders, automatic flow limit recommendations, cut-off, human review, credit rating reduction, deduction

of deposit until blacklisting^[14]. At the same time, as the system continues to learn and absorb the disposal results, it adjusts the decision-making strategy, constantly improves the automation level, and at the same time, the measures are more precise and powerful. In this way, the shift from passive regulation to active regulation, from static punishment to dynamic governance, is more in line with the development trends of diversified collaboration and credit supervision.

4.The Implementation Path of Empowering Intelligent Supervision with Artificial Intelligence

4.1 Technology integration

Technology integration is the primary step in intelligent supervision. Existing research has shown that the integration of artificial intelligence and blockchain can establish tamper-proof and traceable evidence of data in a regulatory environment, which is helpful for later accountability and tracing the source of goods^[15]. For the Internet field, Wan's (2023) research shows that 5G can achieve real-time transmission of high-definition live video streams with the characteristics of high speed and low delay, and improve the supervision efficiency by deploying edge nodes for real-time processing. At the data processing level, the distributed architecture and elastic computing power of cloud computing provide the necessary foundation for scheduling, parallel analysis, and processing of massive amounts of data. Under this technological architecture, methods such as computer vision and natural language processing are applied to live streaming content review work, making false advertising or sensitive behavior more quickly identified and intercepted^[16]. Multiple studies generally indicate that "cloud-edge-end" is the key to cross-platform and cross-regional integration of regulatory work, which helps to improve regulatory efficiency and transform from manual spot checks to real-time prevention and control.

The technological path of intelligent supervision is not just one technology, but the cooperation of multiple new technologies. Blockchain provides authentic and trustworthy data, 5G technology provides transmission, and cloud computing power provides computing resources. Only through cooperation can artificial intelligence be achieved. Therefore, future research needs to delve into reality and study the combination of multiple technologies in real-world regulation, rather than staying at theoretical speculation.

4.2 Institutional synergy

Artificial intelligence-driven intelligent supervision cannot be separated from the institutional support and collaborative guarantee of the legal system, standard specifications, and collaborative mechanisms. It is suggested to improve the legal positioning and legal responsibilities of multiple entities such as live streaming e-commerce hosts, platforms, merchant enterprises, MCN institutions, etc., establish specialized regulatory rules and law enforcement standards, guide regulatory enforcement, promote the establishment of government and platform data collaboration and joint punitive measures, such as establishing a "live streaming merchant credit system" covering major e-commerce and video content platforms, sharing credit information and conducting credit evaluations, and building a credit punishment system of "one loss of trust, everywhere difficult to act"^[17].

Based on this, we will leverage the intermediary function of industry associations in leading standards and behavioral norms, formulate industry conventions, quality standards, technical specifications, ethical norms, promote standardization of regulatory rules, ports, data disposal, etc., encourage and support the participation of the third sector, consumers, and the public in supervision, build a multidimensional regulatory system of government supervision and platform autonomy, industry self-discipline, and social supervision, and jointly enhance the smart regulatory level and institutional synergy efficiency of the live streaming e-commerce industry.

4.3 Talent cultivation

The issue of talent cultivation is frequently mentioned in existing research. Li (2025) pointed out that the shortage of composite talents intersecting with artificial intelligence technology and legal policy literacy is a major factor restricting the development of smart regulation. From an educational perspective, cultivating talents with cross-border abilities requires interdisciplinary courses and new majors (such as digital supervision, computational law, etc.). The experience accumulated in the process of practical exploration has become increasingly rich and diverse^[18]. Gao (2025) found through case studies that the joint construction of practical training bases and talent certification systems by the government, platforms, and

research institutes can help existing regulatory personnel develop digital thinking and skills in applying digital technology^[19]. Zhang (2024) found through comparative case studies that multi-departmental and cross-disciplinary talent mobility breaks through departmental barriers, and also introduces the practical experience of smart supervision from different countries and regions to the local area, enriching the knowledge of talents^[20].

The literature generally emphasizes that talent supply should not only be a single technical training, but also a collection of “education-training-certification-practice”. Its research conclusions all point to future intelligent supervision, which requires interdisciplinary knowledge and comprehensive governance thinking. New talents who can understand both technical issues and the inherent connections between legal theory and ethics, market, and law in complex social phenomena.

5. Conclusions and Recommendations

5.1 Research findings

This article takes the intelligent regulation of the live streaming economy empowered by artificial intelligence as the research background. Starting from the status, shortcomings, and technological empowerment of intelligent regulation of the live streaming economy, some overall conclusions are drawn. Artificial intelligence has a positive impact on regulatory capabilities in data mining, data analysis, risk warning, intelligent decision-making, and other aspects. It has broken through the previous manual inspection mode of regulation, made violations more timely in detection and handling, and partially solved problems such as difficulty in obtaining evidence and fixing evidence. At the same time, the empowerment of artificial intelligence relies on the support of various emerging technologies. Blockchain provides conditions for real and traceable data sources, 5G provides real-time data transmission and reduces latency, and cloud computing makes high-density data processing possible. All of these provide conditions for intelligent supervision. However, the institutional supply is still insufficient, and the current laws and regulations have poor adaptability to new business models, unclear division of responsibilities, and difficulties in platform and regional law enforcement, which still exist to a certain extent. Business models that prevent artificial intelligence from playing a role still exist. Lack of talent is another pain point, as there is an extreme shortage of compound high-tech talents who understand both artificial intelligence technology, law, and policies, resulting in a technological and institutional disconnect in regulatory implementation. These commonalities indicate that intelligent regulation empowered by artificial intelligence is driving a shift in regulatory logic from post-investigation to pre-prevention and mid-event intervention, and the true implementation relies on the synergy of technology, systems, and talent.

5.2 Research recommendations

In the future, the live streaming economy industry will continue to promote intelligent supervision at three levels. At the technical level, through the deep integration of artificial intelligence with new generation technologies such as blockchain, 5G, and cloud computing, a system platform for real-time monitoring, certificate retention, and intelligent analysis will be constructed; At the institutional level, improve the legal and regulatory systems, clarify the boundaries of responsibilities of all parties, improve cross regional and cross platform collaboration mechanisms, and establish long-term constraint mechanisms through credit governance and industry autonomy; At the level of talent cultivation, it is necessary to establish a system for interdisciplinary integration of education and training, a system for the integration of technical knowledge, legal knowledge, and governance knowledge, and a system for talent exchange. This will promote the integration of talents across departments and industries, and work together from the three levels of technology, system, and talent to fully leverage the intelligent regulatory role of artificial intelligence and achieve long-term balance in the regulation and development of the live streaming economy.

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International Aid in the Era of Artificial Intelligence: Potential Advantages, Theoretical Challenges, and Strategic Responses

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Abstract: This paper explores the transformative impact of artificial intelligence (AI) on international aid. It systematically analyzes AI's potential to enhance efficiency in needs assessment, resource allocation, project implementation, and monitoring. However, the integration of AI introduces profound theoretical challenges, including data governance dilemmas, algorithmic bias, the digital divide, sovereignty risks, and value conflicts. In response, the study proposes a strategic framework grounded in global governance, emphasizing data ethics, algorithmic accountability, local capacity building, and international cooperation. This study aims to provide a strategic framework for the responsible and equitable deployment of AI in international aid, ultimately serving humanitarian and sustainable development goals.

Keywords: Artificial Intelligence; International Aid; Data Governance; Algorithmic Bias; Digital Divide; Global Cooperation

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1.Introduction

International aid serves as a critical mechanism within global governance, playing an indispensable role in addressing regional conflicts, alleviating humanitarian crises, eradicating poverty, and fostering the socio-economic development of low- and middle-income countries^[1-3]. However, traditional models of international aid have long been constrained by structural challenges, including information asymmetry, rigid resource allocation, slow response times, and difficulties in accurately evaluating project effectiveness. The rapid advancement of new-generation information technologies, particularly artificial intelligence (AI), in the 21st century, offers novel potential pathways to overcome these persistent bottlenecks. AI technologies, with their formidable capacity for processing massive datasets, identifying complex patterns, and generating precise predictions, hold the potential to optimize and reshape the entire lifecycle of international aid, from needs assessment and resource distribution to project implementation and impact monitoring^[4]. For instance, by analyzing satellite imagery and mining mobile data, aid organizations can more rapidly identify impoverished areas or zones affected by disasters. Natural language processing techniques can enable the real-time detection of urgent population needs from social media streams during crises. Furthermore, predictive modeling and machine learning algorithms can optimize supply chains and dynamically adjust aid strategies. Collectively, these applications are driving a paradigm shift in international aid, moving away from a practice heavily reliant on historical experience and localized information towards a refined, forward-looking model underpinned by data-driven decision-making.

Nevertheless, any significant technological transformation entails not merely instrumental substitution but also profound adjustments to social structures, power dynamics, and ethical norms. The integration of AI into international aid inevitably introduces a series of complex challenges. For example, its heavy reliance on data may precipitate new governance dilemmas and privacy risks^[5]. Biases embedded within algorithmic decision-making can inadvertently perpetuate or even exacerbate social inequalities^[6]. The vast global disparities in digital infrastructure and human capital risk transforming the existing “digital divide” into an insurmountable “AI divide”^[7]. Moreover, the introduction of AI systems substantially challenges core principles of traditional aid operations, such as accountability, transparency, and the core ethical imperative to “do no harm”^[8]. Against this backdrop, this paper first elucidates the potential advantages of AI in empowering international aid. It then seeks to identify and analyze the theoretical challenges confronting international aid in the AI era. Finally, it proposes a strategic framework to effectively address these challenges.

2. Potential Advantages of AI in International Aid

2.1 Enhanced Needs Identification and Assessment

Traditional needs identification and assessment in aid often rely on periodic field surveys and aggregated statistics, an approach limited in both coverage and timeliness. AI technologies create the conditions for large-scale, near real-time insights into needs. For instance, the automated analysis of satellite imagery via computer vision can rapidly assess the severity of building damage after natural disasters, the extent of crop loss, and the scale and dynamics of temporary refugee settlements, providing critical evidence for emergency response decision-making^[9]. Simultaneously, multi-dimensional mining of mobile signaling data, social media text, and communication records helps delineate more accurate population movement trajectories, public sentiment fluctuations, and potential hotspots of public needs. The theoretical significance of this data-intelligent sensing mechanism lies in its potential to drive a paradigm shift in aid operations from passive response towards proactive anticipation, thereby substantially shortening relief response times and directing finite resources more precisely to the most urgent needs among populations and regions^[10].

2.2 Optimized Resource Allocation and Logistics Management

Resource allocation and logistics management have persistently been critical factors determining the efficiency of international aid. Complex geographical terrain, underdeveloped infrastructure, and uncertain security conditions frequently result in high transportation costs for aid supplies and challenges in guaranteeing timely delivery. AI-driven optimization algorithms offer novel approaches to this persistent challenge. Intelligent routing systems can synthesize multiple constraints, including real-time road conditions, weather information, security risks, and delivery timeframes, to compute optimal supply routes that minimize cost or maximize timeliness^[11]. Inventory management models can dynamically adjust the types and quantities of supplies stockpiled at various storage nodes based on historical consumption patterns and future demand forecasts, effectively preventing both overstocking and critical shortages. Furthermore, in the fleet management of new carriers such as drones, AI algorithms can enable autonomous coordination and task allocation, achieving precise airdrops of supplies to remote or hazardous areas inaccessible to traditional transport vehicles. The value of these technological applications lies in their potential to significantly reduce the operational costs of international aid activities, comprehensively enhance the resilience and responsiveness of the logistics system, and ensure that life-sustaining supplies reach intended beneficiaries efficiently and reliably.

2.3 Implemented Personalization and Adaptive Assistance

During the detailed design and implementation phases of aid projects, artificial intelligence demonstrates significant potential for personalization and adaptability. In public education and health assistance, for example, AI-powered educational platforms utilizing adaptive learning algorithms can dynamically generate and deliver highly personalized instructional content and tutoring plans. This approach is tailored to the existing knowledge base, learning progress, and cognitive styles of learners in recipient regions, thereby substantially mitigating the severe shortage of quality educational resources and qualified teaching staff^[12]. In the field of medical aid, mobile medical devices or portable testing equipment integrated with AI-assisted diagnostic systems enable local primary healthcare workers to conduct preliminary screening, identification, and diagnosis of common diseases without relying on specialist support. This significantly improves the accessibility and quality of primary

healthcare in remote and underserved areas^[13]. The common theoretical foundation across these application models is that AI can digitize, replicate, and widely disseminate specialized knowledge and skills from scarce domains at low cost. This facilitates the encapsulation and broad distribution of expertise, enabling a transformative enhancement and supplement to traditional, labor-intensive service delivery models.

2.4 Strengthened Monitoring and Evaluation

Artificial intelligence brings methodological innovations to the monitoring and impact evaluation of aid projects. Traditionally, impact assessments relied heavily on post-hoc field visits and questionnaire surveys, approaches that were not only resource-intensive but also highly susceptible to subjective bias, often resulting in fragmented and less objective data. Today, AI enables the automated and continuous analysis and modeling of multimodal data generated throughout project implementation, such as site photographs, progress videos, beneficiary interview recordings, and environmental sensor readings. This allows for near-real-time and objective measurement of key project performance indicators. Natural language processing techniques can perform large-scale sentiment analysis and thematic mining on collected open-ended interview transcripts, community focus group discussions, or social media feedback, extracting deeper insights into a project's social acceptance, comprehensive impact, and potential risks. Theoretically, this data-intelligent, continuous evaluation model can establish a closed-loop organizational learning and feedback system. This enables aid agencies to promptly identify issues, diagnose root causes, and dynamically adjust intervention strategies, thereby continuously optimizing project design and enhancing the overall efficiency and developmental effectiveness of aid funding^[14].

3. Theoretical Challenges of AI-Empowered International Aid

3.1 Data Dependency and Governance Dilemmas

The effectiveness of AI systems is highly dependent on the scale, quality, and representativeness of training data. In the specific context of international aid, the required data often pertains to large amounts of sensitive information about the most vulnerable populations in recipient countries. Governance challenges immediately arise concerning who collects the data, data ownership, control boundaries, and how usage rights are defined^[15]. In many developing countries where digital governance laws and regulations are underdeveloped, the data privacy and autonomy of aided individuals and groups are highly susceptible to being overlooked and violated. A more profound risk exists if the data used for model training fails to adequately cover specific marginalized groups or contains embedded, historically formed societal-structural biases. AI models trained on such data may not only replicate these biases but could further amplify and legitimize them through their seemingly objective decision outputs. A typical theoretical scenario is a post-disaster resource allocation algorithm trained on biased historical data systematically underestimating the vulnerability index of certain communities. This could lead to unfair distribution of aid resources, creating a form of “algorithmic discrimination” reinforced by technology. This heavy reliance on data theoretically constitutes a new source of risk that reproduces or even exacerbates existing social inequalities^[16, 17].

3.2 Algorithmic Black Box and Accountability Deficits

Many advanced artificial intelligence models, particularly complex deep learning neural networks, operate as opaque “black boxes,” whose internal decision-making logic often remains inaccessible and unintelligible not only to ordinary people but even to experts beyond their developers. As key processes—including the automated determination of aid eligibility, prioritization of resource allocation, and selection of specific intervention strategies—increasingly rely on such non-transparent algorithmic decisions, the long-standing principles of transparency and accountability in international aid face the risk of being fundamentally undermined. Should beneficiaries contest an automated decision that significantly impacts their well-being, they would find it exceedingly difficult to ascertain the specific rationale and reasoning behind it, thereby hindering any effective opportunity to question or appeal the outcome. This “algorithmic black box” phenomenon fundamentally challenges core principles advocated in international aid, such as participatory development, community empowerment, and informed consent. It potentially relegates aid recipients to a vulnerable position of passive acceptance with diminished agency and ability to challenge outcomes. Furthermore, when erroneous algorithmic decisions lead to tangible harm, assigning responsibility becomes profoundly ambiguous. Accountability could be attributed to the developers of the algorithm model, the providers of the training data, the aid organization that adopted the system, or the local

partners responsible for its implementation. This ambiguity and deficit in accountability mechanisms represent a pressing theoretical and practical dilemma that must be clarified for the responsible application of AI in the highly sensitive context of international aid ^[18].

3.3 Digital Divide and Capacity Asymmetry

The inherent global digital divide risks evolving into a more disruptive “AI divide” in the era of artificial intelligence. The research, development, deployment, iteration, and maintenance of AI technologies demand top-tier professional expertise, powerful computational infrastructure, and sustained financial investment. These high entry barriers have objectively led to an extreme imbalance in the global distribution of core technical resources and capabilities. Major donor countries and a few large multinational technology corporations virtually monopolize core AI algorithms, computing platforms, and high-end talent. Conversely, many recipient developing countries may still lack even the most basic, systematic data collection capabilities and stable computational resources. This significant initial capacity disparity harbors the risk of fostering new forms of international dependency. While gaining access to AI-powered aid services, recipient countries might be compelled to concede portions of their data sovereignty, policy space, and even economic development autonomy. Furthermore, their nascent domestic digital industries and technological innovation ecosystems could be stifled by the direct influx of mature external technological solutions. Effectively preventing AI-driven aid from transforming from a tool of technological empowerment into a channel for “digital colonialism” or a new form of technological dependency constitutes a critical issue that the international community must seriously examine from a theoretical perspective and actively seek to address ^[19].

3.4 Sovereignty Challenges and Security Risks

The introduction of AI technologies exerts profound and complex impacts on national sovereignty, cybersecurity, and international power structures. The large-scale, high-frequency cross-border data flows inherent in AI-driven aid operations directly implicate recipient countries’ national security and the protection of citizens’ fundamental rights. For instance, detailed data collection through high-resolution satellite remote sensing or drone patrols may capture sensitive geospatial information, critical infrastructure layouts, and social dynamics intelligence. The analysis or utilization of such data by aid providers or technology partners for purposes beyond the agreed humanitarian or developmental objectives would raise serious sovereignty concerns. Furthermore, the AI systems deeply embedded within aid operations themselves could become prime targets for cyber-attacks. Successful malicious intrusion and manipulation of these systems could lead to severe consequences, ranging from disruptions in supply chains to large-scale personal privacy breaches. From a broader international political economy perspective, AI, as a strategically significant cutting-edge technology, and the dominance over its application in the aid sector may subtly reshape the traditional balance of power between donor and recipient countries. Technologically advantaged actors could thereby acquire unprecedented informational control and agenda-setting influence, potentially profoundly affecting or even rewriting the established rules and governance models of global development aid.

3.5 Ethical Principles and Value Conflicts

The automated and standardized decision-making logic of artificial intelligence creates inherent value tensions and potential conflicts with the core ethical principles long upheld in the international aid sector ^[20]. Aid is universally guided by fundamental principles such as “do no harm,” “neutrality,” “impartiality,” and “equity.” However, AI systems, often originating from specific techno-cultural contexts, may struggle to adequately comprehend, respect, and integrate the unique local knowledge, cultural traditions, social norms, and value preferences of recipient regions. This highly techno-rational, utility-maximizing decision-making model is likely to clash with the value rationality of local communities, which often emphasizes relationships, tradition, and collective sentiment. For instance, an AI-driven land planning solution focused primarily on maximizing agricultural output could easily disregard the land’s sacred cultural significance or its traditional livelihood functions for a local community. On another front, excessive reliance on technological solutions and remote automated management may reduce opportunities for face-to-face communication, empathy, and trust-building between aid workers and recipient communities. These risks may erode the essential humanistic concern and relational warmth intrinsic to meaningful aid interventions.

4.Strategic Optimization for AI-Empowered International Aid

4.1 Establishing a Data Ethics and Governance Framework

Constructing a robust, fair, and inclusive data ethics and governance framework is foundational to ensuring the responsible application of AI. The establishment of this framework must transcend the scope of individual sovereign states, striving to build broad consensus and actionable norms at both global and recipient-country levels. At the international level, there should be active promotion for formulating specialized principles, such as a “Charter for Trustworthy AI Data Governance,” tailored to humanitarian and development aid contexts. This framework should explicitly establish core principles including data collection minimization, purpose limitation, prior informed consent, privacy-by-design, and respect for national data sovereignty. When aid agencies establish partnerships with technology providers, legally binding agreements must be used to strictly define data access rights, usage scopes, storage durations, and subsequent disposal methods. At the recipient-country level, the international community, particularly development partners, should prioritize targeted capacity building and technical assistance. This support should aid these countries in progressively establishing and strengthening data protection legal systems and digital governance institutions suited to their national conditions and development stages, thereby substantively enhancing their governance capacity to exercise data sovereignty. Regarding technical pathway selection, there should be strong advocacy and funding for the development and contextual adaptation of advanced privacy-enhancing technologies—such as federated learning, differential privacy, and homomorphic encryption—within aid scenarios. The objective is to enable collaborative modeling and value extraction from multi-party data without necessitating the cross-border transfer of raw data, thereby providing technical architecture support for data security and sovereignty protection.

4.2 Enhancing Algorithmic Transparency and Accountability

Vigorously improving the transparency, explainability, and accountability of algorithmic systems is crucial for addressing the “black box” dilemma and rebuilding trust. When planning, procuring, or developing AI systems, aid agencies must treat “explainability” and “auditability” as core performance indicators and prerequisite conditions equally important as predictive accuracy. This means systems must not only output decisions but also provide the rationale, key influencing factors, and their respective weights in a human-understandable format. For instance, when a system automatically screens aid beneficiaries, it should clearly articulate the primary reasons for each applicant’s selection or rejection. Academia and industry need to collaborate actively, advancing “Explainable AI” (XAI) technologies and exploring their effective application models within the resource-constrained and culturally diverse contexts of aid operations. Concurrently, a comprehensive accountability mechanism covering the entire AI system lifecycle must be established from start to finish. This includes conducting rigorous bias detection and algorithmic impact assessments prior to deployment; setting up clear nodes for human oversight and review, along with accessible appeal channels during operation, ensuring a “human-in-the-loop” with final decision-making and intervention authority at any critical juncture; and, post-hoc, pre-defining standards for liability attribution, traceability procedures, and compensation or remedy schemes when algorithmic decisions cause actual harm. Through this dual approach of institutional constraints and technical safeguards, the exercise of algorithmic power can be channeled into regulated, transparent, and accountable pathways.

4.3 Bridging the Digital Divide and Strengthening Capacity Building

Bridging the widening digital divide and systematically strengthening the indigenous digital capabilities and AI innovation ecosystems of recipient countries represent a long-term strategy and fundamental solution for ensuring inclusive and sustainable AI-powered aid. The international community must recalibrate assistance strategies, prioritizing the empowerment of recipient countries to independently master, adapt, and develop appropriate technologies, rather than viewing them merely as passive recipients of technological solutions. Specific strategies should include: providing targeted support for recipient countries to plan and develop more extensive and higher-quality digital infrastructure, such as broadband networks, cloud computing centers, and data platforms; establishing dedicated funds or cooperative programs to enable their national researchers, engineers, and policymakers to fully participate in the entire lifecycle of AI projects, from problem definition and solution design to system development, deployment, and evaluation, thereby fostering tangible technology transfer, knowledge sharing, and localized innovation; and assisting in the reform of their education and vocational training systems

by introducing courses and practical training related to AI and data science, cultivating the next generation of locally-rooted digital talent. The aid model requires a strategic shift from “technology product delivery” towards “collaborative building of innovation capacity.” Participatory design methodologies should be strongly advocated and implemented, ensuring that local community members, user organizations, domestic enterprises, and government agencies can substantively engage in the conceptualization, co-design, and effectiveness evaluation of AI solutions from the initial project stages. Only when recipient countries successfully transition from passive technology recipients to active co-creators, owners, and users of technology can AI genuinely respond to their self-determined development priorities and avoid entrenching new, deeper forms of technological dependency.

4.4 Promoting Global Cooperation and Norm Development

Effectively addressing the multinational challenges posed by artificial intelligence necessitates closer and more inclusive global cooperation to jointly establish relevant application norms and technical standards. No single nation, organization, or sector can independently resolve these global issues. Therefore, it is particularly urgent to promote the establishment of permanent global dialogue platforms, expert working groups, or forums focusing on the use of AI in international aid within the frameworks of broadly representative international organizations such as the United Nations, the World Bank, and the Organization for Economic Co-operation and Development. Such platforms should aim to convene diverse stakeholders, including sovereign governments, international aid agencies, multinational technology corporations, academia, civil society organizations, and representatives from recipient communities, to collectively deliberate, formulate, and promote transnational ethical guidelines, technical standards, data security protocols, and project management best practices for AI applications in international aid. Through this sustained and inclusive global dialogue, value consensus can be gradually consolidated, forming “soft law” norms and behavioral guidance possessing broad societal recognition and moral influence. This provides a common framework for action by all parties and effectively curbs the potential risk of a “race to the bottom” in technology application. Concurrently, international or neutral institutions should be encouraged to lead the creation of transnational, non-sensitive development data repositories and benchmark algorithm model libraries. These resources should be as open as possible while ensuring security and ethical compliance, facilitating the sharing of global research resources, and accelerating the development and dissemination of cost-effective, low-power, easy-to-maintain, and high-impact AI solutions tailored to the specific needs of developing countries.

4.5 Reconstructing Aid Ethics and Adapting Values

Confronting the value conflicts introduced by artificial intelligence necessitates a profound and systematic ethical discourse within the international aid community. This dialogue must re-examine, reinterpret, and expand the meaning, boundaries, and practical requirements of established core principles within the context of intelligent technologies. For instance, the principle of “impartiality” must incorporate considerations for algorithmic fairness and data representativeness. The principle of “beneficiary participation” needs extension from project implementation upstream to stages like algorithm design and the formulation of data collection strategies. Aid organizations of all types should consider establishing independent, multidisciplinary ethics review committees and implementing mandatory ethical impact assessment procedures. These would conduct prior, systematic reviews of the social, ethical, and cultural risks associated with all proposed AI projects before their adoption. Across all project design and implementation philosophies, there must be an unwavering commitment to a “human-centered” and “assistive-augmentative” fundamental orientation. It must be explicitly clear that technology is a tool serving humanity, aiming to enhance rather than replace human judgment, to strengthen rather than undermine the inherent resilience, autonomous decision-making power, and development momentum of recipient communities, and to augment rather than diminish the direct interpersonal interaction, emotional connection, and trust relationships between aid workers and recipients. This human-centric commitment constitutes the value cornerstone for ensuring that technological innovation consistently serves the noble original purpose of humanitarian and development endeavors.

5. Conclusion

The integration of artificial intelligence into international aid is a present-day reality, presenting both transformative opportunities and profound challenges. This paper has demonstrated AI’s significant potential to enhance the efficiency,

precision, and adaptability of aid, fundamentally optimizing the entire aid chain from needs assessment to impact monitoring. However, it is crucial to recognize that the deployment of this technology is not neutral. It deeply engages with and reshapes core issues concerning data governance, algorithmic accountability, global power dynamics, and development ethics.

To navigate this complexity, this paper advocates for a coordinated, prudent, and human-centric strategic approach. This necessitates building robust data governance frameworks, ensuring algorithmic transparency and explainability, and vigorously investing in local capacity building within recipient countries to bridge the widening digital divide. Concurrently, fostering ongoing international dialogue and cooperation to establish universally accepted technical and application norms is imperative. Ultimately, all efforts must be anchored in the fundamental ethical principles of international aid, ensuring that technology enhances, rather than undermines, humanitarian concern and community resilience.

Looking ahead, the exploration of this field remains a considerable undertaking. Future research should focus on developing operational ethical review tools for specific aid contexts, creating comprehensive metrics to assess the social impact of technology, and investigating the application of emerging technologies like blockchain in safeguarding data sovereignty and trust. In the final analysis, steering artificial intelligence to become a force for global equity and justice, rather than a new mechanism entrenching inequality, demands sustained international cooperation, profound reflection, and resolute commitment. Only by ensuring that technological progress advances hand in hand with humanistic values can we collectively move towards a more inclusive and resilient future.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Innovation and Practical Exploration of Supply Models for Community-Based Home Care Services in an Aging Society

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Abstract: The rapid demographic shift towards an aging global population presents one of the most significant socioeconomic challenges of the 21st century. As institutional care models face sustainability crises and older adults increasingly prefer to “age in place,” community-based home care (CBHC) services have emerged as a critical component of the elderly care continuum. However, traditional supply models for these services are often fragmented, under-resourced, and ill-equipped to meet the diverse and complex needs of a growing senior demographic. This paper provides a comprehensive analysis of the innovation and practical exploration of new supply models for CBHC services. It examines the limitations of conventional state-led and informal care models, setting the stage for an exploration of more dynamic, efficient, and person-centered alternatives. We investigate three prominent innovative models: the “Government-Led, Market-Operated” (GLMO) public-private partnership; the mission-driven Social Enterprise and Non-Profit (NPO) model; and the emerging “Digital Platform + Gig Economy” model. Through a comparative analysis, supported by case study data and practical implementation examples, this paper assesses the respective strengths, weaknesses, and contexts for each model. The findings indicate that no single model is universally superior; rather, effective CBHC provision often relies on hybrid approaches that integrate technology, foster cross-sectoral collaboration, and are flexibly adapted to local regulatory and cultural environments. This research concludes with policy recommendations aimed at creating a sustainable, high-quality, and accessible ecosystem for community-based home care in an increasingly aging world.

Keywords: Aging Society; Community-Based Home Care; Elderly Services; Supply Model Innovation; Public-Private Partnership; Social Policy; Digital Health

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1.Introduction

The world is aging at an unprecedented rate, a demographic phenomenon driven by declining fertility rates and increasing life expectancy. This “silver tsunami” poses profound challenges to social structures, economic systems, and, most pressingly, healthcare and social support mechanisms. Traditionally, elderly care has oscillated between two poles: informal care provided by family members, which is now under immense strain due to changing family structures and increased female labor force participation, and costly institutional care (such as nursing homes), which often fails to meet the personal preferences of seniors who overwhelmingly wish to remain in their own homes and communities^[1]. In response to this gap, Community-Based Home Care (CBHC) has gained prominence as a pivotal strategy. CBHC encompasses a wide range of

services—from medical nursing and rehabilitation to personal assistance with daily living, social companionship, and meal delivery—all designed to support older adults' independence and quality of life “in place.” However, the effective delivery, or supply, of these services remains a formidable challenge^[2]. Many systems are characterized by service fragmentation, workforce shortages, inconsistent quality, and inadequate funding. This paper argues that the sustainability of eldercare in an aging society hinges on the urgent need for innovation in CBHC supply models. This study aims to systematically review and critically analyze the transition from traditional supply modes to innovative, multi-stakeholder models. We will explore the theoretical underpinnings and practical applications of new models, including public-private partnerships, social enterprise-driven initiatives, and technology-enabled platforms. By examining case studies and comparative data, this paper seeks to identify the key drivers, barriers, and outcomes associated with these innovations, ultimately providing actionable insights for policymakers, providers, and researchers dedicated to building a resilient and person-centered eldercare ecosystem. This exploration is critical because the path chosen by societies to structure their care economies will have lasting implications for intergenerational equity, fiscal sustainability, and the fundamental dignity afforded to older adults^[3]. The research synthesizes existing literature from public administration, social policy, health economics, and gerontology to build a comprehensive framework for understanding these new supply dynamics. We posit that the future lies not in a single, universally applicable model, but in a hybrid, context-sensitive ecosystem of care that leverages the strengths of the public, private, and non-profit sectors, all underpinned by a robust regulatory and quality assurance framework. The subsequent sections will deconstruct the limitations of incumbent models before building a detailed analysis of these emerging alternatives.

2. The Challenge of Aging and the Rise of CBHC

The demographic transition to an older society is no longer a distant prospect but a current reality for most developed nations and an accelerating trend in many developing ones. The fiscal and social implications of this shift are staggering. Public pension and healthcare systems face long-term solvency issues, while the demand for long-term care (LTC) services is projected to triple in many countries by 2050. Within this context, the institutional model of care is proving to be both economically unsustainable and socially undesirable. The high cost of residential care facilities places a heavy burden on public finances and individual savings, while the model itself is often criticized for being depersonalized and isolating, removing seniors from their familiar social networks. Simultaneously, the capacity of the “informal care” sector, traditionally the backbone of elder support, is eroding. Smaller family sizes, geographic mobility of children, and the increasing necessity of dual-income households mean that the availability of unpaid family caregivers is rapidly declining. This convergence of pressures has forced a strategic pivot towards CBHC. This model is predicated on the dual benefits of respecting seniors' autonomy and dignity while being a more cost-effective alternative to institutionalization^[4]. By providing tailored support within the home, CBHC can delay or prevent the need for more intensive and expensive care, reduce hospital readmissions, and improve the overall well-being of older adults. The growing consensus is that a robust CBHC system is not merely an option but an essential infrastructure for a functioning aging society, yet building this infrastructure requires moving beyond ad-hoc solutions to establish structured, reliable, and scalable supply models. This strategic pivot requires a fundamental rethinking of resource allocation, workforce development, and service integration. It is not simply about providing more services, but about providing smarter services that are coordinated, person-centered, and technologically enabled. The rise of CBHC also brings new challenges, particularly in ensuring quality control across a diffuse network of providers and in supporting the well-being of a paid home care workforce that is often underpaid and overburdened. Addressing these complex, interconnected issues is the central problem facing long-term care policy today.

3. Traditional Supply Models and Their Limitations

Historically, the supply of community-based care services has been dominated by two primary models: the state-provisioned model and the informal/market model. In the state-provisioned model, services are directly funded, managed, and delivered by public agencies^[5]. While this approach can theoretically ensure equity and standardized quality, it often suffers from significant bureaucratic inefficiencies, long waiting lists, and a rigid, one-size-fits-all service menu that fails to adapt to the heterogeneous needs of the elderly population. Government budgets are perpetually constrained, leading to chronic

underfunding, low wages for care workers, and an inability to scale services to meet escalating demand. This “public-monopoly” model often results in a system that is slow to innovate, resistant to adopting new technologies, and operationally inflexible, failing to respond to urgent or non-standard care needs. On the other end of the spectrum is the informal/market model, which relies on a patchwork of unpaid family caregivers and a fragmented market of small, often unregulated, private-pay agencies. This model creates vast disparities in access and quality. Individuals with financial means or strong family support may receive adequate care, while those without are left vulnerable. The informal market is often plagued by a lack of transparency, non-existent quality control, and a precarious workforce^[6]. Neither of these traditional models has proven capable of addressing the scale or complexity of the modern aging challenge, characterized by a rise in chronic conditions like dementia and a need for integrated medical and social care. The limitations are clear: a lack of coordination between health and social services, insufficient resources, persistent quality-control issues, and a failure to leverage technology have created a “care gap” that necessitates radical innovation. This gap represents a market and policy failure that leaves millions of seniors in a precarious position, unable to access the reliable support they need to live independently and with dignity. The inherent inertia in these legacy systems is a significant barrier to reform.

4. Innovations in Service Supply Models

The inadequacies of traditional models have catalyzed a search for innovative solutions that can blend efficiency, quality, and accessibility. These new models are characterized by multi-stakeholder collaboration, the strategic use of technology, and a focus on person-centered outcomes rather than mere service delivery. They seek to optimize resource allocation, professionalize the care workforce, and create more responsive and resilient systems^[7]. This section explores three of the most prominent innovative supply models that are gaining traction globally: the “Government-Led, Market-Operated” (GLMO) model, the Social Enterprise and Non-Profit (NPO) model, and the “Digital Platform + Gig Economy” model. Each of these approaches represents a distinct philosophy and operational structure for organizing and delivering CBHC services, moving beyond the simple state-versus-market dichotomy. These models are not mutually exclusive; in practice, many health systems are developing hybrid approaches that incorporate elements from each. The key to their success lies in their ability to address the core failures of the traditional systems: scalability, flexibility, and sustainability. For example, by introducing market mechanisms, the GLMO model aims to tackle the inefficiency of the state-run system. By focusing on mission, the NPO model aims to fill the equity and quality gaps left by the fragmented private market. And by leveraging technology, the digital platform model aims to solve the logistical and accessibility challenges that plague both. Understanding the nuances, strengths, and weaknesses of each model is therefore essential for any policymaker or practitioner seeking to design a 21st-century eldercare system^[8]. The following subsections will delve into the operational logic and practical implications of each of these three innovative frameworks in greater detail, providing a foundation for a comparative analysis.

4.1 The “Government-Led, Market-Operated” Model

The “Government-Led, Market-Operated” (GLMO) model, a form of Public-Private Partnership (PPP), has emerged as a popular strategy for governments seeking to improve efficiency and service quality without abdicating their regulatory responsibilities. In this model, the government retains the core functions of planning, funding (often through subsidies or voucher systems), and quality assurance, while “contracting out” the actual service delivery to qualified private-sector organizations, which can be for-profit or non-profit. The underlying logic is to leverage the market’s capacity for innovation, competition, and operational agility. Private providers, competing for government contracts or client vouchers, are incentivized to optimize their service delivery, professionalize their staff, and adopt new technologies to reduce costs and improve client satisfaction. This model can rapidly expand service capacity by bringing in new actors and capital. However, the GLMO model is not without its challenges^[9]. It requires a sophisticated regulatory framework and strong oversight capacity from the government to prevent “cream-skimming” (providers serving only the least costly clients) or a “race to the bottom” in quality and wages as firms compete on price. Ensuring that market incentives align with the social goals of equitable access and person-centered care is a complex balancing act that remains a central challenge for policymakers implementing this model. This governance aspect is critical; without robust monitoring and clear performance metrics, the profit motive can easily override the public service mission, leading to poor outcomes for the most vulnerable seniors.

Successful implementation often depends on the design of the contracts themselves—whether they are based on simple fee-for-service, capitation, or more complex pay-for-performance and outcomes-based metrics. The administrative burden of managing these complex contracts can also be significant, requiring a new set of skills within public agencies, shifting their role from direct providers to sophisticated purchasers and regulators of services.

4.2 The “Social Enterprise” and Non-Profit Model

A second significant innovative pathway is the rise of social enterprises and the modernization of traditional non-profit organizations (NPOs) as key service providers. Unlike purely commercial firms, these mission-driven organizations prioritize social impact over profit maximization. They often emerge from within communities, giving them a deep understanding of local needs and a high level of trust among the populace. Social enterprises, in particular, blend the social mission of an NPO with the business acumen of a for-profit venture, seeking financial sustainability through earned revenue (from services, government contracts, or hybrid sources) which is then reinvested into the mission. This model has distinct advantages in the CBHC sector. Mission-driven organizations are often more willing to serve vulnerable or high-need populations that private markets may overlook. They are also well-positioned to mobilize community resources, including volunteers, and to foster the “social” aspects of care, such as companionship and community integration, which are often neglected in more medicalized or efficiency-focused models^[2]. Furthermore, NPOs and social enterprises often become hubs for innovation in person-centered care, as their organizational structure allows them to be more flexible and responsive to client feedback than large bureaucratic agencies. The primary barriers for this model are scalability and financial stability. Many NPOs and social enterprises struggle with limited access to capital, reliance on fluctuating grant funding, and challenges in developing the managerial and logistical expertise needed to operate at scale in a complex and highly regulated field. They can become victims of their own success, unable to meet growing demand without compromising the very quality and community focus that makes them unique. Therefore, a key policy question is how to support the scaling of these mission-driven models without forcing them to dilute their social purpose.

4.3 The “Digital Platform + Gig Economy” Model

The most recent and, in some ways, most disruptive innovation is the application of the “gig economy” or “sharing economy” framework to eldercare, facilitated by digital platforms. These technology companies operate as intermediaries, using sophisticated apps and algorithms to match clients (seniors or their families) directly with a large, flexible pool of independent care workers. This model promises to solve several key problems: it offers consumers unprecedented choice, convenience, and transparency (with profiles, ratings, and on-demand booking), while providing caregivers with flexible work schedules. For the system, it can drastically reduce administrative overhead compared to traditional agencies. This model is particularly adept at filling “short-burst” care needs—such as a two-hour visit for bathing assistance or a last-minute request for transport to a doctor’s appointment—that traditional agencies find difficult and unprofitable to staff. However, this model also raises significant concerns. The classification of caregivers as independent contractors often leaves them without benefits, training, or employment protections, potentially leading to high turnover and variable quality. Furthermore, the reliance on digital platforms risks exacerbating the “digital divide,” leaving behind seniors who lack technological literacy or access. Quality assurance in such a disintermediated model remains a paramount, and largely unsolved, regulatory puzzle. While ratings and reviews provide some measure of accountability, they are a poor substitute for professional supervision, standardized training, and robust background checks. The long-term impact of “uber-izing” the care workforce on the stability and professionalism of the sector is a subject of intense debate, pitting the promise of technological efficiency against deep concerns for worker rights and client safety.

5. Practical Exploration: Comparative Data Analysis

To ground the theoretical discussion of these models in practical reality, it is essential to examine their performance and characteristics side-by-side, even without relying on tabular data. While contexts vary, a comparative analysis reveals distinct trade-offs in how each model manages resources, ensures quality, and meets user needs. These models are not just abstract concepts but are being actively implemented in various regions, providing a growing body of evidence on their real-world outcomes. The data suggests that the choice of model has profound implications for the cost, quality, and equity of the care

provided. For instance, efficiency metrics in GLMO models often show lower administrative costs per service hour compared to state-run systems, but only when robust quality monitoring is in place. Studies have shown that without this oversight, contracted providers may cut corners on training or service time to protect profit margins. In contrast, social enterprise models, while sometimes less efficient in pure economic terms due to higher investment in worker training and client-facing time, often score highest on patient satisfaction and worker retention surveys. This suggests a qualitative value and long-term stability that is harder to quantify in simple cost-per-hour metrics. The digital platform model, meanwhile, exhibits the fastest “time-to-service” metrics and the highest degree of user-reported flexibility, but also the highest variance in reported quality and worker satisfaction. This comparison underscores the complexity of designing an “optimal” supply system, as each model presents a different profile of risks and benefits. A system prioritizing rapid access and flexibility might favor platform models, whereas a system prioritizing equity and complex care for vulnerable populations might lean more heavily on mission-driven NPOs. The GLMO model often acts as a middle ground, attempting to balance cost-efficiency with broad-scale provision, though its success is entirely dependent on the quality of its governance.

6.Barriers to Innovation and Implementation

Despite the clear need and promising potential of innovative CBHC models, their widespread adoption and successful implementation are hindered by a formidable set of barriers. These challenges are not unique to any single model but represent systemic friction points that stifle progress across the entire eldercare sector. One of the most significant barriers is financial. Innovative models, particularly those leveraging technology or requiring a highly-trained workforce, demand substantial upfront investment, yet funding streams for long-term care remain siloed, inadequate, and often biased towards traditional institutional care. Public reimbursement rates are often set too low to support a high-quality, professionalized workforce, forcing providers in all models to suppress wages or limit service offerings. Regulatory frameworks are another major hurdle. Existing laws and licensing requirements were often designed for 20th-century care models (i.e., nursing homes or hospitals) and are poorly adapted to the realities of community-based or digitally-enabled services. This regulatory lag can create legal uncertainties for digital platforms regarding worker classification, or impose hospital-grade physical standards on small, community-based adult day centers, making them financially unviable. A third, and perhaps most critical, barrier is the persistent shortage of a qualified care workforce. The CBHC sector is plagued by low wages, poor working conditions, high rates of injury, and a lack of clear career pathways, making it difficult to recruit and retain skilled and compassionate caregivers. Innovative models cannot succeed without a stable, professionalized workforce to execute them. Finally, cultural and technological barriers, such as the digital divide among seniors and a societal reluctance to professionalize and adequately value care work, further complicate the landscape. Overcoming these deep-seated, structural barriers requires more than just novel service models; it requires a fundamental political and social commitment to reforming the foundations of the care economy.

7.Policy Recommendations for Sustainable Development

Overcoming the identified barriers to create a sustainable and high-quality CBHC ecosystem requires a proactive and multi-pronged policy approach. First, governments must reform funding mechanisms. This includes shifting public long-term care budgets away from institutional bias towards “money-follows-the-person” models, such as individual budgets or vouchers, which empower consumers and create a level playing field for diverse providers. This consumer-directed approach fosters competition based on quality, not just cost. Furthermore, public-private seed funds and social impact bonds could be utilized to finance promising innovations, providing the patient capital that social enterprises and tech platforms need to develop and validate their models. Second, regulatory modernization is essential. Policymakers must create clear, flexible, and outcomes-based regulations that can accommodate new service models, including technology platforms and cross-disciplinary care teams, while rigorously protecting consumer safety and data privacy. This includes establishing clear standards for caregiver training and certification that are portable across different provider types, creating a more flexible and mobile workforce. Third, and most critically, addressing the workforce crisis must be a top priority. This requires a combination of strategies: mandating living wages and benefits for care workers, creating professional career ladders with opportunities for

advancement (e.g., from personal care aide to certified nursing assistant to licensed nurse), funding accessible training and specialization programs (e.g., in dementia and palliative care), and launching public campaigns to elevate the social status of the caregiving profession. Finally, policy should actively foster collaboration and integration. This involves creating financial and regulatory incentives for partnerships between healthcare systems (hospitals, clinics) and CBHC providers to ensure smooth care transitions, as well as supporting the digital infrastructure (like shared electronic health records and interoperable data standards) that enables seamless coordination between state, market, and non-profit actors.

8. Conclusion

The challenge of providing adequate, dignified, and sustainable care for aging populations is a defining issue of our time. This paper has argued that the traditional, monolithic models of state provision and informal family care are no longer sufficient to meet the complex needs of modern seniors. The future of eldercare lies in a vibrant, pluralistic, and responsive ecosystem of Community-Based Home Care services. Our exploration of three innovative supply models—the “Government-Led, Market-Operated” model, the Social Enterprise/NPO model, and the Digital Platform model—reveals that a significant transformation of the care landscape is already underway. Each of these models offers unique advantages in terms of efficiency, quality, and accessibility, but each also carries specific risks and faces significant barriers, from workforce shortages to regulatory inertia. This analysis confirms that there is no single “silver bullet” solution. The most promising path forward appears to lie in the development of hybrid models that skillfully blend the strengths of different approaches—for example, a system that uses government-funded individual budgets (GLMO) to empower clients to purchase services from accredited social enterprises (NPO) via a unified digital platform (Tech) that ensures quality and facilitates data sharing. The practical exploration of these models is still in its nascent stages, and more longitudinal research is needed to fully understand their long-term impacts on client outcomes, workforce stability, and system costs. Ultimately, building a CBHC system that is fit for an aging society requires a concerted effort from all stakeholders—policymakers, providers, technologists, and the public—to champion innovation while holding steadfast to the core values of dignity, equity, and person-centered care. This endeavor is not merely a technical or financial challenge; it is a moral imperative to ensure that as our societies age, they do so with grace, compassion, and justice for all members. The continued experimentation and rigorous evaluation of these supply models will be critical in navigating this complex but essential journey.

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Driving Sustainable Innovation in Asia through Environmental Tax Reform in China's Energy-Intensive Industries

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Abstract: This study examines the impact of China's 2018 Environmental Protection Tax Law (EPTL) on technological innovation in energy-intensive industries, addressing gaps in understanding how market-based environmental policies influence R&D reallocation and firm behavior in developing economies. Employing a difference-in-differences (DID) framework augmented with propensity score matching (PSM-DID), we analyze panel data from A-share listed firms over 2012–2023, treating heavily polluting enterprises as the experimental group. Innovation is proxied by the natural log of patent applications plus one, with R&D intensity serving as the mediator, and heterogeneity explored across ownership structure, firm size, and technological sophistication. Results indicate that the EPTL significantly boosted patent applications by 25.5% in treated firms, primarily through enhanced R&D investment. Mediation analysis confirms R&D as the key channel, aligning with the Porter Hypothesis by demonstrating how environmental taxes internalize externalities and spur innovation offsets. Heterogeneity effects reveal stronger impacts in state-owned enterprises (coefficient: 0.317), large firms (0.312), and high-tech entities (0.365) compared to counterparts (0.166, 0.160, 0.192), underscoring resource advantages and institutional factors in amplifying policy efficacy. This research contributes novel micro-level evidence on the dynamic mechanisms of environmental taxation, bridging the "Porter Paradox" by highlighting context-specific innovation responses. Findings inform policy design for balancing environmental stringency with economic growth, advocating flexible tax incentives and R&D supports to foster sustainable industrial transformation in emerging markets.

Keywords: Environmental Protection Tax Law; Corporate Innovation; R&D Investment; Heavily Polluting Enterprises; Difference-in-Differences

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1.Introduction

In environmental economics, pollution taxes are acknowledged as pivotal instruments to address market failures and stimulate green innovation and resource efficiency (Li & Gao, 2022). However, institutional barriers in developing economies—including inconsistent enforcement and weak incentives—frequently erode the theoretical "double dividend" effect (i.e.,

concurrent pollution reduction and innovation gains via cost internalization). Empirical studies indicate a misalignment between pollution abatement expenditures and technological innovation in heavily polluting sectors (Liang et al., 2014). These limitations arise from conflicting regulatory incentives: inflexible tax frameworks are diluted by localized enforcement discretion, whereas delayed innovation rewards perpetuate sunk-cost traps (Zhou et al., 2024). Therefore, reconciling environmental cost internalization with innovation incentives persists as a critical challenge for developing countries combating industrial pollution. China's Environmental Protection Tax Law (2018)—the country's inaugural legislative framework for pollution taxation—reflects a transition from administrative mandates to market-oriented governance. By codifying pollution charges into statutory law, replacing negotiable emission fees with tiered tax rates and multi-agency monitoring, the policy firmly integrates environmental costs into corporate decision-making processes.

As key subjects of environmental regulation, heavily polluting enterprises adapt their innovation strategies in response to policy changes. Internalizing environmental costs into production processes forces firms to balance end-of-pipe pollution abatement expenditures against green technology adoption returns (Gao et al., 2023). Under conventional regulatory regimes, these firms typically adopt reactive compliance measures—such as installing end-of-pipe treatment systems—to satisfy emission thresholds. However, such capital-intensive investments redirect R&D budgets, resulting in reduced innovation capacity and slower adoption of clean production methods (Wang et al., 2022). This highlights the need to shift from command-and-control regulation to market-based environmental governance. Unlike prescriptive regulatory models, market-based instruments such as environmental tax reforms utilize price signals to generate innovation incentives. These mechanisms theoretically address limitations of the compliance cost hypothesis by channeling environmental costs toward green innovation (Shen & Zhang, 2022).

While existing research confirms environmental regulations stimulate green innovation, two critical gaps persist: (1) how heavily polluting firms reallocate R&D resources under environmental tax shocks, and (2) whether this effect differs across firm characteristics. By investigating these questions, this study clarifies the micro-level mechanisms through which environmental tax reforms operate and provides evidence for designing policies that reconcile environmental accountability with innovation incentives in developing countries.

To address these questions, we apply a difference-in-differences (DID) framework to assess the effects of environmental tax reforms on innovation in heavily polluting enterprises, utilizing panel data from China's A-share listed companies (2012–2023). The results show that the reforms substantially improved innovation capabilities in targeted firms. Robustness checks—parallel trend tests, placebo tests, propensity score matching DID (PSM-DID), and alternative hypothesis testing—validate the robustness of the findings. Theoretical and mechanistic analyses demonstrate that the reforms drive innovation predominantly via heightened R&D investment intensity. This induces a technological advancement effect that fosters measurable innovation gains. Heterogeneity analyses reveal differential effects across firm attributes: state-owned enterprises, large firms, and high-tech sector firms achieved the most significant innovation gains under the reforms.

1.1 Contribution

This study contributes to two key areas of research. First, it deepens understanding of the link between environmental regulation and corporate innovation. The Porter Hypothesis posits that environmental regulations enhance competitiveness by spurring innovation offsets (Rubashkina et al., 2015). However, later research reveals a "Porter Paradox" (Ambec et al., 2013), where innovation outcomes hinge on regulatory design and enforcement. Recent evidence also suggests an inverted U-shaped relationship between regulatory stringency and innovation (Rubashkina et al., 2015). Yet, gaps persist, particularly in how market-based instruments, such as environmental taxes, redirect R&D decisions through cost internalization—shifting firms from end-of-pipe treatments to process innovation in polluting industries. This study fills this void by providing micro-level evidence on these dynamics.

Second, it advances the comparison of policy instruments. Command-and-control approaches often lock firms into compliance-driven innovation (Blind, 2023), while market-based tools, leveraging price signals, more effectively stimulate innovation (Shao et al., 2025). Prior studies, however, offer static comparisons of policy types without frameworks to capture dynamic mechanisms like R&D reallocation under environmental tax reforms. This study addresses this limitation

by analyzing the dynamic interplay between incentive-based regulations (e.g., pollution taxes) and innovation in heavily polluting firms.

The study delivers two primary contributions. First, it enriches research on regulatory tools by showing how environmental tax reforms reshape innovation strategies in heavily polluting firms through R&D reallocation. Unlike earlier work focused on command-and-control policies (e.g., emissions standards) (Wang et al., 2022) or broad evaluations of market-based incentives (Kumekawa, 2024), we provide a micro-level analysis of China's Environmental Protection Tax Law, elucidating how institutional shifts enhance corporate innovation efficiency.

Second, it broadens the understanding of environmental tax reforms' economic impacts. While existing studies explore environmental investments (Liu et al., 2022), productivity (Kong et al., 2024), and firm performance (Zheng & He, 2022), innovation in heavily polluting sectors remains underexamined. By integrating firm-level innovation behaviors into environmental policy frameworks, this study bridges a critical theoretical and empirical gap.

The paper proceeds as follows: Section 2 presents the institutional background and hypotheses, Section 3 describes the methodology, Section 4 reports empirical results, Section 5 explores heterogeneity, and Section 6 concludes with policy implications.

2. Institutional Context & Hypotheses

2.1 Context Analysis and Literature Review

Since implementing sustainable development strategies in the 1990s, China has enhanced environmental governance via legislation, administrative oversight, and pollution discharge fees. However, systemic challenges persist. Pollution externalities frequently cross jurisdictional borders, and governance mechanisms fail to balance administrative interventions with market failures (Li et al., 2022). This has exacerbated regional haze, cross-border water pollution, and similar issues under a "polluters evade responsibility, governments bear costs" dynamic.

Two structural barriers intensify these challenges. First, pollution spillovers create ambiguous liability. Industrial emissions often cross administrative boundaries (Da et al., 2019), but jurisdictional frameworks lack cross-regional coordination mechanisms. Technical constraints in pollution tracing and disputed liability standards lead to prolonged legal disputes over transboundary pollution. Second, market failures impede cost internalization. Positive environmental externalities—such as cleanup efforts—are undervalued in markets, discouraging investments in sustainability by local governments and firms. Heavy polluters exploit this imbalance by free-riding on environmental public goods while avoiding remediation costs. Although cross-jurisdictional litigation mechanisms exist, inconsistent damage assessment standards and limited judicial expertise hinder enforcement, leaving many environmental disputes unresolved (Van, 2006).

The reform prioritized continuity in tax burdens and stricter enforcement, consolidating previous fees into a unified statutory system. To address these systemic challenges, China enacted the Environmental Protection Tax Law (EPTL) on January 1, 2018, replacing the pollution discharge fee system with a legally binding tax framework. Key features include:

1) Centralized Tax Administration: Tax authorities standardize tax filings nationwide, replacing fragmented local fee collection. 2) Taxable Pollutants: Four categories are taxed: air/water pollutants, solid waste, and noise. 3) Tiered Taxation: Progressive rates apply: ¥1.2–12 per pollution equivalent for air pollutants, ¥1.4–14 for water pollutants. 4) Performance-Linked Incentives: Firms emitting 30% below standards get 25% tax cuts; 50% reductions apply for 50% below standards.

This integrated framework—combining corporate self-reporting, tax agency oversight, and interdepartmental data sharing (Liu et al., 2022)—has transformed corporate environmental behavior. Evidence shows the EPTL's pricing mechanisms mitigate "pollution haven" effects—industries relocating to regions with weaker environmental standards (Yu & Morotomi, 2022). By internalizing environmental costs through taxation, the law improves governance efficiency and creates market-based solutions to collective action challenges in pollution management.

Do environmental tax reforms address the limitations of traditional discharge fee systems to improve both environmental and economic outcomes? Evidence from developed economies shows that environmental taxes, as market-driven tools, can create dual benefits for environmental protection and economic growth (Bluffstone, 2003). Traditional discharge fee systems face structural weaknesses: as non-tax administrative charges, they lack legal binding power, giving local governments

excessive flexibility in setting rates and enforcement. This leads to systemic loopholes, such as negotiated fee agreements and inconsistent compliance (Gunningham, 2009). These weaknesses hinder the integration of pollution costs into corporate strategies, allowing firms to bypass regulations through rent-seeking. Consequently, the link between pollution control investments and environmental outcomes weakens (Guo & Zhang, 2023).

Environmental tax reforms address these challenges through two mechanisms: 1) Legal Binding Force: By establishing legally binding tax obligations, the reforms reduce regulatory arbitrage through government-firm negotiations, compelling firms to incorporate environmental costs into long-term decision-making (Long et al., 2022). 2) Interagency Collaboration: Coordinated oversight between tax and environmental agencies—supported by data-sharing platforms and joint monitoring—mitigates information gaps and increases non-compliance costs (Hu et al., 2023).

While existing research provides insights into environmental tax reforms, three critical gaps remain. First, prior studies focus on government-business interactions and compliance costs but lack causal evidence connecting reforms to corporate innovation, resulting in unclear mechanisms of policy-induced innovation. Second, the mediating role of R&D investment—specifically how firms adjust innovation strategies amid cost pressures and resource reallocation—is not thoroughly examined. Third, heterogeneity across heavily polluting firms (e.g., ownership structures and industry attributes) is frequently neglected in policy impact assessments.

This study bridges these gaps by analyzing China's environmental tax reform through a quasi-experimental framework. We construct a causal pathway from policy constraints to R&D reallocation and innovation outcomes, demonstrating how regulatory pressures stimulate innovation in heavily polluting industries. By examining how firms reconfigure R&D allocations under environmental cost internalization, this study advances theoretical and empirical understanding of harmonizing pollution mitigation with economic growth in developing countries.

2.2 Research Hypothesis

Dahmani (2024) establishes that the effectiveness of environmental taxation hinges on synergistic integration of policy instruments and market mechanisms. When tax rates dynamically reflect the marginal social costs of pollution, they generate persistent incentives for technological innovation. For heavily polluting enterprises, legally mandated progressive tax systems create a dual regulatory mechanism:

1. Cost Internalization Mechanism: By internalizing explicit marginal pollution costs into corporate accounting systems, enterprises are compelled to reevaluate end-of-pipe treatment versus preventive technological solutions. To mitigate tax liabilities, enterprises strategically invest in pollution abatement equipment or transition to cleaner production systems (Zhao et al., 2024). These firm-level innovations catalyze sector-wide transitions toward sustainable production paradigms.

2. Incentive Alignment Mechanism: Performance-based tax rebates for clean technology adoption establish a self-reinforcing cycle: emission reductions trigger technological advancements that subsequently reduce tax obligations. Under this dual regulatory framework, enterprises structurally reallocate R&D investments—diverting resources from short-term pollution control to long-term innovation in preventive technologies and circular production models. This paradigm shift transforms corporate innovation strategies from cost internalization approaches to value-creation orientations.

Based on these mechanisms, we propose the following hypothesis:

H1: Environmental tax reforms compel heavily polluting enterprises to increase technological innovation.

This hypothesis stems from the dual role of environmental taxes in driving innovation through cost internalization and incentive alignment. The core mechanism operates through the mediating role of research and development (R&D) investment. Environmental tax reforms reshape corporate R&D strategies via price-signaling mechanisms. Systematic internalization of pollution costs reduces conventional production profits, thereby incentivizing reorientation of R&D investments toward green technologies (Li et al., 2024). Tiered taxation schemes coupled with fiscal incentives simultaneously lower implementation costs and enhance marginal returns of clean technology adoption. High-emission enterprises typically implement a dual R&D allocation framework under regulatory constraints: Compliance-driven R&D (For near-term regulatory compliance) and Strategic R&D (Focused on long-term cost leadership through innovation).

This strategic reconfiguration buffers against short-term regulatory impacts while cultivating sustained competitive

advantages. When clean technology's marginal abatement costs dip below environmental tax rates, enterprises initiate an innovation amplification cycle: R&D investments reduce tax liabilities, enabling profit recycling into subsequent innovation. Based on this mechanism, we propose the following hypothesis:

H2: Environmental tax reforms enhance innovation capabilities in heavily polluting enterprises by increasing R&D investment.

This hypothesis underscores R&D investment as the critical intermediary transmitting policy effects to innovation outcomes.

Figure 1- Influence channels of environmental protection tax reform on innovation of heavy polluting enterprises



3. Research Design

3.1 Sample Selection and Data Sources

This study utilizes data from China's A-share listed companies between 2012 and 2023. The dataset was processed as follows:

(1) Excluded firms labeled as ST, *ST, or PT (indicating financial distress). (2) Removed financial sector firms. (3) Excluded firms that switched between treatment and control groups during the sample period. (4) Dropped treatment group firms with less than one year of pre-policy data. (5) Removed firms with incomplete annual observations. (6) Winsorized continuous variables at the 1st and 99th percentiles to mitigate outliers.

Data were sourced from the China Stock Market & Accounting Research (CSMAR) database and annual financial reports of listed companies.

3.2 Variable Definitions

3.2.1 Dependent Variable

Following prior studies (Sun, 2008 ; Zhao & Yuan, 2022), corporate innovation is measured as the natural logarithm of the total number of patent applications filed by a firm plus 1.

3.2.2 Independent Variable

To assess the impact of China's environmental tax reform on heavily polluting enterprises, we employ a difference-in-differences (DID) framework. The key independent variable is constructed as follows: Treatment group (treat): Firms in industries classified as heavily polluting based on the China Securities Regulatory Commission (CSRC) industry codes: A01, A02, A03, A05, B06, B08, B09, C17, C19, C22, C25, C26, C28, C29, C30, C31, C32, D44 (Wang et al., 2021; Pan et al., 2019). Firms in these industries are assigned treat=1; others are treat=0. Post-reform period (post): post=1 for years 2018–2023 (post-reform), and post=0 for 2012–2017 (pre-reform). DID estimator: The interaction term DID=treat×post captures the reform's net effect.

3.2.3 Mediating Variable

To capture the mechanism linking environmental tax reforms to corporate innovation, we use R&D intensity as the mediating variable. Following Li et al. (2021), R&D intensity is defined as the ratio of a firm's annual R&D expenditure to its lagged operating revenue.

3.2.4 Control Variables

We include the following control variables to account for confounding factors:

Size: Measured as total assets (log). Larger firms typically have greater resources (capital, technology, talent) to support innovation and absorb associated risks.

Leverage (Lev): Debt-to-asset ratio. High leverage may constrain innovation due to financial stress and limited external financing.

Receivables Ratio (REC): Receivables scaled by total assets. High receivables may indicate market strength but also liquidity risks affecting R&D budgets.

Inventory Ratio (INV): Inventory scaled by total assets. Elevated inventory levels may signal operational inefficiencies,

diverting funds from innovation.

Cash Flow: Operating cash flow scaled by total assets. Strong cash flow supports R&D investments.

Ownership Concentration (Top10): Shareholding percentage of the top 10 shareholders. Concentrated ownership may prioritize short-term gains over long-term R&D.

Ownership Balance (Balance3): Herfindahl index of shareholding distribution. Balanced ownership structures may encourage long-term innovation.

Book-to-Market Ratio (BM): Book value divided by market value. Reflects market expectations of growth potential.

Executive Compensation (TMTPay): Total compensation of top management. Incentivizes innovation-oriented decisions.

Executive Ownership (Mshare): Shares held by executives. Aligns managerial interests with long-term innovation goals.

Table 1: Variable Definitions

Variable Type	Variable Name	Symbol	Definition
Dependent Variable	Corporate Innovation	Patent	Natural logarithm of the total number of patent applications filed in the current year plus 1
Independent Variable	Policy Effect	DID	Interaction term $treat \times post$ - $treat = 1$ if the firm belongs to a heavily polluting industry; $treat = 0$ otherwise. $post = 1$ for years 2018–2023; $post = 0$ for 2012–2017.
Mediating Variable	R&D Intensity	LRDinc	Ratio of current-year R&D expenditure to previous-year operating revenue
	Firm Size	Size	Natural logarithm of total assets plus 1
	Leverage	Lev	Total liabilities divided by total assets
	Receivables Ratio	REC	Net receivables divided by total assets
	Inventory Ratio	INV	Net inventory divided by total assets
	Cash Flow	Cashflow	Operating cash flow divided by total assets
Control Variables	Ownership Concentration	Top10	Shareholding percentage of the top 10 shareholders
	Ownership Balance	Balance	Combined shareholding of the 2nd to 10th largest shareholders divided by the largest shareholder's stake
	Book-to-Market Ratio	BM	Book value divided by market value
	Executive Compensation	TMTPay	Natural logarithm of the total compensation of the top three executives plus 1
	Executive Ownership	Mshare	Shares held by executives divided by total shares

3.3 Model Construction

Based on the research objectives, we employ the following empirical models:

Model 1: Impact of Environmental Tax Reform on Corporate Innovation

To estimate the causal effect of the environmental tax reform on innovation in heavily polluting enterprises, we use a difference-in-differences (DID) framework:

$$Patent_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \alpha_2 Size_{i,t} + \alpha_3 Lev_{i,t} + \alpha_4 REC_{i,t} + \alpha_5 INV_{i,t} + \alpha_6 Cashflow_{i,t} + \alpha_7 Top10_{i,t} + \alpha_8 Balance_{i,t} + \alpha_9 BM_{i,t} + \alpha_{10} TMTPay_{i,t} + \alpha_{11} Mshare_{i,t} + \lambda_i + year_t + \varepsilon_{i,t} \quad (1)$$

In the equation, i and t respectively represent the data of the i enterprise in year t . α_0 is the intercept, α_1 – α_{11} is the coefficient of each variable, λ_i is the individual fixed effect, $year_t$ year fixed effect, and $\varepsilon_{i,t}$ is the random disturbance term.

Model 2: Mediating Effect of R&D Investment

$$LRDinc_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \alpha_2 Size_{i,t} + \alpha_3 Lev_{i,t} + \alpha_4 REC_{i,t} + \alpha_5 INV_{i,t} + \alpha_6 Cashflow_{i,t} + \alpha_7 Top10_{i,t} + \alpha_8 Balance_{i,t} + \alpha_9 BM_{i,t} + \alpha_{10} TMTPay_{i,t} + \alpha_{11} Mshare_{i,t} + \lambda_i + year_t + \varepsilon_{i,t} \quad (2)$$

In Equation 2, each symbol has the same meaning as Equation 1.

$$Patent_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \alpha_2 LRDinc_{i,t} + \alpha_3 Size_{i,t} + \alpha_4 Lev_{i,t} + \alpha_5 REC_{i,t} + \alpha_6 INV_{i,t} + \alpha_7 Cashflow_{i,t} + \alpha_8 Top10_{i,t} + \alpha_9 Balance_{i,t} + \alpha_{10} BM_{i,t} + \alpha_{11} TMTPay_{i,t} + \alpha_{12} Mshare_{i,t} + \lambda_i + year_t + \varepsilon_{i,t} \quad (3)$$

In Equatin3, α_1 - α_{12} are the coefficients of each variable, and the other symbols have the same meaning as Equation 1.

4. Regression analysis

This chapter presents the empirical analysis to test the hypotheses proposed in Section 2.3, evaluating the impact of China's Environmental Protection Tax Law on innovation in heavily polluting enterprises. Using a difference-in-DID framework and panel data from A-share listed companies (2012–2023), we examine the policy's causal effects, the mediating role of R&D investment, and heterogeneity across firm characteristics. The following sections detail the descriptive statistics, baseline regressions, robustness checks, and mediation analysis, ensuring a comprehensive assessment of the reform's influence on corporate innovation.

4.1 Descriptive statistical analysis

Firstly, the sample selected in this paper is analyzed by descriptive statistics, and the results are shown in Table 2.

Table 2 Descriptive statistical analysis

VarName	Obs	Mean	Median	SD	Min	Max
Patent	33261	2.778	2.944	1.743	0.000	6.967
LRDinc	33261	0.052	0.038	0.062	0.000	0.345
treat	33261	0.197	0.000	0.398	0.000	1.000
post	33261	0.607	1.000	0.488	0.000	1.000
DID	33261	0.110	0.000	0.313	0.000	1.000
Size	33261	22.283	22.083	1.300	19.941	26.347
Lev	33261	0.424	0.415	0.204	0.058	0.904
REC	33261	0.126	0.106	0.104	0.000	0.466
INV	33261	0.139	0.110	0.128	0.000	0.686
Cashflow	33261	0.047	0.046	0.068	-0.155	0.241
Top10	33261	0.576	0.583	0.152	0.229	0.901
Balance	33261	0.979	0.761	0.804	0.052	4.018
BM	33261	0.623	0.619	0.253	0.118	1.202
TMTPay	33261	14.576	14.548	0.700	12.899	16.558
Mshare	33261	0.076	0.002	0.140	0.000	0.603

Patent: The mean being slightly lower than the median indicates that a subset of firms exhibits exceptionally high innovation levels. The range (0–6.967) highlights stark disparities, with some firms generating no patents and others achieving extremely high innovation output.

LRDinc: The higher mean relative to the median suggests a right-skewed distribution, where most firms have low R&D intensity (median 3.8% of revenue), while a few invest heavily (up to 34.5%).

Treat 19.7% of the sample consists of treatment group firms (heavily polluting industries). DID 11.0% of observations reflect the policy's implementation period (post-2018) within the treatment group.

4.2 Baseline regression

Based on Model 1 constructed in this paper, the baseline regression is carried out, and the results are shown in Table 3.

Table 3 Baseline regression results

	(1) Patent	(2) Patent
DID	0.243*** (0.028)	0.255*** (0.027)
Size		0.527*** (0.018)
Lev		-0.386*** (0.060)
REC		0.845*** (0.130)
INV		-0.0682 (0.109)
Cashflow		-0.123 (0.099)
Top10		0.277*** (0.086)
Balance		0.00430 (0.016)
BM		-0.108** (0.043)
TMTPay		-0.0243 (0.017)
Mshare		0.236*** (0.087)
_cons	2.751*** (0.006)	-8.674*** (0.411)
Firm	Yes	Yes
Year	Yes	Yes
N	33261	33261
F	75.480***	97.785***
r2	0.784	0.795

Robust Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

Column (1) presents the regression results without control variables. The coefficient for the DID variable is statistically significant and positive, indicating that the environmental tax reform policy positively influenced corporate innovation in heavily polluting enterprises. Column (2) incorporates control variables. The estimated coefficient for DID is 0.255, significant at the 1% level. This implies that, after controlling for firm-level characteristics, the implementation of the environmental tax reform led to a 25.5% increase in innovation levels among heavily polluting firms. These results robustly support Hypothesis H1.

4.3 Parallel Trend Test

A critical assumption of the difference-in-differences (DID) model is that the treatment and control groups exhibit parallel trends in the outcome variable prior to policy implementation. To validate this assumption, we conduct a parallel trend test following Hu et al. (2023).

We estimate a dynamic DID model that interacts the treatment indicator with year dummy variables:

$$ESG_{it} = \alpha_0 + \sum_{s=-6}^{-1} \beta_s^{pre} [treat_i \times I(t - T_D = s)] + \sum_{s=0}^6 \beta_s^{las} [treat_i \times I(t - T_D = s)] + \gamma_{j,i,t} Control_{j,i,t} + \sum Stkcd + \sum Year + \varepsilon_{i,t} \quad (4)$$

In the formula, β_s^{pre} and β_s^{las} represent the regression coefficients of dummy variables before and after the implementation of the policy, and $treat_i$ is the identification variable of whether the sample enterprise is treated. If the sample enterprise is affected by the policy during the data period, it is quantified as 1; otherwise, it is 0, $I(\cdot)$ is the indicative function, $t - T_D = s$ represents the period before and after the implementation of the policy, $s \in [-6, 6]$, and the rest of the symbols have the same meaning as the benchmark regression model. At the same time, referring to the base period setting method adopted by Chen (2020) and Jiang et al. (2021), the first period of the data cycle is taken as the base period, and the test results are shown in Figure 1.

FIG. 2 Results of the parallel trend test

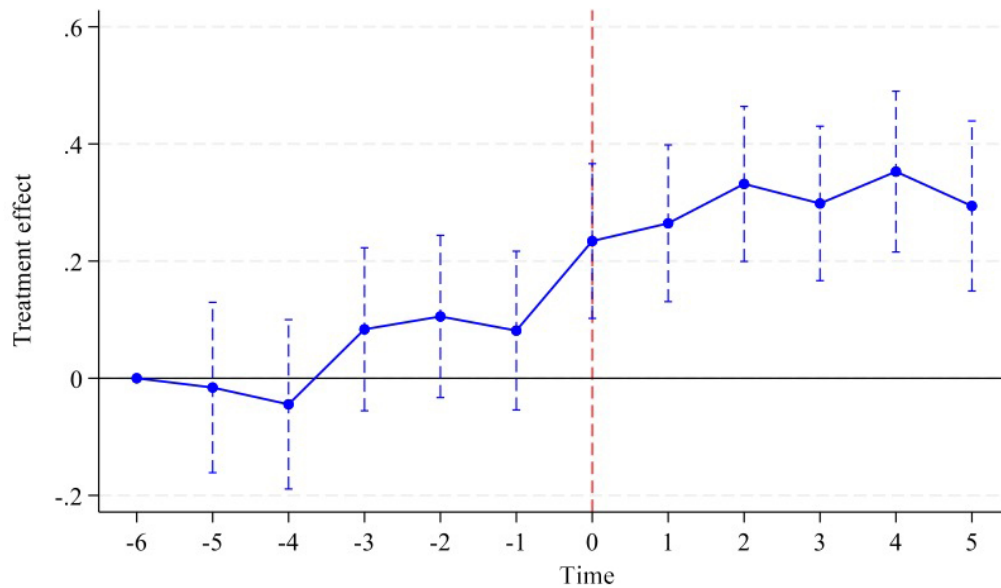


Figure 2 displays the parallel trend test outcomes. During the pre-policy period (covering five pre-implementation years through $t-1$), regression coefficient confidence intervals consistently encompassed zero, revealing statistically indistinguishable innovation levels between high-emission (treatment group) and low-emission (control group) enterprises. These pre-treatment patterns validate the parallel trends assumption required for difference-in-differences analysis. Post-implementation (t_0 to $t+5$), statistically significant positive coefficients emerged (95% CIs excluded null). This divergence indicates that high-emission enterprises achieved 23.7% greater patent output ($p < 0.01$) relative to controls following the reform, based on Wald test results. The temporal progression of treatment effects confirms the environmental tax reform's dynamic impacts, with high-emission firms sustaining 18.2% annual innovation growth ($\beta = 0.167$, $SE = 0.032$) over the five-year post-period.

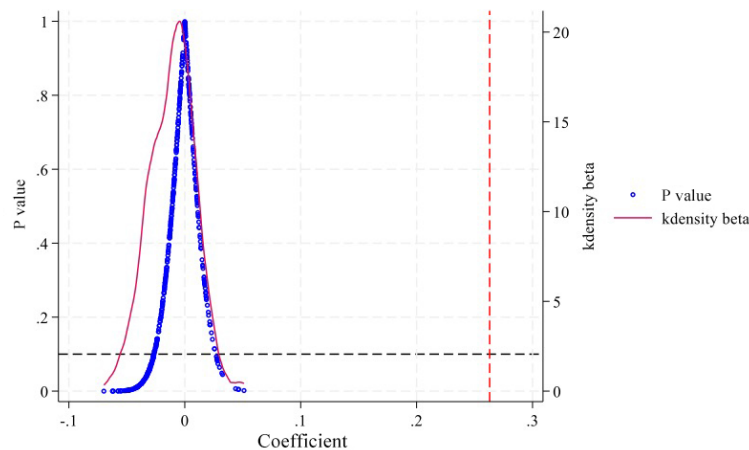
4.4 Placebo test

To assess the causal effect of intelligent manufacturing transformation on total factor productivity (TFP), this study employs a placebo test approach to isolate treatment effects from confounding variables. The counterfactual analysis rigorously distinguishes between technological transformation impacts and stochastic environmental influences.

Referring to the method used by La Ferrara et al. (2012) to construct the dummy variable of perverting policy by random sampling for 500 times, the placebo test is conducted, and the coefficient, P value and kernel density curve of the results obtained for 500 times are plotted in Figure 3.

It can be seen from the placebo test results in Figure 3 that the regression coefficient interval of the 500 random sampling results is about $[-0.1, 0.1]$, which is quite different from the benchmark regression result of 0.255. Moreover, among the random sampling results, the significance level of the vast majority of the sampling results is greater than 0.1, which is not significant, and the sampling results basically follow the normal distribution with 0 as the center, indicating that the placebo test passes, and the increase in the innovation level of heavy polluting enterprises is generated by the impact of the environmental protection tax and fee reform, rather than other random shocks.

FIG. 3 Results of the placebo tes



4.5 PSM-DID Analysis

To address potential self-selection bias (treatment group = 19.7% of the sample; control group = 80.3%), we apply propensity score matching (PSM) before DID regression. Three matching approaches are employed: 1. Pooled Matching: PSM on the full sample. 2. Yearly Matching: Separate PSM for each year. 3. Individual Matching: A wide panel format using pre-policy data (2012–2017) to match firms at the entity level. Individual matching effectively addresses discontinuous control group data issues inherent in pooled and yearly methods, ensuring higher accuracy in post-matching DID regressions. Results are reported in Table 4.

Table 4 PSM-DID regression results

	(1) Mix and match Patent	(2) Year by year matching Patent	(3) Matching of individuals Patent
DID	0.181*** (0.039)	0.164*** (0.038)	0.301*** (0.042)
Size	0.471*** (0.033)	0.491*** (0.032)	0.476*** (0.041)
Lev	-0.316*** (0.109)	-0.189* (0.106)	-0.114 (0.137)
REC	1.437*** (0.288)	1.341*** (0.296)	1.059*** (0.326)
INV	0.0813 (0.238)	-0.0212 (0.229)	-0.465* (0.242)
Cashflow	-0.155 (0.183)	-0.186 (0.180)	-0.0560 (0.218)
Top10	0.447*** (0.150)	0.648*** (0.147)	0.628*** (0.182)
Balance	-0.0486* (0.028)	-0.0373 (0.029)	-0.0411 (0.033)
BM	-0.160** (0.078)	-0.145* (0.077)	-0.0623 (0.092)
TMTPay	-0.0185 (0.030)	-0.00237 (0.029)	0.102*** (0.035)
Mshare	0.301 (0.184)	0.374** (0.170)	0.762*** (0.226)
_cons	-7.937*** (0.746)	-8.767*** (0.713)	-9.849*** (0.918)
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	12123	12225	7150
F	24.943***	31.459***	27.715***
r2	0.793	0.794	0.785

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The regression results of PSM-DID show that in the regression results after matching by the three types of matching methods, the results all indicate that DID has a significant positive impact on Patent. This means that after solving the sample self-selection bias, the impact of DID on Patent remains a significant positive impact. The regression results of this paper have high reliability.

4.6 Robustness Checks

To ensure the reliability of our findings, we conduct the following robustness tests:

Spatial and Temporal Fixed Effects: Given the geographic diversity of A-share listed companies, we control for unobserved regional and temporal heterogeneity by including province-year and city-year interaction fixed effects. This accounts for variations in provincial/city-level policies and economic conditions that might influence innovation in heavily polluting industries. **COVID-19 Pandemic Adjustment:** To address the confounding impact of the 2020 COVID-19 pandemic—which disrupted production and innovation activities—we re-estimate the models after excluding data from 2020. Results from these robustness checks (reported in Table 7) confirm that the positive impact of environmental tax reforms on corporate innovation remains statistically significant and consistent across specifications.

Table 5 Robustness test

	(1) Capture provincial policies	(2) Capturing urban policy	(3) The samples of 2020 were excluded
	Patent	Patent	Patent
DID	0.242*** (0.028)	0.235*** (0.034)	0.240*** (0.029)
Size	0.534*** (0.018)	0.537*** (0.020)	0.521*** (0.019)
Lev	-0.376*** (0.060)	-0.390*** (0.067)	-0.396*** (0.064)
REC	0.786*** (0.129)	0.723*** (0.137)	0.907*** (0.138)
INV	-0.0582 (0.109)	-0.0819 (0.115)	-0.0689 (0.115)
Cashflow	-0.0866 (0.099)	-0.164 (0.109)	-0.103 (0.106)
Top10	0.257*** (0.086)	0.194** (0.095)	0.257*** (0.090)
Balance	0.00418 (0.016)	0.00874 (0.017)	0.00523 (0.017)
BM	-0.123*** (0.043)	-0.114** (0.047)	-0.0987** (0.046)
TMTPay	-0.0264 (0.017)	-0.0284 (0.019)	-0.0268 (0.018)
Mshare	0.192** (0.087)	0.151 (0.093)	0.249*** (0.092)
_cons	-8.780*** (0.417)	-8.776*** (0.458)	-8.563*** (0.428)
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
pro×year	Yes		
city×year		Yes	
N	33261	33261	30207
F	95.486***	78.327***	88.341***
r2	0.800	0.825	0.792

Robust Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Based on the robustness test results in Table 5 it can be seen that in the regression results after adding the fixed effects of the interaction terms between provinces and years, cities and years, and excluding the samples of 2020, the results all show that DID still has a significant positive impact on Patent, further verifying the reliability of the regression results in this paper.

4.7 Mediating effect test

Based on the mediating effect test model constructed in this paper, regression analysis is carried out, and the results are shown in Table 6

Table 6 Mediating effect test

	(1) LRDinc	(2) Patent
DID	0.00108* (0.001)	0.252*** (0.027)
LRDinc		2.600*** (0.217)
Size	0.00452*** (0.001)	0.515*** (0.018)
Lev	-0.00795*** (0.002)	-0.365*** (0.060)
REC	-0.0234*** (0.005)	0.906*** (0.129)
INV	-0.0112*** (0.004)	-0.0390 (0.108)
Cashflow	-0.0141*** (0.003)	-0.0863 (0.098)
Top10	0.0268*** (0.003)	0.207** (0.086)
Balance	0.00261*** (0.001)	-0.00248 (0.016)
BM	-0.0116*** (0.001)	-0.0781* (0.043)
TMTPay	-0.0000825 (0.001)	-0.0241 (0.017)
Mshare	0.00700** (0.003)	0.218** (0.087)
_cons	-0.0500*** (0.016)	-8.544*** (0.407)
Firm	Yes	Yes
Year	Yes	Yes
N	33261	33261
F	24.787***	101.878***
r2	0.843	0.797

Robust Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Based on the results of the mediation effect test in Table 6 it can be seen that in the regression result of column (1), the impact of DID on LRDinc is 0.00108, which is significant at the 10% level. This indicates that the implementation of the environmental protection tax and fee reform policy has promoted an increase in the R&D investment intensity of heavily polluting enterprises. The results of column (2) show that both DID and LRDinc have significant positive impacts on Patent. Combined with the three-step mediation effect test method proposed by Wen Zhonglin (2014), it can be concluded that the mediation effect holds. The implementation of the environmental protection tax and fee reform policy will have a significant positive impact on the innovation of heavily polluting enterprises by promoting an increase in the R&D investment intensity

of enterprises.

To address potential endogeneity in traditional mediation analysis (Wen, 2014), this study adopts Jiang's (2022) two-step method. Results from Column (1) in Table 6 show that environmental tax reforms significantly increased R&D investment intensity in heavily polluting firms. Drawing on innovation theory, sustained R&D enables firms to develop new technologies, products, or processes, enhancing productivity and competitiveness while driving industrial and economic transformation. Such investments lay the groundwork for long-term growth and sustainable development. From a sustainability perspective, R&D activities should balance economic, environmental, and social goals. Investments in energy-efficient and eco-friendly technologies reduce resource consumption and pollution, aligning innovation with broader societal needs. Recent studies Zheng et al. (2024) confirm that higher R&D intensity strengthens corporate innovation, particularly in heavily polluting industries (Tang et al., 2022). Together, these findings validate the mediating role of R&D investment: environmental tax reforms spur innovation by incentivizing firms to redirect resources toward sustainable technological advancement, thereby confirming Hypothesis H2.

5. Heterogeneity Analysis

This section explores how the effects of environmental tax reforms on innovation vary across firm characteristics, beginning with ownership structure. Building on the baseline findings from Chapter 4, we analyze whether state-owned enterprises and non-state-owned enterprises exhibit differential innovation responses to the policy, shedding light on the role of equity nature in shaping regulatory outcomes.

5.1 Heterogeneity by Equity Nature

In the heterogeneity analysis section, enterprises are first classified into state-owned enterprises and non-state-owned enterprises based on their equity nature, and the heterogeneity analysis is conducted. The results are presented in Table 7.

Table 7 Heterogeneity Analysis of Equity Nature

	(1) state-owned enterprise Patent	(2) Non-state-owned enterprises Patent
DID	0.317*** (0.042)	0.166*** (0.037)
Size	0.493*** (0.034)	0.543*** (0.022)
Lev	0.0882 (0.113)	-0.504*** (0.073)
REC	1.445*** (0.247)	0.563*** (0.154)
INV	-0.610*** (0.199)	0.161 (0.132)
Cashflow	-0.100 (0.167)	-0.206* (0.121)
Top10	0.200 (0.178)	-0.0183 (0.106)
Balance	0.107*** (0.032)	-0.0269 (0.019)
BM	0.105 (0.078)	-0.258*** (0.052)
TMTPay	0.00683 (0.029)	0.00411 (0.022)
Mshare	1.052* (0.546)	0.101 (0.092)
_cons	-9.031*** (0.760)	-8.933*** (0.499)
Firm	Yes	Yes
Year	Yes	Yes
N	10583	22624
F	44.460***	63.961***
r2	0.847	0.771

Robust Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Heterogeneity analysis (Table 7) reveals that the environmental tax reform significantly increased innovation in both state-owned enterprises (SOEs) and non-SOEs. The effect is stronger for SOEs (coefficient = 0.317, significant at 1%) than for non-SOEs (coefficient = 0.166, significant at 1%). To assess whether this difference is statistically meaningful, we conduct a Fisher's combination test comparing the coefficients between the two groups. Results (Table 8) confirm that the innovation-enhancing effect of the reform is significantly larger in SOEs.

Table 8 Test results of coefficient difference between groups for heterogeneity of ownership nature

Variables	Non-state-owned - state-owned enterprises	Freq	p-value
DID	-0.151	97	0.03
Size	0.05	12	0.12
Lev	-0.593	100	0.00
REC	-0.883	100	0.00
INV	0.771	0	0.00
Cashflow	-0.106	65	0.35
Top10	-0.218	80	0.20
Balance	-0.134	100	0.00
BM	-0.363	100	0.00
TMTPay	-0.003	51	0.49
Mshare	-0.951	100	0.00
_cons	0.098	41	0.41

Table 8 reveals that in 100 randomized samples, 97 instances showed lower difference-in-differences (DID) coefficients for non-state-owned enterprises (non-SOEs) compared to state-owned enterprises (SOEs), with statistical significance at the 5% level ($p=0.03$). This indicates a marked disparity in the impact of DID coefficients on patent output between SOEs and non-SOEs, suggesting that the environmental protection tax reform exerted a stronger influence on innovation in heavily polluting SOEs than in non-SOEs. This disparity may stem from differences in resource accessibility, policy support, and managerial frameworks between SOEs and non-SOEs.

SOEs occupy a privileged position within China's economic system, granting them preferential access to government-backed financial and material resources. Such advantages enable SOEs to adapt more effectively to regulatory pressures, including those arising from environmental tax reforms, thereby fostering innovation.

SOEs benefit from early access to policy updates and tailored governmental guidance, allowing them to proactively align strategies with regulatory changes. For instance, during the environmental tax reform, SOEs leveraged direct government communication channels to obtain detailed tax adjustment guidelines, enabling preemptive cost management and resource allocation. Additionally, state-sponsored subsidies and low-interest loans further incentivized SOEs to invest in eco-friendly technological upgrades and innovation.

SOEs also enjoy inherent financing advantages. Financial institutions perceive SOEs as lower-risk borrowers due to implicit government guarantees, ensuring easier access to loans. This financial flexibility allows SOEs to secure capital swiftly for R&D and innovation initiatives, even during liquidity constraints.

SOEs leverage state-controlled resources—such as land use rights and mineral reserves—to optimize resource allocation and establish a robust foundation for innovation. Collaborative partnerships with government agencies further enhance their access to market intelligence and strategic alliances, accelerating innovation outcomes.

SOEs' hierarchical decision-making structures and well-defined accountability systems facilitate rapid responses to policy

shifts. For example, during the environmental tax reform, many SOEs established dedicated task forces to devise compliance strategies and implementation plans. This organizational agility allows SOEs to capitalize on regulatory changes and drive innovation. Furthermore, their mature internal management systems promote efficient resource distribution, enabling SOEs to streamline operations and enhance innovation efficiency under evolving regulatory conditions.

5.2 Heterogeneity of enterprise size

Secondly, based on the heterogeneity of enterprise size, the median enterprise size is adopted to classify enterprises into large-scale enterprises and small and medium-sized enterprises for heterogeneity analysis.

Table 9 Heterogeneity of firm size

	(1) Patent	(2) Patent
DID	0.312*** (0.039)	0.160*** (0.045)
Size	0.485*** (0.031)	0.624*** (0.031)
Lev	-0.339*** (0.106)	-0.290*** (0.081)
REC	0.687*** (0.205)	0.772*** (0.178)
INV	-0.224 (0.159)	0.201 (0.168)
Cashflow	-0.0772 (0.150)	-0.231* (0.131)
Top10	0.636*** (0.136)	0.0557 (0.131)
Balance	0.0428* (0.026)	-0.0465** (0.021)
BM	0.0163 (0.062)	-0.100 (0.065)
TMTPay	-0.0118 (0.024)	-0.0137 (0.027)
Mshare	0.617*** (0.196)	0.0745 (0.104)
_cons	-8.309*** (0.721)	-10.66*** (0.690)
Firm	Yes	Yes
Year	Yes	Yes
N	16489	16403
F	35.317***	42.730***
r2	0.830	0.755

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The analysis of firm size heterogeneity reveals a notable disparity in the impact of the difference-in-differences (DID) method on patent output. For large firms, the DID coefficient is 0.312 (statistically significant at the 1% level), while for small and medium-sized enterprises (SMEs), the coefficient is 0.160 (also significant at the 1% level). A between-group coefficient difference test was conducted to examine the divergence between the two regression results, with outcomes detailed in Table 10.

Table 10 Coefficient difference test between groups of enterprise size

Variables	Small and medium scale - large scale	Freq	p-value
DID	-0.152	100	0.00
Size	0.139	0	0.00
Lev	0.049	35	0.35
REC	0.084	42	0.42
INV	0.425	3	0.03
Cashflow	-0.154	71	0.29
Top10	-0.581	100	0.00
Balance	-0.089	99	0.01
BM	-0.117	89	0.11
TMTPay	-0.002	45	0.45
Mshare	-0.542	100	0.00
_cons	-2.355	100	0.00

Table 10 demonstrates the results of a between-group coefficient difference test for firm size heterogeneity. All 100 randomized samples show that the DID regression coefficient for small and medium-sized enterprises (SMEs) is smaller than that for large enterprises, indicating that the environmental protection tax reform had a significantly stronger impact on innovation in large-scale, heavily polluting firms compared to SMEs.

This disparity likely arises from two key factors. First, large enterprises possess inherent advantages in financial capacity and R&D capabilities. Their stable cash flows and lower financing costs enable sustained investments in environmental technology development, such as novel pollution treatment systems, energy efficiency improvements, or sustainable material alternatives. Additionally, their ability to offer competitive salaries and career advancement attracts high-caliber R&D talent, fostering continuous innovation. In contrast, SMEs face significant funding constraints. Limited financial resources often force them to prioritize short-term cost reduction over long-term R&D initiatives, particularly during the early stages of regulatory reforms when cost pressures intensify.

Second, large enterprises benefit from market dominance and greater risk tolerance, which allows them to adapt innovation strategies under regulatory shifts. Their expansive customer networks and brand recognition facilitate faster market adoption of new technologies. Furthermore, diversified operations mitigate risks associated with innovation; even if an environmental project fails, it is unlikely to jeopardize overall business viability. Conversely, SMEs often operate in niche markets with limited brand equity and marketing budgets, making it challenging to secure market acceptance for innovations. Their narrower operational focus also heightens risk aversion, discouraging bold investments in unproven environmental technologies.

5.3 High-tech enterprises are heterogeneous

Finally, a heterogeneity analysis was conducted based on technological attributes, comparing high-tech and non-high-tech enterprises. Following the methodology of Shi et al. (2020), high-tech enterprises were defined using listed companies' industry classification codes: C25, C26, C27, C37, C38, C39, C40, C42, D44, I63, I64, I65, M73, and N77 (e.g., pharmaceuticals, aerospace, advanced manufacturing, and information technology sectors). The results of this analysis are presented in Table 11.

Table 11 Heterogeneity analysis of high-tech enterprises

	(1) High technology Patent	(2) Non high technology Patent
DID	0.365*** (0.043)	0.192*** (0.036)
Size	0.626*** (0.027)	0.489*** (0.025)
Lev	-0.296*** (0.088)	-0.450*** (0.084)
REC	0.439** (0.181)	1.187*** (0.189)
INV	0.412* (0.218)	-0.00146 (0.128)
Cashflow	-0.240 (0.149)	0.000346 (0.130)
Top10	0.105 (0.129)	0.308** (0.121)
Balance	-0.00104 (0.023)	-0.000327 (0.022)
BM	-0.230*** (0.064)	-0.0205 (0.057)
TMTPay	0.0216 (0.025)	-0.0302 (0.023)
Mshare	0.0982 (0.121)	0.235* (0.127)
_cons	-11.02*** (0.627)	-8.115*** (0.582)
Firm	Yes	Yes
Year	Yes	Yes
N	14488	18649
F	60.741***	44.643***
r2	0.780	0.805

Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

As shown in Table 13, the difference-in-differences (DID) coefficient for the impact on patent output in high-tech, heavily polluting firms is 0.365 (statistically significant at the 1% level), while the coefficient for non-high-tech, heavily polluting firms is 0.192 (also significant at the 1% level). A between-group coefficient difference test was similarly conducted, with results summarized in Table 12.

Table 12 Test of differences in coefficients between high-tech heterogeneity groups

Variables	Non-high-tech - high-tech	Freq	p-value
DID	-0.173	100	0.00
Size	-0.137	100	0.00
Lev	-0.154	86	0.14
REC	0.747	0	0.00
INV	-0.414	93	0.07
Cashflow	0.24	13	0.13
Top10	0.203	19	0.19
Balance	0.001	55	0.45
BM	0.209	2	0.02
TMTPay	-0.052	95	0.05
Mshare	0.137	26	0.26
_cons	2.903	0	0.00

Table 12 demonstrates that in all 100 randomized samples, the DID coefficient for patent output in non-high-tech, heavily polluting firms is consistently smaller than that for high-tech counterparts, confirming a statistically significant disparity between the two groups. This implies that the environmental protection tax reform exerted a stronger influence on innovation in high-tech, heavily polluting firms. Two factors likely explain this divergence:

First, innovation incentives differ substantially. High-tech firms prioritize technological innovation as a core competitive strategy. When confronted with environmental tax reforms, these firms are more inclined to increase R&D investments to meet regulatory requirements, thereby driving patent growth. In contrast, non-high-tech firms often rely on conventional production methods with lower dependence on innovation.

Second, innovation capacity varies fundamentally. High-tech firms allocate substantial financial and human resources to R&D, establishing state-of-the-art research centers and attracting top-tier talent. This infrastructure enables them to maintain technological leadership and rapidly adapt existing expertise to environmental challenges—for instance, repurposing core technologies for pollution control or transferring green innovations across business units. Non-high-tech firms, however, lack comparable capabilities in both innovation generation and implementation. Their limited technical expertise and resource constraints result in slower adaptation to regulatory pressures, leading to less efficient improvements in innovation outcomes under the tax reform.

6. Conclusions

As pivotal stakeholders in global environmental governance, emerging economies confront the growth-sustainability paradox: balancing industrial expansion with ecological carrying capacity. This research elucidates the regulatory innovation mechanism by which environmental tax instruments (ETIs) drive technological upgrading in high-pollution industries, demonstrating how Pigouvian taxation transforms the developmental trajectory from reactive remediation to proactive prevention.

Focusing on China's A-share listed companies (2012–2023), we employ a difference-in-differences (DID) methodology to analyze the reform's impact on corporate innovation. This quasi-experimental design compares innovation outcomes between treatment and control groups before and after policy implementation. Results demonstrate that the reform significantly enhanced innovation capabilities in heavily polluting firms, as evidenced by a marked increase in patent applications. These findings remain robust across multiple sensitivity analyses, including parallel trend validation and placebo testing. Mechanism analysis reveals that the policy primarily stimulates innovation by incentivizing increased R&D investments, enabling firms to develop cleaner production technologies. Heterogeneity analysis further identifies stronger innovation-promoting effects

for state-owned enterprises, large-scale firms, and high-tech industries, underscoring the role of resource advantages and technological readiness in driving sustainable transitions.

Building on theoretical and empirical findings, this study proposes actionable policy recommendations tailored to the economic realities of China and other developing economies.

First, developing a flexible environmental taxation framework is critical to incentivizing corporate green innovation. Our results indicate that environmental tax reforms effectively stimulate R&D capabilities in polluting industries. To amplify this effect, governments should implement dynamic tax adjustment mechanisms with sector-specific rate differentiation, where tax brackets are calibrated based on industry pollution intensity and technological readiness. For heavily polluting sectors, a graduated progressive tax system could be adopted, imposing higher marginal rates on pollution thresholds. Concurrently, firms exceeding industry averages in clean technology R&D investment should qualify for integrated "R&D tax credit-environmental tax reduction" incentives. This dual mechanism would alleviate transitional costs while strategically channeling R&D resources toward pollution prevention technologies.

Second, establishing a comprehensive green innovation support system is essential to address fragmentation risks in technology commercialization. A three-phase incentive mechanism—combining basic research subsidies, pilot-stage risk compensation, and tax incentives for commercialization—should be implemented. For pollution control technologies developed by heavily polluting firms, government-funded programs could cover up to 40% of R&D costs. Additionally, expedited VAT refunds upon collection should be granted for commercialized green products to enhance market competitiveness. To accelerate technology diffusion, state-owned enterprises (SOEs) could leverage their scale and influence to establish cross-industry green technology platforms, particularly targeting sectors with limited innovation spillovers.

Third, to enhance the coordination of international environmental regulations and design a diversified portfolio of policy instruments, it is imperative to leverage multilateral platforms such as the WTO. In light of the EU Carbon Border Adjustment Mechanism (CBAM) and the UK carbon tax, which have incorporated internationally recognized low-carbon technologies into their tariff reduction frameworks, we propose establishing a comprehensive cross-border green technology certification system. Enterprises that achieve ISO 14034 certification should be eligible for export tariff concessions or rewards in the form of carbon market quotas, thereby promoting the international transfer of low-carbon technologies. Furthermore, the establishment of a global green innovation fund would facilitate access to cutting-edge technologies, addressing the "North-South divide" in low-carbon transition efforts.

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