Journal of Information Systems Engineering and Management
2025, 10(22s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

The Factors Influencing Artificial Intelligence Adoption Intention in Enterprise Management

Shuai Miao[1], Sarana Photchanachan[2]

[1]*PhD candidate, Faculty of Management, Shinawatra University, EMAIL: ms612252@163.com,*
[2]*PhD, Advisor, Dean, Faculty of Management, Shinawatra University, EMAIL: sarana.p@siu.ac.th.*

ARTICLE INFO

Received: 10 Dec 2024

Revised: 28 Jan 2025

Accepted: 14 Feb 2025

ABSTRACT

With the rapid development of artificial intelligence, the adoption of artificial intelligence has also brought many challenges, including technology ethics, data privacy, employee adaptability, market competition, etc. Especially in the highly competitive market environment, how enterprises can effectively use artificial intelligence to improve their competitiveness has become an important topic of common concern in academia and the business community. This study aims to explore the factors that affect the adoption of artificial intelligence in the context of emerging technology acceptance, and through analysis and summary, help enterprises better use artificial intelligence to help them improve management efficiency and performance. This study uses the Technology Acceptance Model (TAM) model combined with the Technology-Organization-Environment (TOE) framework to explore the factors that affect the adoption of artificial intelligence from the perspective of the impact of artificial intelligence on individuals and organizations. Using quantitative methods, the original data will be collected through questionnaires. Data analysis using 500 employees in Shanxi Province. The results of the study are expected to help enterprises better use artificial intelligence to improve management efficiency and performance.

Keywords: Adoption Intention, Artificial Intelligence, Technology Acceptance.

1.Introduction

1.1Background of study

In the business environment of the 21st century, artificial intelligence is no longer a distant concept, but is gradually becoming a core part of enterprise strategy and operations. With the rapid development of artificial intelligence technology and the emergence of advanced AI tools such as ChatGPT, enterprises are facing unprecedented opportunities and challenges (Haenlein&Kaplan, 2019; Chui et al., 2018). The application of artificial intelligence has not only changed traditional business models, but also reshaped the decision-making process, customer service, production efficiency, and human resource management of companies (Davenport&Ronanki, 2018). Despite the enormous potential of artificial intelligence, its application in enterprise management is influenced by many factors (Tornatzky&Fleischer, 1990).

By introducing artificial intelligence that can mimic and learn from human thinking machines, information exchange between various links in the supply chain can be promoted (Gao, S.H., 2020). At the same time, digital information can be used to replace assets such as inventory and transportation equipment, which can help businesses connect with other customers, upstream and downstream suppliers, and partners (Min, 2010). It can also help marketers make more informed choices in complex situations based on information systems.

The integration of data analysis, neural networks, and knowledge mapping techniques has created an information system to assist in solving marketing problems (Stalidis et al., 2015); Deep learning has also had a significant disruptive impact on auditing work (Issaetl., 2017); On the other hand, enterprises can use artificial intelligence technology to conduct risk supervision. Enterprises can use artificial intelligence related technologies to analyze employees' emails in real time, monitor sensitive words, and detect anomalies as soon as possible. They can also test business decisions through algorithmic games to determine if they have potential fraudulent motives (Hirsch, 2018); Some scholars also believe that companies can use artificial intelligence to predict employee turnover intentions, and can use knowledge maps to mine textual information to obtain human resource sentiment data(Strohmeier&Piazza, 2015).

1.2 Problem statement

At present, many models and frameworks have been developed to explain users' adoption of new technologies. These models and frameworks introduce factors that may affect user acceptance, such as the theory of reasoned action (TRA), the technology acceptance model (TAM), the unified theory of technology acceptance and use (UTAUT), and the technology, organization, and environment (TOE) framework.

In previous studies, the perspective of the TOE framework focused on analyzing the willingness to adopt AI from the technical, organizational, and environmental levels. The maturity, reliability, and integration capabilities of AI technology with existing IT infrastructure directly affect adoption decisions (Lorica & Nathan, 2018). Environmental factors such as market competition pressure, policies and regulations, and ethical issues also affect the adoption of artificial intelligence. Enterprises need to consider the impact of the external environment when adopting artificial intelligence (Soni, Sharma, Singh & Kapoor, 2021). However, existing research based on the TOE framework mainly focuses on macro-level technical, organizational, and environmental factors, and pays less attention to perceptual factors at the individual level.

From the perspective of the technology acceptance model (TAM), the impact of users' perceived usefulness and perceived usability of artificial intelligence technology on their adoption intention is emphasized. Perceived usefulness refers to the degree to which people believe that applying a certain system can improve work efficiency, while perceived usability refers to people's perception of the ease of use of a specific technical system (Davis, 1989). Although the TAM model can effectively explain the user's acceptance of artificial intelligence technology, it mainly focuses on the perceptual factors at the individual level, while ignoring the influence of macro factors such as technology, organization, and environment. Therefore, existing research often only focuses on one aspect and lacks a comprehensive analysis of both aspects, resulting in an incomplete understanding of the intention to adopt artificial intelligence.

This study is guided by the Technology Acceptance Model (TAM), retains the three core variables of adoption intention, perceived usefulness, and perceived ease of use, and adopts the basic assumptions of TAM to ensure the consistency and coherence of the research. At the same time, in order to comprehensively examine the impact of external factors, this study supplements the technology-organization environment (TOE) framework as an external variable, comprehensively considering the three dimensions of technology, organization, and environment. Therefore, this study combines these two perspectives to develop a new artificial intelligence adoption model to more accurately understand and predict artificial intelligence adoption intention.

1.3 Research Questions and Objectives

This study aims to explore the key influencing factors and their mechanisms of artificial intelligence adoption intention in enterprise management. The dependent variable is artificial intelligence adoption intention (AI), and the independent variables are infrastructure (I), top management support (TMS), competitive pressure (CS), perceived usefulness (PU), and perceived ease of use (PEOU).

Research questions	Research objectives
What are the factors that affect the adoption of artificial intelligence technology by enterprises?	Identify the key factors affecting enterprise AI adoption.
What is the path of influence of different factors on the intention to adopt artificial intelligence?	Analyze the impact path of each factor on AI adoption intention
How can enterprises adopt artificial intelligence in management more effectively?	Based on the research results, provide effective strategies and implementation paths for the adoption of AI in enterprise management.

1.4 Conceptual Framework

On the basis of the Technology Acceptance Model (TAM), adoption intention, perceived usefulness and perceived ease of use in the TAM model were selected as individual-level variables, and infrastructure, top management support and competitive pressure in the technology organizational environment (TOE) were introduced as organizational-level variables, and a conceptual framework consisting of six variables and their relationships was constructed. As shown in **Figure 1.1**.

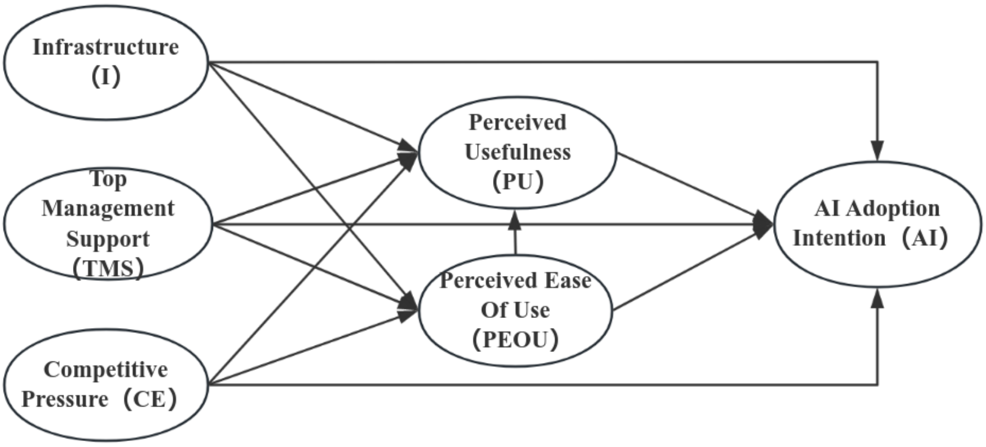

Figure 1.1 Research Conceptual Framework

1.5 Research Hypotheses

The intention to adopt artificial intelligence refers to the positive propensity and plan of individuals or organizations to employ artificial intelligence technology for achieving specific goals or solving particular problems. This intention is affected by multiple factors, including the characteristics of the technology itself (such as ease of use, reliability, and functionality), internal conditions within the organization (such as culture, resources, and leadership support), external environmental factors (such as market pressure, laws and regulations, and policy guidance), as well as considerations at the individual level (such as trust in the technology, acceptance, and skill level). The intention to adopt artificial intelligence is a crucial antecedent for predicting the actual adoption behavior and holds significant importance for promoting the application and popularization of artificial intelligence technology in various industries. Based on the above summary, this study proposes 12 hypotheses, as shown in **Table 1.1**.

Table 1.1 Research Hypotheses

NO	Hypotheses
H1a	Infrastructure has a positive impact on perceived usefulness
H1b	Infrastructure has a positive impact on perceived ease of use
H1c	Infrastructure has a positive impact on AI adoption intention
H2a	Top management support has a positive impact on perceived usefulness
H2b	Top management support has a positive impact on perception and usability
H2c	Top management support has a positive impact on AI adoption intention
H3a	Competitive pressure has a positive impact on perceived usefulness
H3b	Competitive pressure has a positive impact on perceived ease of use
H3c	Competitive pressure has a positive impact on AI adoption intention

H4a	Perceived ease of use has a positive impact on AI adoption intention.
H4b	Perceived usefulness has a positive impact on AI adoption intention.
H5	Perceived ease of use has a positive impact on perceived usefulness.

1.6 Scope of the Study

1.6.1 Scope of Contents

The goal of this study is to explore the influencing factors of artificial intelligence adoption through empirical research and statistical analysis, and to provide effective suggestions for the adoption of artificial intelligence and the improvement of enterprise management efficiency.This study explores the factors that influence the intention to adopt artificial intelligence within the scope of accepting and applying new technologies. In the context of the ubiquity of artificial intelligence, analyzing the factors that influence the adoption of artificial intelligence by enterprises is of great significance for enterprises to deploy and develop artificial intelligence technology and balance the advantages and disadvantages of artificial intelligence use.

1.6.2 Scope of Population

The population of this study is employees in high-tech enterprises in Shanxi Province who are currently applying or planning to use artificial intelligence technology.

1.6.3 Scope of Variables

Based on the literature review and previous research results, this study will propose 6 research variables within the theoretical framework of the Technology Acceptance Model (TAM) and the Technology Organization Environment (TOE).

Independent variables: infrastructure, top management support, competitive pressure, perceived usefulness, perceived ease of use

Dependent variables: AI adoption intention.

2. Literature Review

2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was proposed by the American scholar Davis in 1989. Its theoretical source is the rational behavior theory, but it also absorbs the reasonable core of the self-efficacy theory, the expectation theoretical model and the change adoption theory. The original purpose of TAM model is to explain the factors that computer is widely accepted, and later it is widely used to explain and predict the individual acceptance behavior of information technology. The research history of technology acceptance model is a continuous process. However, the problems that scholars care about solving in different periods have distinct changes. According to the different research directions, the research evolution of technology acceptance model can be roughly divided into three stages: Taking the model framework as the research focus, the internal factors of the model as the research focus, and the introduction of new theories into the model as the research focus.

This study analyzes the motivation for the evolution of the TAM model. With the emergence of new problems, researchers continue to incorporate new theories into TAM to expand its scope of application. TAM started with the theory of reasoned action (TRA) and the theory of planned behavior (TPB), and gradually integrated the innovation diffusion theory (IDT), the use and gratification theory (U&G) and the usability theory. With the empirical research of a large number of scholars, the credibility of TAM in the academic community has been continuously enhanced, and the model itself has been improved day by day. The focus of research has also shifted from the initial discussion of the model framework and internal elements to the in-depth study of the external factors of the model. In addition, the rapid development of information technology is also a key factor in promoting TAM research. At first, only employees of large enterprises could use information systems, and most of them were exposed to enterprise-oriented software. However, over time, information systems are no longer limited to professional users, but gradually popularized to ordinary home users. The research objects of TAM have also expanded from corporate employees to the general public. At the same time, as society continues to pay more attention to the "digital divide" and "digital fairness", TAM researchers have begun to pay attention to the problem of special groups using personalized systems.The TAM model is shown in **Figure 2.1**:

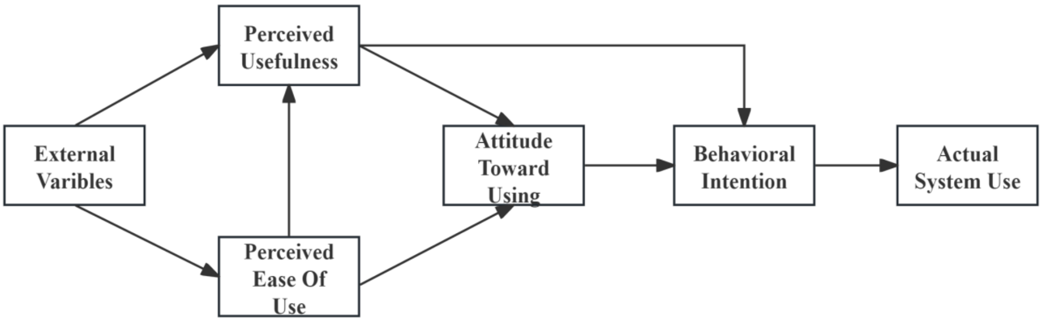

Figure 2.1 Technology Acceptance Model

From figure 2-1, it can be seen that the user's willingness to use the information system (BI) determines the use behavior, and the use attitude (AT) and perceived usefulness (PU) together determine the use intention (BI=AT PU). The use attitude is affected by the combination of perceived usefulness and perceived ease of use (PEOU) (AT=PU+PEOU). Perceived ease of use affects the attitude as well as the usefulness, while External variables indirectly affect the attitude and behavior intention through affecting the usefulness and ease of use, thus affecting the behavior of the actors; Here, the external variables defined by Davis include task characteristics, user characteristics, system design characteristics and policy influence, which are some measurable factors.

2.2 Technology Organization Environment (TOE) Framework

The TOE (Technology Organization Environment) theoretical framework was first proposed by two scholars, Tornatzky and Fleischer, in their 1990 book "The Process of Technological Innovation". This theory suggests that an organization's adoption of an innovative technology is mainly influenced by three factors: technology, the organization itself, and the external environment (Tan, F.C.,2016). Among them, technical factors refer to various technical measures applied in the operating system, as well as the adaptability of technology to the organization and whether technology can bring potential benefits to the organization (Tan,F.F. & Fan, 2016), including not only the technology currently in use, but also the technology commonly existing in the market (Baker, 2012). Organizational factors have received considerable data support in empirical research, involving various aspects such as the size, structure, and idle resources of enterprise departments, as well as the internal structure and regulations of government departments, which involve various aspects of the organization. Including organizational characteristics and resources (Nguyen et al., 2022), reflecting the internal structure and processes of the enterprise; External environmental factors mainly refer to social development, political background, and local traditional customs, among which there are significant pressures, stimuli, and regulatory constraints in this field, such as external demands and pressure from superiors. The TOE framework is mainly used to systematically consider these three factors, and is a general framework for artificial intelligence application research. It can also be used to study and comprehensively analyze the different influencing factors of enterprise adoption of innovative technologies. However, the TOE framework has strong adaptability and high conciseness, and can be adjusted and modified according to different research fields or subjects.

2.3 Research on AI Adoption Intentions

Existing studies usually understand the adoption of AI as a unidimensional concept, namely, the procedures and functions of AI. The higher the intention to adopt AI, the higher the frequency of adoption by the subject and the more times it is adopted. Studies have found that the adoption and commercialization of AI are closely related to its definition (Fredstrom et al., 2022). Therefore, the deep connotation of AI adoption intention varies depending on its definition. This study defines AI adoption intention as the tendency to use AI to achieve goals and tasks in corporate management. In existing studies, the measurement method of AI adoption is subjective scoring by corporate personnel, but the scoring objects are divided into two categories: adoption purpose and adoption intention. First, in terms of adoption purpose, Issa et al. (2022) regarded AI adoption as a unidimensional concept and developed a measurement scale consisting of three items. Baabdullah et al. (2019) regarded AI adoption as a unidimensional concept and developed a measurement scale consisting of three items. (2021) developed a 4-point measurement scale for AI practices in small and medium-sized enterprises. Pill Artificial Intelligence and Sivathanu (2020b) developed a four-item measurement scale for the adoption of AI technologies in talent acquisition. Braganza et al. (2021) developed a five-point scale for employees' adoption of AI at work based on existing literature.

In terms of adoption intention, Lee et al. (2022) asked companies to rate three types of AI technologies used in the production or development of products and services when measuring AI adoption. The specific technologies included natural language processing (such as speech and pattern recognition and chatbots), computer vision (such as image tagging and recognition), and machine learning (such as recommendations and predictions). Companies rated the adoption level of the three technologies separately (1=not used, 2=testing stage, 3=0%-5%, 4=5%-25%, 5=25%-50%, 6=50% and above), and finally selected the company with the highest score of the three technologies to determine the AI adoption score of the company.

3.Research Methodology

3.1 Questionnaire Design

This paper mainly conducts an online questionnaire survey on employees of Shanxi enterprises. The specific method is to conduct an online survey on the survey subjects in the form of a self-filled questionnaire through "Wenjuxing". The questionnaire is roughly divided into two main parts: 1. Basic personal information; 2. Based on the above theoretical model, refer to the existing relevant scales at home and abroad, and combine the characteristics of this study to extract measurement indicators suitable for this study. At the same time, in order to ensure the accuracy and effectiveness of the questionnaire results, a certain number of survey subjects were selected for testing before the formal distribution of the questionnaire. According to the feedback from the problems in the test process, the questionnaire design was adjusted. Finally, the questionnaire was distributed on the basis of ensuring the overall rationality of the questionnaire.

3.2 Data Analysis

SPSS was used to conduct data description analysis and reliability and validity analysis to verify data quality and assumptions. Descriptive statistics were used to describe demographic variables and measurement items, such as frequency, mean, standard deviation, and correlation coefficient. Reliability and validity analysis includes: 1) Reliability analysis using SPSSAU software; 2) Validity analysis using SPSSAU, and analysis through confirmatory factor analysis (CFA) to confirm that the correspondence between measurement factors and scale items is consistent with the prediction. 3) Structural equation model (SEM) fitting and hypothesis verification were performed through Amos. This chapter introduces the research method steps in detail. The first part is the research design. Then, operational items of variables were proposed from the measurement dimension to form a preliminary questionnaire. Next, the methods and steps of data analysis were explained in detail. Then, through reliability and validity tests and preliminary tests, items that did not meet the standards were eliminated to form the final formal questionnaire. Finally, a large-scale questionnaire survey was conducted to collect sample data.

4.Results and Discussion

4.1Reliability and validity test

This paper uses SPSS to process the questionnaire data. The overall Cronbach's α value of each scale in the questionnaire is greater than 0.8, and the reliability is high. The item-to-item correlation of each scale item is greater than 0.5, and the internal consistency is high. At the same time, after testing, it was found that the KMO value of the questionnaire was 0.942, which can indicate that the scale structure validity meets the standard.

4.2 Model Fitting and Hypothesis Testing

The fitting of the model in this paper is mainly based on RMSEA, X2/df, IFI, TLI, CFI, PGFI, PNFI and other indicators used to evaluate the fitness of the structural equation model (SEM) for comprehensive testing.The results are shown in Table 4.1below.

Table 4.1 Model Fit Index Results

Common indicators	X²/df	GFI	RMSEA	RMR	CFI	NFI
Judgment criteria	<3	>0.9	<0.08	<0.05	>0.9	>0.9
Fitting effect	1.124	0.945	0.016	0.043	0.994	0.951

Table 4.1 shows the results of the model fitting index. It can be seen from the table that the X2/df value is 1.124, which is less than 5, the CFI value is 0.945, which is greater than 0.9, and the RMSEA value is 0.016, which is less than 0.08. The RMR value is 0.043, which is less than 0.05, the CFI value is 0.994, which is greater than 0.9, and the NFI value is 0.951, which is greater than 0.9. It can be seen that the fitting index is well adapted. Therefore, the overall fit of the model is ideal.

Among the 12 hypotheses proposed in this study, H1a, H1b, H1c, H2a, H2b, H2c, H3a, H3b, H3c, H4a, H4b, and H5 have passed the model verification, and the hypothesis is established, that is, infrastructure affects perceived usefulness, infrastructure affects perceived ease of use, infrastructure affects adoption intention, top management support affects perceived usefulness, top management support affects perceived ease of use, top management support affects adoption intention, competitive pressure affects perceived usefulness, competitive pressure affects perceived ease of use, competitive pressure affects adoption intention, perceived ease of use affects adoption intention, perceived usefulness affects adoption behavior, and perceived ease of use affects perceived usefulness. The hypothesis test results are shown in Table 4.2.

Table 4.2 Standardized output results of the AI adoption model assumptions

Paths	**Unstandardized path coefficients**	**S.E.**	**C.R.**	**P**	**Standardized path coefficients**
PEOU←I	0.173	0.057	3.025	0.002**	0.165
PEOU←TMS	0.263	0.058	4.523	0.000***	0.260
PEOU←CE	0.281	0.058	4.816	0.000***	0.265
PU←I	0.264	0.058	4.551	0.000***	0.238
PU←TMS	0.164	0.058	2.807	0.005**	0.154
PU←CE	0.263	0.059	4.426	0.000***	0.235
PU←PEOU	0.228	0.054	4.180	0.000***	0.215
AI←I	0.140	0.058	2.412	0.016*	0.130
AI←TMS	0.277	0.059	4.682	0.000***	0.266
AI←CE	0.145	0.059	2.438	0.015*	0.132
AI←PEOU	0.134	0.054	2.467	0.014*	0.130
AI←PU	0.172	0.056	3.087	0.002**	0.176

Note:*p<0.05 **p<0.01 ***p<0.001

5.Conclusion and Recommendation

5.1 Conclusion

This chapter first summarizes the theoretical results of the study, verifies the effects of perceived usefulness, perceived ease of use, top management support, and competitive pressure on the intention to adopt artificial intelligence, and proposes a theoretical framework that integrates the TAM and TOE models. Based on this, this study proposes corresponding theoretical contributions and managerial implications, pointing out that organizational infrastructure, top management support, and competitive pressure have a positive impact on the intention to adopt artificial intelligence, and that individual-level perceived usefulness and perceived ease of use have a positive impact on the intention to adopt artificial intelligence. At the organizational level, top management support is the key factor affecting the adoption of artificial intelligence, while individual-level perceived usefulness is the key factor affecting the intention to adopt artificial intelligence. Finally, this study points out its limitations, such as limited sample size and single research method, and proposes directions for future research, such as expanding the sample range and combining case analysis. It is hoped that this study can provide readers with valuable insights and lay the foundation for future research.

5.2Implication

The theoretical contribution of this study is not limited to supplementing and expanding the existing literature, but also to constructing a more comprehensive and in-depth analytical framework. First, by integrating the technology-organization-environment (TOE) framework and the technology acceptance model (TAM), this study breaks the limitations of the previous single theoretical model and provides a multi-dimensional and multi-level perspective to understand the willingness to adopt artificial intelligence (AI). This integration not only enriches the theoretical connotation, but also provides new directions for future research. For example, the study can further explore the interaction between different variables, or verify the universality of the model in different industries and cultural contexts. Secondly, by introducing three variables, "infrastructure", "top management support" and "competitive pressure", this study deeply analyzes the complex influence mechanism of these factors on the willingness to adopt AI. This not only expands our understanding of the factors affecting AI adoption, but also provides theoretical reference for understanding the adoption of other emerging technologies. For example, future research can explore the role of these factors in the adoption process of other technologies, or analyze the changes in the importance of different factors in different technology life cycles. Finally, this study verifies the proposed theoretical model through empirical research methods, providing a solid empirical basis for AI adoption research. This not only enhances the credibility of the theory, but also provides reference research methods and data analysis techniques for subsequent research.

From a practical perspective, this study provides valuable practical guidance for enterprise managers and policymakers. For enterprises, this study emphasizes the key role of infrastructure construction and high-level support in the process of AI adoption. Enterprises should pay attention to the upgrade and maintenance of IT infrastructure to ensure that it can support the application of AI technology. At the same time, enterprise executives should actively participate in the formulation and implementation of AI strategies, provide necessary resources and support to promote the widespread application of AI technology within the enterprise. In addition, enterprises should pay close attention to market competition pressure, regard it as an important driving force for promoting AI adoption, and enhance their competitiveness through AI technology. For policymakers, this study points out that the government should increase investment in AI infrastructure construction, such as building national AI computing centers and data centers, to provide basic support for the research and development and application of AI technology. At the same time, the government should formulate and improve AI ethical norms and laws and regulations to ensure the safe and reliable application of AI technology. In addition, the government should actively promote the training and introduction of AI talents to provide talent guarantee for the development of the AI industry. Finally, this study also provides an important reference for global companies to enter the Chinese market. With the rapid development of China's AI market, global companies should have a deep understanding of the characteristics of the Chinese market, formulate targeted market entry strategies, and actively respond to localization challenges to seize the huge opportunities brought by China's AI market.

References

[1] Cascio, W. F., & Shurygailo, S. (2003). E-Leadership and virtual teams. *Organizational Dynamics*, 31(4), 362-376.

[2] Conboy, K. (2009). Agility from first principles: Reconstructing the concept of agility in information systems development. Information Systems Research, 20(3),

[3] McAfee, A., & Brynjolfsson, E. (2017). Machine, platform, crowd: Harnessing our digital future. *W.W. Norton & Company*.

[4] Porter, M. E., & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review*, 92(11), 64-88.
[5] Rigby, D. K., Sutherland, J., & Takeuchi, H. (2016). Embracing agile. *Harvard Business Review*, 94(5), 40-50.
[6] Bartlett, C. A., & Ghoshal, S. (2002). Managing across borders: The transnational solution (2nd ed.). *Harvard Business School Press*.
[7] Eccles, R. G., Ioannou, I., & Serafeim, G. (2014). The impact of corporate sustainability on organizational processes and performance. *Management Science*, 60(11), 2835-2857.
[8] Ghemawat, P. (2007). Redefining global strategy: Crossing borders in a world where differences still matter. *Harvard Business School Press*.
[9] Golden, T. D., & Veiga, J. F. (2005). The impact of extent of telecommuting on job satisfaction: Resolving inconsistent findings. *Journal of Management*, 31(2), 301-318.
[10] Porter, M. E., & Kramer, M. R. (2006). Strategy and society: The link between competitive advantage and corporate social responsibility. *Harvard Business Review*, 84(12), 78-92.
[11] Davenport, T. H., & Harris, J. G. (2007). Competing on analytics: The new science of winning. *Harvard Business School Press*.
[12] Kotler, P., & Keller, K. L. (2012). Marketing management (14th ed.). *Pearson Education*.
[13] Lam, J. (2003). Enterprise risk management: From incentives to controls. *John Wiley & Sons*.
[14] Peelen, E., & Beltman, R. (2013). Customer relationship management (2nd ed.). *Pearson Education Limited*.
[15] Power, M. (2007). Organized uncertainty: Designing a world of risk management. *Oxford University Press*.
[16] Ulrich, D., & Dulebohn, J. H. (2015). Are we there yet? What's next for HR? *Human Resource Management*, 54(3), 225-236.
[17] Buell, P. H. (2018). Tie me to the mast: Artificial intelligence & reputation risk management. *The Journal of Business Strategy*, 39(1), 61-64.
[18] Hirsch, P. (2018). Tie me to the mast: Artificial intelligence & reputation risk management. *The Journal of Business Strategy*, 39(1), 61-64.