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The role of institutional innovation and artificial intelligence in the corporate eco-innovation - a case study of high-tech enterprises in Liaoning province of China

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ABSTRACT

This research investigates the intricate interplay of institutional factors and technological adoption in the context of corporate ecological innovation. Grounded in the New Institutionalism Theory and the Technology-Organization-Environment (TOE) framework, the study explores how formal and informal institutional innovations shape the behavior and capabilities of companies engaged in ecological innovation in Liaoning Province, China. Furthermore, the research examines the role of Artificial Intelligence (AI) in promoting ecological innovation. The study classifies AI into three categories: data analytics and predictive AI, automation and intelligent production AI, and customer service and user experience AI. These dimensions are investigated in terms of their influence on ecological innovation, revealing how each element contributes to enhancing companies' capabilities in addressing ecological challenges. The research proposes hypotheses regarding the positive influence of these AI dimensions on ecological innovation outcomes. The findings from this research contribute to the education of the intricate dynamics between institutional innovations, technological adoption, and corporate ecological innovation. The insights garnered are crucial for policymakers, businesses, and researchers striving to cultivate sustainable practices and innovation in 'the contemporary economic and environmental milieu.

Contribution/ Originality: It provides significant theoretical and practical value to the study of the impact of institutional innovation and artificial intelligence on enterprise eco-type innovation, especially in the case of medium- and high-tech enterprises in China, looking at the role of institutional innovation and artificial intelligence in enterprise eco-type innovation.

1. INTRODUCTION

In underscoring the pivotal role of innovation in high-quality development, General Secretary Xi Jinping profoundly revealed that innovation serves as the primary driving force leading development (CCTV, 2023)[1]. The 18th Party Congress also underscored the importance of upholding and enhancing the existing system, while simultaneously developing a novel, scientific, standardized, and operationally effective system through institutional innovation. This approach is designed to provide a more robust institutional foundation for the advancement of socialism with Chinese characteristics (People's Daily Online, 2016). Meanwhile, green technology research and development for global and regional synergistic governance has emerged as a social concern, seeking coordinated

[1] CCTV refers to China's Central Television Program. It represents the highest-level report in China.

and sustainable development (Ministry of Science and Technology, 2022). The rule of law has also facilitated green development, serving as the "ecological chapter" of the practical requirements of Xi Jinping's rule of law thinking (Zhai & Chang, 2019).

In Liaoning Province, institutional innovation plays a pivotal role in the ecological type of innovation observed among enterprises. The Liaoning government guides enterprises to innovate in the direction consistent with Liaoning's economic development and social progress through the development direction stipulated by the system. Policies and regulations serve as crucial instruments for management and regulation. By employing targeted institutional innovation, policies become more scientific and rational, effectively promoting the development of eco-type innovation. For example, the Liaoning government has issued policies on scientific and technological innovation, industrial upgrading, and talent training to guide enterprises to prioritize and invest in innovative activities in the field of ecology and to promote the transformation and upgrading of the Liaoning economy.

In terms of AI, it is expected to navigate the digital economy into a new phase as a key digital technology. According to the White Paper on AI Ecology in China's Digital Economy Era 2021, at least 65% of the top 1,000 companies have utilized AI tools such as voice recognition and machine learning. Enterprises are combining AI technology with eco-friendly innovations to facilitate intelligent enhancements, develop novel products and services, and expand their markets and user bases. Through data analysis and machine learning, AI can assist enterprises better grasp market demand and optimize production processes, thus improving production efficiency and product quality. In addition, according to the Wang, Visvizi, Nan, and Meng (2024) country's green technology innovation is experiencing a period of accelerated growth, reflecting the rapid development of eco-based innovation. In terms of customer service and user experience, the implementation of AI has resulted in enhanced efficiency and precision in customer service, while increasing user satisfaction and loyalty to the company.

Overall, it is of significant theoretical and practical value to study the impact of institutional innovation and artificial intelligence on enterprise eco-type innovation, especially in the case of medium- and high-tech enterprises in Liaoning Province. A comprehensive investigation into the influence of institutional innovation and artificial intelligence on enterprise eco-type innovation, when considered alongside the available data, can provide substantial support for promoting the ecological transformation of industrial structure and economic development model.

2. LITERATURE AND HYPOTHESES

2.1. Theoretical Models

2.1.1. New Institutionalist Theory

The new institutionalist theory is a theoretical framework that focuses on the impact of institutions on social and economic behavior. The theory emphasizes the importance of institutions in elucidating the behaviour of organizations and individuals, particularly in explaining economic and social transformation, organizational coordination and policy implications. The fundamental premise of the new institutionalism theory is that institutions are not just a simple accumulation of rules and regulations, but a way of modeling social norms and behaviors that involve multiple dimensions of organization, coordination mechanisms, and culture. Williamson (1985) *The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting*, the seminal work of the new institutionalism in the field of economics, focuses on the economics of transaction costs and emphasized the role of institutions in solving problems of cooperation and coordination. North (1990) on the other hand, developed a theory of institutional change in Institutional Change: Governmental Change and Institutional Evolution, which emphasized the critical impact of institutional evolution on economic development and transformation.

2.1.2. Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment (TOE) framework is a comprehensive theoretical framework for the analysis and understanding of organizational adoption of new technologies (Tornatzky, Fleischer, &

Chakrabarti, 1990). The framework encompasses factors such as technology, organizational structure, and the external environment in order to reveal how these factors interact and influence an organization's adoption and use of technology. The core idea of the TOE framework is that technology adoption is a complex process that is influenced by a variety of factors both inside and outside the organization.

In the TOE framework, technological factors include the characteristics of the new technology, its usability, and its compatibility with other existing technologies. Organizational factors focus on the organization's internal structure, culture, leadership, and technical competence of employees. Additionally, environmental factors consider the impact of external markets, regulations, and competitive forces on the organization.

The objective of this framework is to assist researchers and policy makers in gaining a more comprehensive understanding of the factors that contribute to the varying degrees of willingness and success among organizations in adopting and implementing new technologies. The TOE framework provides a systematic and analytical approach to the decision-making process of technology adoption in organizations. The framework has been extensively utilized in the fields of information systems, innovation management, etc., and has emerged as a robust instrument for explaining and predicting organizational technology adoption behavior.

2.2. Institutional Innovation (II)

2.2.1. Definition and Classification of Institutional Innovation

According to institutional theory, the majority of extant literature classifies institutions as either formal or informal, with economist North (1990) in his book *Institutions, Institutional Change and Economic Performance* detailing the role of formal and informal institutions in shaping economic performance and behavior. North defines formal institutions as "rules established by legislators and backed by coercive force in a given place at a given time", while informal institutions are "habits, conventions, and social norms that govern behavior," emphasizing the interplay between the two in the economic system. interaction. Moreover, Huntington (1968) in *Political Order in Changing Societies*, distinguishes between two types of institutions: "the form of rules" and "the substance of norms". Additionally, economists Acemoglu and Robinson (2012) also provide an in-depth analysis of the distinction between formal and informal institutions in their book *Why Nations Fail: The Origins of Power, Prosperity, and Poverty*. They explore how institutions shape a nation's economic performance, emphasizing that the interplay between strong formal institutions (such as laws and policies) and robust informal institutions (such as culture and social norms) is crucial for a country's long-term prosperity.

Since the introduction of institutional economics, institutions have become an important environmental factor influencing the behavior of micro-organizations (Coase, 1973). Formal institutions are mainly based on external legal systems, political structures and market contracts, while informal institutions are mainly social norms and values, which are implicit and have a subtle effect on economic entities and social agents (North, 1990). In the study of firms' eco-type innovations, these two aspects of institutions have complex and significant impacts on firms' behavior and innovation capabilities, therefore, it is beneficial to consider them separately to gain a deeper understanding of how institutions shape firms' eco-type innovations. In particular, formal institutions provide clear policy guidelines on the direction of eco-type innovations, while informal institutions exert a significant influence on firms' innovation capabilities, for example, through the formation of social trust. These two interact with each other and jointly shape the behavior and capability of enterprises in eco-type innovation. Therefore, this paper categorizes institutional innovation into the following two distinct dimensions:

2.2.1.1. Formal System Innovation

Formal institutional innovation encompasses explicitly regulated elements of the legal system, the political structures and the market transaction contract. In the context of Liaoning Province, the government issues policies on scientific and technological innovation, industrial upgrading, and talent cultivation. These policies clarify the direction and focus of enterprise innovation, and lead the direction of enterprise ecological-type innovation through institutional innovation, which provides enterprises with strong policy support and directional guidance (Xinhua, 2024). Concurrently, the government also promotes the advancement of corporate eco-type innovation by enhancing the administration system related to social and ecological categories, elevating the standard of social and ecological governance, optimizing the social management system, and overseeing the implementation of social and ecological protection (May, 2022).

2.2.1.2. Informal Institutional Innovation

Informal institutional innovation is dominated by social norms and values, which are characterized by implicitization. In the context of Liaoning Province, social trust is regarded as a pivotal element of informal institutions, exerting a significant influence on macroeconomic growth and the capacity of enterprises to engage in eco-innovation (Li, Zhang, & Li, 2019). The concept of social trust encompasses not only social attributes, but also economic attributes, which drive the strategic response and organizational behavior adjustment in the process of corporate innovation through the mechanism of normative and cognitive legitimacy. Accordingly, this study employs the concept of social trust as a proxy for informal institutional innovation and examines its influence on corporate ecological innovations.

2.2.2. The Influence of Formal Institutional Innovation on Corporate Ecological Innovation

A substantial corpus of literature supports the important impact of formal institutional innovations on organizational behavior and innovation. According to North (1990) institutional theory, formal institutional innovations represent society's formal prescriptions for problem-solving, offering broad applicability in regulating and guiding firm behavior. The role of formal institutions in guiding firms to invest more actively in the direction of eco-type innovations is further substantiated by a study on policy documents and institutional innovations in Liaoning Province. The study posits that formal institutions can exert a beneficial influence in the domain of eco-type innovation by providing clear guidance to firms through explicit laws, regulations and policy norms. In particular, the policies and regulations on green technology innovation developed by the Liaoning Provincial Government, such as the Guiding Opinions on Accelerating the Establishment of a Sound Green, Low-Carbon, and Circular Development Economic System, provide clear support for firms to engage actively in eco-innovation. In addition, the evolution of institutions is closely related to social factors, while formal institutional innovations are universal across society, thus constituting important norms for business behavior (North, 1990).

Based on the above background, the following hypotheses are proposed in this paper:

H_1: Formal institutional innovations have a positive impact on corporate ecological innovation.

2.2.3. The Influence of Informal Institutional Innovation on Corporate Ecological Innovations

In this study, social trust, as a central component of informal systems and an important building block of social capital, was selected as a representative of informal systems. This is due to its pivotal role in social capital theory, wherein social trust exerts a profound influence on organizational and individual behavior. Consequently, gauging the extent of social trust can effectively illustrate the prospective influence of informal elements such as social norms and values, within the institutional context in which firms operate on their eco-innovation capabilities.

In an institutional setting, social trust can affect firms' eco-innovation capabilities through three main mechanisms (North, 1990). First, from the perspective of social capital, social trust functions as a lubricant, enhancing the total factor productivity of firms. Social capital includes trust relationships between economic and social agents; commonly shared norms and standards; and social networks and value interactions. Social trust, as a component of social capital, can facilitate the rapid dissemination of information, communication within enterprises, and collection and dissemination of knowledge. It can also reduce principal-agent costs, thereby enhancing the total factor productivity of enterprises and, in turn, their enhance eco-innovation capabilities (Chen & Hung, 2014).

Second, social trust can provide stable expectations in the context of enterprise financing, reduce the costs with information asymmetry, and alleviate the financing constraints and institutional barriers in the innovation process (Liao, 2020). In the context of innovation, which is often characterized by high uncertainty and complexity, social trust, as a form of collective identity shaped by social norms, provides stakeholders with a sense of stability and predictability. This, in turn, has the potential to reduce the costs associated with financing and transactions, while simultaneously creating a more favourable social support environment and a more inclusive system for acquiring corporate eco-innovation resources. In a favorable social trust environment, enterprises are more likely to obtain support from multiple stakeholders, including business partners, venture capital firms, and the government, and thus access more innovation resources (Hillman, Withers, & Collins, 2009).

In addition, social trust, as a social governance mechanism, can reduce the opportunistic tendencies of firms in the innovation process (Irfan, Razzaq, Sharif, & Yang, 2022). As a social moral code and industry norm, social trust can increase the opportunity cost of firms' opportunistic behaviors, thereby encouraging firms focus more on building genuine innovative capabilities to meet the value expectations of external social stakeholders.

Based on the above background, the following hypotheses are proposed in this paper:

H_2: Social trust, as a proxy for informal institutional innovations, has a positive impact on corporate ecological innovation.

2.3. Artificial Intelligence

2.3.1. Definition and Classification of Artificial Intelligence

The definition of Artificial Intelligence (AI) has been interpreted in various ways in academic research. According to Parentoni (2020) AI is the study of how computer systems perform tasks that typically require the characteristics of human intelligence. AI systems can simulate intelligent human behavior through learning, reasoning, and problem-solving. This definition emphasizes the wide range of applications of AI in simulating and performing tasks with the ability to mimic human intelligence.

The idea that AI has a significant impact on firms' eco-type innovation output is widely supported in the relevant literature. Munodawafa and Johl (2019) show that data analytics and predictive AI can provide firms with accurate predictions of eco-environmental changes and market demand through big data analytics, thus supporting firms to make more scientific and precise decision-making and planning of eco-type innovations. In addition, automated and intelligent production-based AI can improve the production efficiency and quality of eco-type innovation products, providing the possibility for enterprises to respond to eco-challenges more intelligently in the production process (Wang, Huang, Xia, & Shi, 2024). Customer service and user experience-based AI, on the other hand, enhances the efficiency of interactions between enterprises and users by applying AI technologies in customer service and interactive experiences, improves user satisfaction and loyalty, and creates opportunities for enterprises to build closer user relationships in eco-based innovations (Peruchini, Da Silva, & Teixeira, 2024).

This categorization of three types of AI is also supported by other researchers. For example, Jöhnk, Weißert, and Wyrtki (2021) emphasized the multi-level impact of different types of AI on firm innovation in their study. Based on the entire market of medium- and high-tech firms in Liaoning Province, this paper, by combing the literature on AI, finds that firms' understanding and application of these three types of AI are closely related to firms' eco-category innovation outputs. Therefore, in measuring the impact of AI on corporate eco-type innovation, this paper draws on the scale developed by scholars such as Dwivedi et al. (2021) which subdivides the AI variables into three comprehensive dimensions: data analysis and prediction-based AI, automation and intelligent production-based AI, and customer service and user experience-based AI. The specific reasons are as follows:

2.3.1.1. Data Analytics and Predictive AI

Data analytics and predictive AI provide a scientific basis for companies to make decisions and planning in eco-type innovation by using advanced data analytics to predict ecological changes, market demand and other factors based on large-scale data sets. According to Davenport and Harris (2007) data analytics is the process of collecting, cleaning, and analyzing massive data to obtain practical information. In eco-based innovation, this AI application can help companies better understand environmental issues and market demands, enabling them to develop eco-innovation strategies with greater precision. For example, by analyzing environmental monitoring data and market trends, companies can predict future ecological challenges and formulate corresponding eco-based innovation plans (Li & Huang, 2023).

2.3.1.2. Automated and Intelligent Productive AI

Automation and Intelligent Productive AI uses artificial intelligence technology to automate and intelligentize the production process of a company. According to Groover (2007) automation is the automation of production processes through the introduction of automatic control systems that reduce or replace human intervention. In eco-based innovation, this AI application can improve the productivity and quality of eco-innovation products. For example, by applying automated AI systems to the manufacturing process, companies can manage resources more efficiently, reduce waste, and produce more environmentally friendly products, thus promoting eco-based innovation (Chen & Jin, 2023).

2.3.1.3. Customer Service and User Experience-based AI

Customer service and user experience-based AI applies AI technology to customer service, interaction experience, and other areas. According to Wirtz and Lovelock (2016) this application creates opportunities for companies to build closer user relationships in eco-type innovations by improving the efficiency of interactions between companies and users, and enhancing user satisfaction and loyalty to companies. For example, through intelligent customer service systems, enterprises can respond more quickly and accurately to users' environmental needs and provide personalized service experiences, thus promoting more active user participation and support for the enterprise's eco-innovation (Cheng & Jiang, 2020).

2.3.2. Artificial Intelligence and Corporate Ecological Innovation

For the impact of AI on corporate eco-type innovation, when corporations use data analytics and predictive AI technologies for big data analysis to predict ecological changes, market demand, and other factors, just as the process by which green consumers perceive the unique value attributes of green products and form a willingness to buy, corporations have been able to use data analytics and predictive AI to better understand ecological challenges and market trends, so that eco-innovation strategies can be more accurately formulated. Studies have shown that data analytics play a key role in corporate decision-making, including predicting future market demands and environmental changes (Davenport & Harris, 2007). Therefore, this paper proposes the following hypothesis:

H_3: Data analytics and predictive AI have a positive impact on corporate ecological innovation.

Similarly, automated and intelligent production-based AI improves the production efficiency and quality of eco-friendly innovative products by automating and intelligentizing the production process. The application of such AI systems in the production process can effectively reduce resource wastage and drive companies to produce more environmentally friendly products, in line with green consumer demand for green products. Relevant studies support this view, for example, the introduction of automation systems in manufacturing helps to improve production efficiency and quality (Groover, 2007).

Therefore, the following hypotheses are proposed in this paper:

H_4: Automated and intelligent productive AI has a positive impact on corporate ecological innovation.

In addition, customer service and user experience-based AI is applied to improve the efficiency of interactions between enterprises and users, and to enhance users' satisfaction and loyalty to enterprises. Similar to the process of forming positive intentions of green consumers towards green products, by improving user experience, enterprises can better satisfy consumers' needs and enhance their trust and loyalty towards them. Related studies have shown that user experience and satisfaction are important factors influencing consumers' purchase intention (Kim & Forsythe, 2008).

Therefore, the following hypotheses are proposed in this paper:

H_5: Customer service and UX-based AI have a positive impact on corporate ecological innovation.

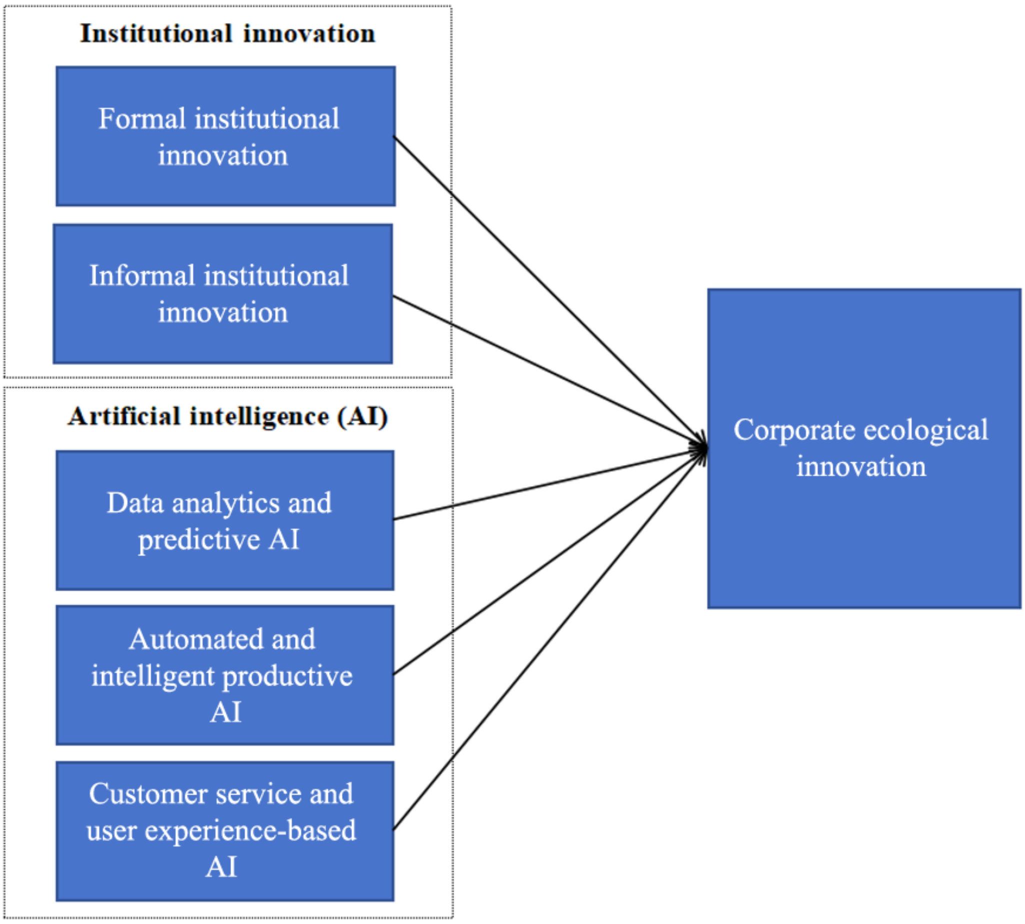

Figure 1. Hypotheses and assumption relationships.

The Figure 1 indicates the hypotheses relationship and the theoretical modelling, based on which, the data and analysis are carried out.

3. METHODOLOGY

3.1. Sample Selection and Data

This study takes medium- and high-tech enterprises in Liaoning Province as the research object, aiming to explore the impact of institutional innovation and AI innovation on the ecological type of innovation of enterprises in the region of Liaoning Province. In terms of sample selection and data sources, this paper selects medium- and high-tech enterprises in Liaoning Province from 2013 to 2023 as the research sample.

This study uses the Enterprise Search database to retrieve companies listed in A-share companies, while social trust data sources include the "2000 China Entrepreneurial Survey System" and the "China Urban Business Credit Environment Index". The formal system data relies on the "2008 China Business Environment Report". To ensure the reliability of the results, the initial samples were processed as follows: (1) excluding the financial and insurance industry samples; (2) excluding the insolvent samples; and (3) excluding the samples with missing relevant variables. Eventually, unbalanced panel data with 1564 sample observations for 223 firms in Liaoning Province are obtained. To exclude the influence of outliers on the regression results, all continuous variables are Winsor-shrunk at the 1% level.

3.2. Measurement of Variables

3.2.1. Dependent Variable: Corporate Ecological Innovation

In terms of innovation output, one can look at the firm's total factor productivity (TFP) in terms of what the firm actually achieves in the ecological domain. TFP reflects the additional productivity realized by a firm for a given level of inputs, as a reflection of the firm's capacity to innovate.

When using the questionnaire method to study the eco-based innovation outputs of enterprises, this paper focuses on the actual achievements of enterprises in the eco-field as well as the changes in their TFP, and the questionnaires are mainly distributed to the managers of medium- and high-tech enterprises in Liaoning Province. First, the questionnaire will find out the firms' specific performance in eco-innovation, including whether they have launched eco-friendly products, adopted sustainable business measures, or what innovations they have achieved in environmental protection. Second, we will study the impact of eco-innovation on firms' TFP, and explore whether firms have realized additional productivity under certain input levels as a reflection of their innovative capacity. In addition, we will examine the impact of eco-innovation on firms' overall performance and competitiveness, including market share gains, brand image improvements, and position in the industry. Finally, we will understand the firms' goals and strategies for eco-innovation, including their commitments to environmental protection and sustainable development, and how these commitments are translated into actual innovation initiatives. Through a detailed and specific questionnaire design, this paper aims to gain a comprehensive understanding of firms' innovation activities in the eco-field, and to provide strong data support for an in-depth study of the impact of institutional innovation on firms' eco-type innovations.

3.2.2. Independent Variable: Institutional Innovation and Artificial Intelligence

3.2.2.1. Institutional Innovation

Institutional innovation, as an important component of enterprise innovation, includes both formal and informal institutions. Formal institutions involve external norms such as legal, political, and market contracts, while informal institutions reflect the common norms and values of society. In this study, we use the degree of innovation in formal and informal systems as a measure of institutional innovation.

A measurement approach to informal institutional innovation:

This paper adopts the social trust measurement method based on Tang and Yang (2024) commissioned the "Chinese entrepreneurs survey system" in 2000 questionnaire survey, based on entrepreneurs survey data to obtain China's 31 provinces, autonomous regions, and municipalities directly under the Central Government of the weighted average of the region's corporate trust index. Since this paper focuses on the enterprise trust index in Liaoning Province, the scope of the questionnaire is adjusted, and the content of the survey is mainly about the trust issues related to the leadership of high-tech enterprises in Liaoning. The question was designed as "Based on your experience, which enterprises in the Liaoning region do you think are more trustworthy (in that order)?" which in turn was weighted to determine the final score based on a 5-point scale and the proportion of the corresponding number of people (Zhang & Ke, 2002).

Formal institutional innovation measurement:

In order to measure the level of formal institutional innovation environment in which firms are located, this paper adopts the marketization index in the China Sub-Provincial Marketization Index 2018 compiled by Wang, Fan, and Hu (2019) which includes, legal system, factor market development, and product market development. The total score of the marketization index is used to measure the marketization process, with a higher score representing a higher degree of marketization and a more complete formal system.

3.2.2.2. Artificial Intelligence

To test hypotheses H4, H5 and H6 in the study, this paper draws on Baabdullah, Alalwan, Slade, Raman, and Khatatneh (2021) to design an academic questionnaire focusing on the acceptance and application intensity of AI in new energy enterprises. The questionnaire aims to provide insights into companies' attitudes towards AI within the new energy sector and its potential impact on innovation inputs and outputs.

The target audience of this survey is companies engaged in business in the new energy sector, with a special focus on those companies that have applied or plan to apply AI technologies. The target audience of the questionnaire includes top management, innovation and research & development teams, and departments directly related to the application of AI technologies. A 5-point Likert scale was utilized to investigate the acceptance of AI by enterprises, aiming to understand the popularity of AI among enterprises in the new energy field. It also provides a detailed understanding of the AI projects that companies are currently implementing in the new energy sector, as well as the actual application of AI in their business.

3.2.3. Control Variables

Drawing on the studies of Kijkasiwat, Hussain, and Mumtaz (2022) and Fatma and Chouaibi (2023) the variables at the level of firm financial characteristics and corporate governance characteristics are mainly selected as control variables, including firm size (Size), gearing ratio (Lev), profitability (Roa), age of listing (Age), and nature of property rights (State), Board size (Board), executive power (Dual), and analyst tracking (lnAnalyst). In addition this paper controls for year fixed effects and industry fixed effects.

4. FINDINGS

4.1. Descriptive Statistical Analysis

There are 299 respondents in the questionnaire, and the table shows the basic personal information of the respondents. First of all, from the gender point of view, 33.1% are male and 66.9% are female; from the age point of view, the proportion of respondents aged 46-55 years old is the highest, 27.8%, and the proportion of respondents aged 56 years old or above is the lowest, 9.4%; from the occupation point of view, the proportion of personnel from institutions is the highest, 41.1%, and the proportion of government civil servants is the lowest, 8.4%; from the education point of view, the proportion of respondents with bachelor's degree or college degree From the perspective of education, respondents with bachelor's degree or college degree accounted for the highest proportion of 49.2%, while those with master's degree or above accounted for the least proportion of 11%; from the perspective of monthly income, respondents with monthly income of less than 3,000 yuan accounted for the most proportion of 31.8%, while those with monthly income of more than 10,000 yuan accounted for the least proportion of 17.7%.

Observing the mean value of corporate ecological innovation, the Table 1 indicates that among the respondents, women's corporate ecological innovation is higher than men's; the mean value of corporate ecological innovation is the highest for respondents aged 46-55, and the lowest for respondents aged 36-45; enterprise workers' corporate ecological innovation is higher than that of other occupations; respondents with master's degree and above have higher corporate ecological innovation than those with other education levels; respondents with monthly income of Respondents with a monthly income of less than 3,000 yuan have the lowest corporate ecological innovation, and those with a monthly income of more than 10,000 yuan have the highest corporate ecological innovation.

Table 1. Basic information about the interviewees.

	Item	N	Percentage	Mean value of CEI
Gender	Male	99	33.1	3.96
	Female	200	66.9	4.02
Age	18-25 years old	69	23.1	4.01
	26-35 years old	56	18.7	3.95
	36-45 years old	63	21.1	3.98
	46-55 years old	83	27.8	4.02
	Over 56 years old	28	9.4	4.00
Occupation	Enterprise employee	85	28.4	4.02
	Public institution staff	123	41.1	3.99
	Student	66	22.1	4.01
	Civil servant	25	8.4	4.01
Education	Junior secondary and below	54	18.1	3.96
	Senior secondary	65	21.7	4.00
	Undergraduate	147	49.2	4.01
	Master and above	33	11.0	4.02
Monthly disposable income	Less than ¥3000	95	31.8	3.95
	¥3000-6000	87	29.1	3.97
	¥6000-10000	64	21.4	3.98
	¥10000 and above	53	17.7	3.99

Furthermore, the Table 2 indicates that the mean value reflects the concentration of the data, and the standard deviation reflects the fluctuation of the data. Descriptive statistical analysis of the data shows that the mean value of all variables is close to 4, indicating that most respondents chose the option of "agree more" when filling out the questionnaire.

The variable with the highest mean value is customer service and user experience AI, which indicates that the respondents have the highest level of agreement with the customer service and user experience AI variable, while the variable with the lowest mean value is data analysis and predictive AI, which indicates that the respondents have the lowest level of agreement with the data analysis and predictive AI variable. The standard deviation of all variables is concentrated around 0.9.

The variable with the highest standard deviation is data analysis and predictive AI, which indicates that there is a large difference in the level of agreement between respondents on the data analysis and predictive AI variable, while the variable with the lowest standard deviation is formal institutional innovation, which indicates that there is the smallest difference in the level of agreement between respondents on the formal institutional innovation variable.

Table 2. Descriptive statistics.

Item	N	Min.	Max.	Mean	S.D.
Formal institutional innovation	299	1.00	5.00	3.9592	0.87044
Informal institutional innovation	299	1.00	5.00	3.7866	0.98571
Data analytics and predictive AI	299	1.00	5.00	3.7308	0.98810
Automated and intelligent productive AI	299	1.00	5.00	3.9922	0.90997
Customer service and user experience-based AI	299	1.00	5.00	4.0279	0.91855
Corporate ecological innovation	299	1.00	5.00	3.9624	0.92507

4.2. Confidence Analysis and Validity Analysis

In this paper, SPSS (26.0) was used for reliability analysis and factor analysis. At present, scholars generally use Cronbach's Alpha value to measure the internal consistency level of the questionnaire in the reliability analysis, and the higher the Cronbach's Alpha value, the higher the internal consistency level, i.e., the scale reliability level is high. The usual specific judgment criterion is that if the Cronbach's Alpha value is higher than 0.7, it indicates a high level of reliability, which is the ideal state (Zhou, 2014). In this study, all scale questions in the questionnaire were put into SPSS software for reliability analysis, and the results obtained are shown in Table 3. The total reliability coefficient of the scale is 0.817. Specifically, the Cronbach's alpha values of the six coefficients of formal institutional innovation, informal institutional innovation, data analytics and predictive AI, perceived automated and intelligent productive AI, perceived customer service and user experience-based AI, and corporate ecological innovation are all greater than 0.75, which indicates that the data of the questionnaire has a certain degree of reliability, and the data is relatively reliable.

Table 3. Reliability analysis results.

Factor	Cronbach's alpha value	
Formal institutional innovation	0.815	0.817
Informal institutional innovation	0.818	
Data analytics and predictive AI	0.773	
Automated and intelligent productive AI	0.752	
Customer service and user experience-based AI	0.758	
Corporate ecological innovation	0.803	

The purpose of validity analysis in empirical testing is to ensure the validity of the measurement results, which can generally be analyzed in terms of content validity and construct validity to detect the validity level of the measurement scale. The measurement scales used in this study are mature scales that have been practically tested by previous scholars, thus ensuring that they have a high level of content validity. In addition, this study used factor analysis to test construct validity. Lin and Lu (2010) stated that if the factor loading of a measurement question is greater than 0.4, it indicates that the questionnaire has a good level of construct validity. In addition, Wan (2018) stated that data are suitable for factor analysis if the Kaiser-Meyer-Olkin (KMO) value of the measurement questions is higher than 0.6 and the sig. (p-value of significance corresponding to Bartlett's test of sphericity) is ≤ 0.05. The Table 4 indicates that since the KMO value of the whole questionnaire is 0.908, sig.=0.000, and the KMO values of institutional innovation, artificial intelligence and corporate ecological innovation are all above 0.6, sig.=0.000, the data are suitable for factor analysis.

Table 4. KMO and Bartlett test.

KMO		**0.908**
Bartlett test	Approx. chi-square	4494.093
	df	276
	Sig.	0.000

Table 5 shows the results of the factor analysis. The factor loadings, which are the correlation coefficients between each original variable and each public factor, reflect the importance of each variable to the public factor. Through the size of the factor loading value, the importance of each original variable in the corresponding public factor can be obtained. The larger the absolute value of the factor loading value, the stronger the relationship between that public factor and the original variable. As can be seen from the table, the standardized loading coefficient values in all scale questions are greater than 0.6, and most of the factor loadings reach 0.7 or 0.8 or more, indicating that the variables meet the factor requirements. Taken together, the scale has good validity. The comprehensive reliability and validity analysis shows that the data have reliability and validity and can be analyzed subsequently.

Table 5. Factor analysis results.

Factor	Item	Factor loading					
Formal institutional innovation	FII1	0.619					
	FII2	0.688					
	FII3	0.730					
	FII4	0.768					
	FII5	0.731					
Informal institutional innovation	III1		0.801				
	III2		0.792				
	III3		0.824				
	III4		0.821				
	III5		0.838				
Data analytics and predictive AI	DAP1			0.732			
	DAP2			0.753			
	DAP3			0.782			
	DAP4			0.765			
Automated and intelligent productive AI	AIP1				0.804		
	AIP2				0.769		
	AIP3				0.838		
Customer service and user experience-based AI	CSUE1					0.847	
	CSUE2					0.829	
	CSUE3					0.727	
Corporate ecological innovation	CEI1						0.784
	CEI2						0.818
	CEI3						0.808
	CEI4						0.773

4.3. Correlation Analysis

To analyze the correlation between the variables of institutional innovation, artificial intelligence and corporate ecological innovation, this study uses the Pearson correlation analysis method to test. As shown in Table 6, there is a positive correlation between formal institutional innovation, informal institutional innovation, data analytics and predictive AI, automated and intelligent productive AI, customer service and user experience-based AI and corporate ecological innovation.

At the same time, most of the correlation coefficients between the research variables reached statistically significant levels, with the strongest correlation between customer service and user experience-based AI and automated and intelligent productive AI, with a correlation coefficient of 0.808, and the weakest correlation between data analytics and predictive AI and formal institutional innovation, with a correlation coefficient of 0.172, which basically coincides with the research hypotheses proposed in this paper.

Thus, it shows that the measurement scale used in this study can better reflect the theoretical model constructed in the study, and the data meet the requirements for further regression analysis.

Table 6. Pearson's correlation coefficient between different variables.

		FII	III	DAP	AIP	CSUE	CEI
FII	Pearson's r	1					
	Sig. (2-tailed)						
	N	299					
III	Pearson's r	0.423**	1				
	Sig. (2-tailed)	0.000					
	N	299	299				
DAP	Pearson's r	0.172**	0.398**	1			
	Sig. (2-tailed)	0.003	0.000				
	N	299	299	299			
AIP	Pearson's r	0.398**	0.280**	0.708**	1		
	Sig. (2-tailed)	0.000	0.000	0.000			
	N	299	299	299	299		
CSUE	Pearson's r	0.344**	0.278**	0.698**	0.808**	1	
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		
	N	299	299	299	299	299	
CEI	Pearson's r	0.352**	0.323**	0.354**	0.449**	0.425**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	
	N	299	299	299	299	299	299

Note: FII=Formal institutional innovation; III=Informal institutional innovation; DAP=Data analytics and predictive AI; AIP=Automated and intelligent productive AI; CSUE=Customer service and user experience-based AI; CEI=Corporate ecological innovation.
**p<0.01, the minimum significance level P value obtained is less than 0.01.

4.4. Hypothesis Testin

In this paper, corporate ecological innovation is taken as the dependent variable, and formal institutional innovation, informal institutional innovation, data analysis and predictive AI, automation and intelligent production AI, and customer service and user experience AI are taken as independent variables for multiple regression analysis. First Table 7 reflects the fit of the model, R is 0.724, and the adjusted R-square of the decidable coefficient is 0.512, which indicates that these five independent variables can explain 51.2% of the variation of the dependent variable. The value of Durbin-Watson (DW) is 1.691, and the result is in the range of 0-4, which indicates that the data meets the independence requirements of the multiple regression analysis.

Table 7. Summary of regression analysis model.

R	R^2	Adjusted R^2	Se	DW
0.724	0.524	0.512	0.472	1.691

Table 8 shows the analysis of variance in the multiple regression analysis. The value of F is a test of significance of the regression equation and can be used to determine whether the linear relationship between the explained variables and all the explanatory variables in the model is significant in the aggregate. The model corresponds to an F value of 22.214 and a Sig value of 0.000, which is less than 0.05, indicating that at least one of the independent variables in the model is able to explain some of the variance in the dependent variable, i.e., indicating that the regression model developed is significant.

Table 8. Analysis of variance (ANOVA).

	Sum of squares	df	Mean square	F	Sig.
Regression	59.217	5	11.843	22.214	0.000
Residuals	156.215	293	0.533		
Total	215.432	298			

Table 9 shows the significance of the effect of each independent variable on the dependent variable. According to the variance inflation factor (VIF) value in the covariance statistics, the VIF of all items is less than 10, which indicates that there is no multicollinearity in the data, and it meets the conditions of multiple regression analysis. In addition, the regression coefficient values of formal institutional innovation (β=0.151 , p=0.015<0.05), informal institutional innovation (β=0.152 , p=0.012<0.05), and automation and intelligent production AI (β=0.213 , p=0.022<0.05) reached statistical significance, and the p-values of the corresponding t-tests were all less than 0.05, indicating that these three variables have a significant positive effect on corporate ecological innovation. The coefficients corresponding to formal institutional innovation, informal institutional innovation, and automation and intelligent production AI are 0.147, 0.131, and 0.204, respectively, indicating that when formal institutional innovation, informal institutional innovation, and automation and intelligent production AI change by one unit, satisfaction changes by 0.147, 0.131, and 0.204 units, respectively. In addition, the size of β value can illustrate the intensity of the influence of the independent variables on the dependent variable, i.e., the intensity of the influence of these three variables on corporate ecological innovation is ranked as automation and intelligent production AI > informal institutional innovation > formal institutional innovation. The p-value of the corresponding t-test for data analytics and predictive AI (β=0.060 , p=0.464>0.05) and customer service and user experience-based AI (β=0.122 , p=0.167>0.05) is greater than 0.05, which indicates that the positive influence of data analytics and predictive AI and customer service and user experience-based AI on corporate ecological innovation is not significant. Therefore, H1, H2 and H4 are supported, however, H3 and H5 are not supported.

Table 9. Multiple linear regression (MLR) analysis.

	Unstandardized coefficients		Standardized coefficients	t	p	Collinearity statistics	
	B	Std. error	β			Tol	VIF
(Constant)	1.446	0.250		5.776	0.000		
Formal institutional innovation	0.147	0.060	0.151	2.457	0.015	0.659	1.517
Informal institutional innovation	0.131	0.052	0.152	2.525	0.012	0.686	1.459
Data analytics and predictive AI	0.052	0.071	0.060	.733	0.464	0.369	2.709
Automated and intelligent productive AI	0.204	0.089	0.213	2.299	0.022	0.287	3.480
Customer service and user experience-based AI	0.115	0.083	0.122	1.386	0.167	0.321	3.117

4.5. Discussion of the Findings

4.5.1. Influence of Formal and Informal Institutional Innovation on Corporate Ecological Innovation

This study reveals that both formal and informal institutional innovations significantly impact corporate ecological innovation in medium- and high-tech enterprises in Liaoning Province. Formal institutional innovation, represented by government policies and regulations, plays a vital role in guiding corporate behavior towards ecological innovation. This aligns with the findings of North (1990) who emphasized the importance of structured legal and policy frameworks in shaping economic activities. For instance, enterprises that operate within a well-developed institutional environment are more likely to engage in eco-innovation practices, as they receive clearer directives and support from the government, leading to enhanced innovation outputs.

On the other hand, informal institutional innovation, such as social trust and norms, also contributes to corporate ecological innovation. This finding highlights the subtle yet significant influence of cultural and societal expectations on corporate behavior. Informal institutions create a conducive environment where companies feel the societal pressure to innovate in environmentally friendly ways. This is consistent with the views expressed by Acemoglu and Robinson (2012) who argue that strong informal institutions, alongside formal ones, are crucial for fostering sustainable economic development.

4.5.2. Impact of Artificial Intelligence on Corporate Ecological Innovation

The study also revealed that the implementation of artificial intelligence (AI) within the domain of automation and smart production exerts a considerable positive influence on corporate eco-innovation. These findings indicate that as companies integrate AI-driven automation into their production processes, they become more effective in reducing resource waste and improving the efficiency and quality of their eco-friendly products. The implementation of automated AI has been demonstrated to markedly enhance production efficiency. This is achieved by optimizing production processes and reducing the necessity for manual intervention. Consequently, companies are able to produce eco-friendly products in a more expedient and cost-effective manner, which in turn mitigates the adverse impacts on the environment. For instance, the implementation of automated systems within the manufacturing process can diminish energy consumption and waste generation, thereby facilitating the attainment of green production objectives. This perspective is further reinforced by the findings of Chen and Jin (2023) study, which underscores the pivotal role that AI plays in enhancing productivity and asserts that it can assist firms in achieving green innovations through an intelligent approach. This indicates that the implementation of automated AI not only enhances efficiency in corporate eco-innovation but also plays a pivotal role in broader environmental protection initiatives. In contrast, while data analytics and predictive AI are of critical importance in strategic decision-making, their impact on corporate eco-innovation is relatively insignificant. This may be since data-driven AI applications are still in the exploratory phase regarding their potential applications in the field of eco-innovation. It is possible that organizations have not yet fully understood how to utilize these data analytics tools in order to facilitate sustainable innovation. The application of data analytics and AI typically provides insights regarding market demand, environmental changes, and other pertinent factors, which can inform long-term strategies for eco-innovation. However, Davenport and Harris (2007) highlight that while data analytics techniques can provide a wealth of information, their effective implementation often necessitates a high level of organizational readiness and expertise on the part of the firm. This indicates that firms may encounter obstacles in terms of technical comprehension, data integration, and operational intricacy when employing data analytics AI for eco-innovation, which may consequently impact its immediate efficacy in eco-innovation. Consequently, the full potential of data analytics AI has yet to be realized. Enterprises must enhance their data processing and innovation integration capabilities to more effectively leverage this technology for eco-innovation.

Furthermore, the influence of customer service and user experience-oriented artificial intelligence (AI) on eco-innovation within enterprises is found to be inconsequential. This may be attributed to the fact that the primary functions of such AIs are centered on optimizing customer interactions and enhancing user satisfaction, which are relatively constrained in their capacity to drive direct eco-innovation. While the provision of good customer service and the creation of an optimal user experience can assist in enhancing a brand's image and fostering customer loyalty, they are not directly involved in an organization's production processes or product development. Consequently, while these types of AI technologies can enhance customer recognition of the firm, their role in driving innovation in the ecological domain is more indirect. Moreover, a considerable number of enterprises are primarily focused on operational efficiency and user satisfaction when implementing customer service-type AI, rather than on achieving ecological objectives through these technologies. This discrepancy in the application of technology may have resulted in a diminished contribution to eco-innovation.

5. RECOMMENDATIONS

5.1. Suggestions for Enhancing the Role of Institutional Innovation in Liaoning in Corporate Eco-type Innovation

Liaoning, as an important industrial base in China, has been actively promoting the development of institutional innovation and enterprise eco-type innovation. However, to enhance the role of institutional innovation in enterprise eco-type innovation, efforts are still needed in the following areas:

5.1.1. Insist On Strengthening Policy Support and Continuing to Promote Institutional Innovation

In recent years, Liaoning Province has gradually introduced relevant support systems for enterprise eco-innovation, but the support under the improvement of system innovation is still insufficient, Liaoning should insist on strengthening the policy support for enterprise eco-innovation and capture the development trend of the times to introduce the results of system innovation in a timely manner. In terms of funding, to carry out ecological innovation enterprise loan financing difficulties to provide targeted assistance, encourage the introduction of new financial models and institutions to provide better financial support for enterprises, learning Jiangsu Province, the government - banks - enterprises to jointly promote the development of green financial system. In terms of talent protection, talent is the core force to promote ecological innovation. Liaoning should increase the introduction and cultivation of high-end talents, and attract more excellent talents from home and abroad to Liaoning by providing good working environment and living conditions. At the same time, the government should also strengthen the cultivation and incentives for talents and provide them with more development opportunities and platforms. Industry-university-research cooperation is also an important way to promote ecological class innovation. Liaoning has a number of famous universities and research institutes, which should actively carry out institutional innovation, produce relevant innovations, and guide these institutes to cooperate with enterprises to carry out eco-innovation projects, which can be promoted through the establishment of joint research and development funds, and the provision of technical guidance and talent support. In addition, the Liaoning government should continue to optimize a series of traditional approval procedures and formalities carried out in the process of eco-innovation by innovative enterprises, especially to give key support to those projects with major breakthroughs and industry-led effects, to improve the strength and effectiveness of substantive policy support to reduce the difficulty and cost of eco-innovation by enterprises, and to promote the progress of eco-innovation by enterprises. Liaoning's support for emerging eco-innovation enterprises is relatively small, and there is also a time lag in institutional innovation support and guidance. The development trend of the industry should be captured in a timely manner, and institutional policies should be introduced in time to guide enterprises to clarify the direction and goals of ecological innovation. For emerging industries and technologies, timely innovation of the corresponding standards and norms, so that institutional innovation with the times, overall consideration, to maintain market order norms and stability. Establish and improve relevant regulations, pay attention to the development of new fields in a timely manner, and manage and guide enterprises to standardize and regulate the development of eco-innovation.

5.1.2. Improve the Pattern of Institutional Innovation and Strengthen Inter-Firm and International Cooperation and Exchanges

Inter-enterprise cooperation and exchange is an important way to promote innovation in the ecological category of enterprises. By improving Liaoning's institutional innovation pattern and opening up new development cooperation ideas, it actively promotes cooperation and exchange among enterprises, and promotes information sharing and technological cooperation among enterprises by organizing industry forums, technology exchanges and other activities. At the same time, the government can also encourage enterprises to carry out cooperation through the establishment of cooperation funds and other innovative ways to further promote the development of enterprise ecological class innovation. International cooperation and exchange is also an important way to promote enterprise eco-type innovation. Liaoning should actively carry out cooperation and exchanges with international advanced technology enterprises and research institutions to enhance the level and competitiveness of Liaoning's eco-type innovations through the introduction of advanced technology and management experience. In addition, the government should strengthen its support and guidance for international cooperation programs and provide more facilities and guarantees for international cooperation. In conclusion, enhancing the role of institutional innovation in Liaoning in enterprise eco-type innovation requires the joint efforts of the government, enterprises, universities and research institutions. Only by strengthening policy guidance and support, promoting industry-university-research cooperation, cultivating and introducing high-end talents, strengthening inter-firm cooperation and exchanges, and strengthening international cooperation and exchanges can institutional innovation in Liaoning play a greater role in enterprise ecological-type innovations, and promote the sustainable development and transformation and upgrading of Liaoning industry.

5.2. Suggestions for Enhancing the Role of Artificial Intelligence in Liaoning in Corporate Eco-Class Innovation

The application and development of Artificial Intelligence (AI) technology is receiving increasing attention and has had a profound impact on a wide range of industries. To enhance the role of AI in enterprise eco-type innovation, here are a few suggestions:

5.2.1. Establishment of an AI Industrial Ecosystem and Strengthening of Innovation and Integration with Ecological Fields

Enhancing the role of AI in enterprise eco-type innovation first requires laying a good foundation for the excellent development of AI. The Liaoning government should formulate relevant policies and actively promote on-the-ground practices to promote the development of the AI industry, including supporting the incubation, innovation, and research and development of AI enterprises, encouraging AI enterprises to cooperate with other industries, and promoting the industrialization and commercial application of AI technology, as well as expanding AI industrial parks to attract more AI enterprises and related institutions to form an industrial agglomeration effect. n addition, we have set up public welfare science popularization learning programs on the mechanism and application of AI technology to pave the way for the subsequent integration with the enterprises' own eco-innovation, to improve the enterprises' knowledge and application ability of AI technology, so that AI technology is no longer simply imitated in the promotion of eco-innovation, and to strengthen the understanding of the mechanism of AI technology, so as to make the technology compatible with their own enterprises when integrating it into their eco-innovation, and to improve the degree of integration and optimize the results of innovation. degree of integration, optimize the innovation results, and apply them to the production and management process. For enterprises with small scale or low management level, we provide special support for the introduction of AI technology, so as to better solve the corresponding financial and talent difficulties in AI-enabled enterprise eco-innovation. The degree of data sharing and openness directly determines the application effect of AI technology, and indirectly has an impact on the ecological type of innovation results that enterprises integrate into the technology. The development of AI technology requires a large amount of data support, and the government can promote data sharing and openness, facilitate the circulation and utilization of data, and provide enterprises with more comprehensive and accurate data support. At the same time, the government can also formulate relevant regulations to standardize the collection, storage and use of data, and safeguard data security and privacy. The government and management should strengthen the concern for data protection, standardize data operation and continuously monitor the risk of privacy leakage based on the improvement of data sharing and openness, to better enable the integration of AI technology in the application of ecological type of innovative fields.

5.2.2. Improve the Mechanism for Cultivating and Introducing Artificial Intelligence Talents

Talent is the key, and the combination of artificial intelligence and eco-innovation requires the support of high-quality talents who can master the two fields and promote the joint progress of the fields. By strengthening education and training in the field of artificial intelligence and the actual practice of integration with eco-innovation, we can cultivate more relevant professionals, and provide more high-quality composite talents to support the development of artificial intelligence technology and the integration with eco-innovation. In addition, the government can also formulate relevant policies to attract more composite talents with cutting-edge AI technology and related eco-industry knowledge to come to Liaoning, for example, by providing a good working environment and living conditions in Zhejiang Province and setting up a talent incentive program, among other measures.

5.2.3. Promoting Technological Integration of Enterprises and Strengthening International Cooperation and Exchanges

The Government can encourage enterprises to make use of AI technology for intelligent upgrading, accelerate integration with ecological innovation fields, and improve the productivity and competitiveness of enterprises. The Government can also provide relevant technical and financial support to help enterprises introduce AI technology and equipment, and promote the digital transformation and intelligent upgrading of enterprises. The application of AI technology in eco-friendly innovation fields can draw on the latest developments abroad and actively cooperate. Enterprises and the government should actively carry out cooperation and exchanges with international advanced technology enterprises and research institutes, introduce advanced technology and management experience, and learn about the world's practical application status, so as to promote the innovation and development of Liaoning's AI technology in the field of eco-based innovation.

In conclusion, enhancing the role of AI in Liaoning in enterprise eco-type innovation requires the joint efforts of many parties, including the government, enterprises, universities and research institutions. It is only through the efforts of establishing an AI industrial ecology, strengthening talent cultivation and introduction, promoting intelligent upgrading of enterprises, enhancing data sharing and openness, and strengthening international cooperation and exchanges that AI technology in Liaoning can play a greater role in enterprise eco-type innovations, and promote the sustainable development and transformation and upgrading of Liaoning's industry.

6. LIMITATIONS AND FUTURE PROSPECTS

6.1. Limitations

Although this study empirically analyzes the impacts of institutional innovation and artificial intelligence on firms' eco-based innovation outputs among medium- and high-tech firms in the age of digital intelligence, there are still some limitations. First, the scope of the study is limited to medium- and high-tech firms in Liaoning Province, which may not adequately represent the national diversity and complexity. Therefore, the results of the study need to be interpreted with caution when generalizing to other regions. Second, this study focuses on the impact of social trust on the construction of innovation capability of medium- and high-tech firms, and does not explore in depth other potential factors, such as industry characteristics and government policies, which may have an important impact on innovation capability. Finally, this study used cross-sectional data, which could not capture the long-term changes and development trends of innovation capacity building, and a longitudinal research design could be considered for future studies.

6.2. Future Prospects

Future research can be expanded in the following ways. First, the research sample can be expanded to cover more regions and industries to improve the external validity of the study. Second, more potential factors, such as corporate culture and leadership style, can be introduced to study in-depth the relationship between them and innovation capacity building. In addition, qualitative research methods such as in-depth interviews and case studies can be used to dig deeper into the mechanisms and paths of social trust on the innovation of medium- and high-tech enterprises. In terms of research methodology, a longitudinal research design can be adopted to track the long-term changes in the construction of enterprise innovation capacity and to understand its development trend more comprehensively. Finally, the values of traditional Chinese culture can be combined to further study its role in the eco-innovation environment of medium- and high-tech enterprises and provide deeper cultural support for promoting the development of China's digital economy era. These expansions will contribute to a more comprehensive and in-depth understanding of the impact of institutional innovation and AI on corporate eco-type innovations, and provide a stronger reference for future policy making and corporate practice.

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REFERENCES

Acemoglu, D., & Robinson, J. A. (2012). *Why nations fail: The origins of power, prosperity, and poverty*. New York: Crown Business.

Baabdullah, A. M., Alalwan, A. A., Slade, E. L., Raman, R., & Khatatneh, K. F. (2021). SMEs and artificial intelligence (AI): Antecedents and consequences of AI-based B2B practices. *Industrial Marketing Management, 98*, 255-270. https://doi.org/10.1016/j.indmarman.2021.09.003

CCTV. (2023). *High-quality development depends on innovation. CCTV English*. Retrieved from https://english.cctv.com/

Chen, P.-C., & Hung, S.-W. (2014). Collaborative green innovation in emerging countries: A social capital perspective. *International Journal of Operations & Production Management, 34*(3), 347-363. https://doi.org/10.1108/IJOPM-06-2012-0222

Chen, Y., & Jin, S. (2023). Artificial intelligence and carbon emissions in manufacturing firms: The moderating role of green innovation. *Processes, 11*(9), 2705. https://doi.org/10.3390/pr11092705

Cheng, Y., & Jiang, H. (2020). How ai-driven chatbots impact user experience. *Journal of Broadcasting & Electronic Media, 64*(4), 592-614. https://doi.org/10.1080/08838151.2020.1834296

Coase, R. H. (1973). The nature of the firm. *Economica, 4*(16), 386–405.

Davenport, T. H., & Harris, J. G. (2007). Competing on analytics: The new science of winning. *Harvard business Review Press, Language, 15*(217), 24.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., . . . Eirug, A. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, 101994.

Fatma, B. H., & Chouaibi, J. (2023). Corporate governance and firm value: A study on European financial institutions. *International Journal of Productivity and Performance Management, 72*(5), 1392-1418. https://doi.org/10.1108/IJPPM-05-2021-0306

Groover, M. P. (2007). *Automation, production systems, and computer-integrated manufacturing*. India: Pearson Education.

Hillman, A. J., Withers, M. C., & Collins, B. J. (2009). Resource dependence theory: A review. *Journal of Management, 35*(6), 1404-1427.

Huntington, S. P. (1968). *Political order in changing societies*. New Haven: Yale University Press.

Irfan, M., Razzaq, A., Sharif, A., & Yang, X. (2022). Influence mechanism between green finance and green innovation: Exploring regional policy intervention effects in China. *Technological Forecasting and Social Change, 182*, 121882. https://doi.org/10.1016/j.techfore.2022.121882

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*(1), 5-20. https://doi.org/10.1007/s12599-020-00676-7

Kijkasiwat, P., Hussain, A., & Mumtaz, A. (2022). Corporate governance, firm performance, and financial leverage across developed and emerging economies. *Risks, 10*(10), 185. https://doi.org/10.3390/risks10100185

Kim, J., & Forsythe, S. (2008). Adoption of virtual try-on technology for online apparel shopping. *Journal of Interactive Marketing, 22*(2), 45-59. https://doi.org/10.1002/dir.20113

Li, C., & Huang, M. (2023). Environmental sustainability in the age of big data: Opportunities and challenges for business and industry. *Environmental Science and Pollution Research, 30*, 119001–119015. https://doi.org/10.1007/s11356-023-30301-5

Li, L., Zhang, P., & Li, X. (2019). Regional economic resilience of the old industrial bases in China—a case study of Liaoning Province. *Sustainability, 11*(3), 723. https://doi.org/10.3390/su11030723

Liao, Z. (2020). Is environmental innovation conducive to corporate financing? The moderating role of advertising expenditures. *Business Strategy and the Environment, 29*(3), 954–961.

Lin, L. Y., & Lu, C. Y. (2010). The influence of corporate image, relationship marketing, and trust on purchase intention: The moderating effects of word-of-mouth. *Tourism Review, 65*(3), 16-34. https://doi.org/10.1108/16605371011083503

May, C. K. (2022). Complex adaptive governance systems: A framework to understand institutions, organizations, and people in socio-ecological systems. *Socio-Ecological Practice Research, 4*, 39–54. https://doi.org/10.1007/s42532-021-00101-7

Ministry of Science and Technology. (2022). *Notice on the issuance of the special plan for scientific and technological innovation in the field of ecological and environmental protection in the 14th five-year plan ministry of science and technology of the people's republic of China*. Retrieved from https://www.most.gov.cn/

Munodawafa, R., & Johl, S. (2019). Big data analytics capabilities and eco-innovation: A study of energy companies. *Sustainability, 11*(15), 4254. https://doi.org/10.3390/su11154254

North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge: Cambridge University Press.

Parentoni, L. (2020). *Artificial intelligence. In: Sellers, M., Kirste, S. (eds) Encyclopedia of the philosophy of law and social philosophy*. Dordrecht: Springer. https://doi.org/10.1007/978-94-007-6730-0_745-1.

People's Daily Online. (2016). *Xi Jinping on innovation people's daily online*. Retrieved from https://www.people.cn/

Peruchini, M., Da Silva, G. M., & Teixeira, J. M. (2024). Between artificial intelligence and customer experience: A literature review on the intersection. *Discover Artificial Intelligence, 4*(1), 4. https://doi.org/10.1007/s44163-024-00105-8

Tang, T., & Yang, L. (2024). Shaping corporate ESG performance: Role of social trust in China's capital market. *China Finance Review International, 14*(1), 34-75. https://doi.org/10.1108/CFRI-07-2023-0187

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *The processes of technological innovation*. Lexington: Lexington Books.

Wan, W. (2018). *Customer service and user experience AIs, green consumption cognition and green consumption behavior*. Wuhan: Huazhong Agricultural University.

Wang, J., Visvizi, A., Nan, F., & Meng, F. (2024). *Placing China's green technology innovation in a context. In: Visvizi, A., Troisi, O., Corvello, V. (eds) Research and innovation forum 2023*. Paper presented at the RIIFORUM 2023. Springer Proceedings in Complexity. Springer. https://doi.org/10.1007/978-3-031-44721-1_36.

Wang, S., Huang, X., Xia, M., & Shi, X. (2024). Does artificial intelligence promote firms' innovation efficiency: Evidence from the robot application. *Journal of the Knowledge Economy*, 1-22. https://doi.org/10.1007/s13132-023-01707-w

Wang, X. L., Fan, G., & Hu, L. P. (2019). *Report on marketization index of China by Province*. Beijing, China: Social Science Literature Publishing House.

Williamson, O. E. (1985). *The economic institutions of capitalism: Firms, markets, relational contracting*. New York: Free Press.

Wirtz, J., & Lovelock, C. (2016). *Services marketing: People, technology, strategy* (8th ed.): World Scientific Publishing Co. Inc. https://doi.org/10.1142/y0001.

Xinhua. (2024). *NE China's liaoning strives for full revitalization*. Retrieved from https://english.www.gov.cn/news/202404/23/content_WS6627967ac6d0868f4e8e6585.html

Zhai, T., & Chang, Y.-C. (2019). The contribution of China's civil law to sustainable development: Progress and prospects. *Sustainability, 11*(1), 294. https://doi.org/10.3390/su11010294

Zhang, W., & Ke, R. (2002). Social trust and financial asset allocation: Evidence from Chinese firms. *Journal of Corporate Finance, 18*(2), 209-230.

Zhou, C. (2014). Research on the influence of telephone brand image on consumers' willingness to buy —— from the perceived risk perspective in network environment. Unpublished Master's Thesis, Nanjing Normal University.