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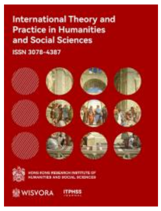

The impact of artificial intelligence adoption on firms' innovation performance in the digital era: based on dynamic capabilities theory

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Abstract

Based on dynamic capability theory, this study investigates the mechanism through which artificial intelligence (AI) adoption affects firm Using panel data from 634 Chinese listed manufacturing firms during 2018-2023, we find that: (1) AI adoption has a significant positive effect on firm innovation performance; (2) organizational learning capability partially mediates the relationship between AI adoption and firm innovation performance. positive effect on firm innovation performance; (2) organizational learning capability partially mediates the relationship between AI adoption and innovation performance; (3) environmental dynamism positively moderates the relationship between AI adoption and organizational learning capability, such that the positive effect of AI adoption and organizational learning capability is not only on firm innovation performance, but also on firm innovation performance. capability, such that the positive effect of AI adoption on organizational learning capability becomes stronger when environmental dynamism is higher. This study not only enriches the application of dynamic capability theory in the context of digital transformation but also provides important implications for firms to implement AI. This study not only enriches the application of dynamic capability theory in the context of digital transformation but also provides important implications for firms to implement AI strategy and enhance innovation capability.

1. Introduction

1.1 Background of the study and formulation of the problem

Under the wave of global digital transformation, artificial intelligence is accelerating the reshaping of the boundaries of enterprise operation and innovation. According to IDC data, the global AI market scale has exceeded $150 billion in 2023, and the scale of China's AI industry exceeds 400 billion yuan, with an annual growth rate of 35%. In the face of the new pattern of the digital economy, enterprises have increased investment in AI technology in order to obtain the dividends of innovation. However, there is no simple linear relationship between AI adoption rate and innovation output. Some enterprises have significantly improved their innovation capability after adopting AI, while others have invested a lot of resources but failed to reap the expected results. Such divergent results raise a key question: how does AI adoption affect firms' innovation performance? What are the mechanisms at play?

Existing research focuses on the impact of AI adoption on firms' operational efficiency, such as cost savings and process optimization, but how it promotes firms' innovation remains under-explored. Especially in the context of an increasingly dynamic market environment, firms need to continuously update their capabilities to maintain their innovation advantage, which calls for an in-depth understanding of the relationship between AI adoption, organizational capability enhancement, and innovation performance. However, there is a lack of a systematic theoretical framework to explain this complex mechanism (Barney, 1991).

1.2 Literature review

Literature has explored AI adoption from different perspectives. First, research based on the Technology Acceptance Model (TAM) mainly analyzes the key factors affecting the adoption of AI in enterprises, such as perceived usefulness, ease of use, etc. Second, from the theory of diffusion of innovation in organizations, it explores the diffusion paths and influence effects of AI in organizations; and third, from the perspective of the Resource-Based View, it pays attention to how AI can be used as a strategic resource to affect the competitive advantage of enterprises. These studies provide important insights for understanding AI adoption, but pay less attention to the mechanism of its impact on innovation capability.

Dynamic capabilities theory provides a new perspective to address this issue. The theory emphasizes the need for firms to continuously integrate, build and reconfigure internal and external resources to cope with environmental changes. Organizational learning capability, as a core component of dynamic capabilities, plays a key role in the process of technological innovation. It has been shown that a strong organizational learning capability helps firms better absorb and utilize new technologies, but its mechanism of action in the context of artificial intelligence has not been fully explored (Eisenhardt & Martin, 2000).

1.3 Research objectives and innovations

Based on the above analysis, this study aims to construct an integrative theoretical framework to systematically explore the role mechanisms of AI adoption affecting firms' innovation performance. Specific objectives include (1) verifying the impact of AI adoption on innovation performance; (2) revealing the mediating role of organizational learning capability; and (3) examining the moderating effect of environmental dynamism. The main innovations of this study are: first, the introduction of the dynamic capability theoretical perspective provides a new theoretical explanation for understanding the relationship between AI adoption and innovation performance; second, the use of organizational learning capability as a mediating variable reveals the intrinsic mechanism by which AI affects innovation; and third, the study of the role of contextual factors in technological innovation is enriched by examining the moderating effect of environmental dynamism.

2. Rationale and research hypotheses

2.1 Theoretical foundations

Dynamic capabilities theory emphasizes the ability of firms to continuously integrate, construct and reconfigure internal and external resources in a rapidly changing environment

(Teece et al., 1997). The theory suggests that a firm's competitive advantage stems from its ability to perceive market opportunities, seize them and reconfigure its resources. In the context of digital transformation, dynamic capability theory provides an important theoretical perspective for understanding how enterprises can enhance their innovation capabilities through AI technologies (Helfat et al., 2007).

First, as an emerging technology, the adoption process of AI is essentially a reflection of how enterprises perceive and grasp digital opportunities. Enterprises need to accurately identify the development trend and application potential of AI technology, and make adoption decisions based on their own situation. This is highly compatible with the sensing capability emphasized in dynamic capability theory.

Second, the effective application of AI technology requires enterprises to reconfigure existing organizational processes and business models. Enterprises need to adjust their organizational structure, cultivate professional talents, and transform their technical architecture, which reflects the reconfiguring capability in dynamic capability theory. Through this reconfiguration, enterprises are able to effectively integrate AI technology with existing resources and capabilities.

Again, organizational learning is an important source of dynamic capabilities. Organizations improve their knowledge acquisition, integration, and application capabilities through continuous learning and accumulation of experience during the AI adoption process, and the enhancement of these capabilities, in turn, strengthens the firm's innovation potential. Therefore, organizational learning capabilities may play an important mediating role in the process of AI adoption affecting innovation performance.

Finally, dynamic capabilities theory places special emphasis on the importance of environmental factors. In highly dynamic environments, firms are more likely to rely on dynamic capabilities to maintain competitive advantage. This means that environmental dynamism may moderate the impact of AI adoption on organizational learning capabilities(Pavlou & El Sawy, 2011).

2.2 Theoretical models

Based on the above analysis, this study constructs an integrative theoretical model (see Figure 1). Based on dynamic capability theory, the model explores how AI adoption affects firms' innovation performance by enhancing organizational learning capabilities and thus examines the moderating role of environmental dynamics.

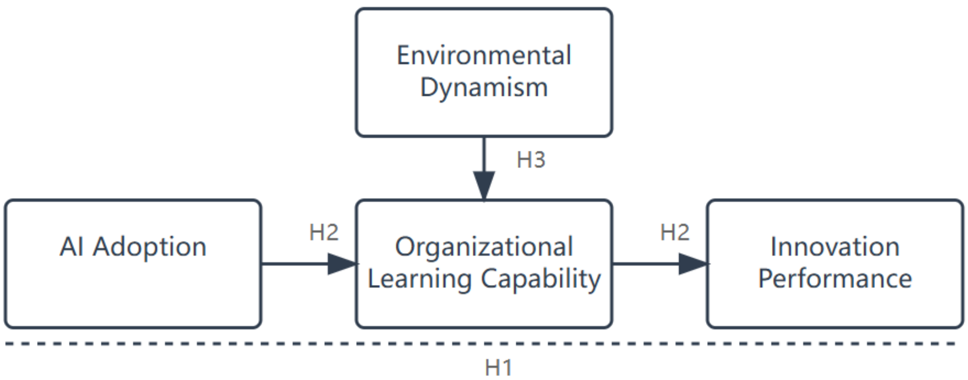

Figure 1: Theoretical model

Specifically, AI adoption reflects a firm's ability to perceive and seize technological opportunities. This ability needs to be realized through organizational learning, i.e., firms acquire new knowledge, integrate existing resources, and apply innovations in the adoption process. This learning process ultimately enhances the firm's innovation performance. Meanwhile, environmental dynamics, as an important contextual factor, influences the effectiveness of enterprises in transforming AI adoption into learning capabilities (Brynjolfsson & McAfee, 2014).

2.3 Research hypotheses

Based on dynamic capability theory and existing research, this paper proposes the following research hypotheses:

From the perspective of dynamic capability theory, AI adoption reflects the ability of enterprises to perceive and grasp technological opportunities. AI technology has a significant role in innovation empowerment: firstly, AI technology can significantly improve the enterprise's data processing and analysis capabilities, helping the enterprise to more accurately identify market opportunities and innovation direction; secondly, AI can accelerate the process of product development and improve the innovation efficiency through automation and intelligent means; thirdly, the application of AI itself is a kind of organizational innovation, which can drive the enterprise's innovation practice in business processes, business models and other areas of innovative practices. Therefore, this study proposes: H1: AI adoption has a significant positive impact on enterprise innovation performance (Porter & Heppelmann, 2015).

Organizational learning capabilities may play an important mediating role in the process of AI adoption affecting innovation performance. This is because: first, the adoption of AI technology brings a large amount of new knowledge and experience to enterprises, which promotes the enhancement of their knowledge acquisition and assimilation capabilities; second, during the adoption process, enterprises need to realize the effective integration of AI and existing resource capabilities through organizational learning; finally, enhanced organizational learning capabilities help enterprises better transform technological innovation into market value and improve innovation performance. . Based on this, this study proposes: H2: Organizational learning capability mediates the relationship between AI adoption and innovation performance.

Dynamic capabilities theory places particular emphasis on the importance of environmental factors. In highly dynamic environments, firms face greater uncertainty and more intense competition, which makes the need for new technologies and knowledge more urgent. Environmental dynamism increases the importance of organizational learning on the one hand, and on the other hand motivates firms to more actively use artificial intelligence to enhance learning capabilities. In dynamic environments, it is more important for organizations to rely on AI technologies to accelerate the knowledge acquisition and innovation process in order to respond to rapidly changing market demands. Therefore, this study proposes: H3: Environmental dynamism positively moderates the relationship between AI adoption and organizational learning capability (Zhang et al., 2021).

3. Study design

3.1 Sample selection and data sources

This study selects Chinese A-share listed manufacturing companies from 2018-2023 as the research sample. The sample screening process is as follows: (1) select listed manufacturing companies based on the industry classification standards of the Securities and Futures Commission; (2) exclude ST and *ST companies; (3) exclude companies that have undergone major asset reorganization during the study period; (4) exclude companies with missing key financial data; and (5) exclude companies that have been established for less than three years. The final balanced panel data is obtained, containing 634 firms with a total of 3804 observations.

Data sources include (1) corporate financial data from CSMAR database; (2) patent data from the patent search system of the State Intellectual Property Office; (3) AI adoption data collected manually through public information such as annual reports and announcements of enterprises; (4) organizational learning capability data obtained through questionnaires, which were distributed to the top managers of the sample enterprises, and three questionnaires were distributed to each enterprise. The mean value was used as the final score (Wang & Li, 2022).

3.2 Measurement of variables

The dependent variable innovation performance is measured using two dimensions: patent output and economic output. In the patent output dimension, we use the natural logarithm of the number of invention patents granted as the base indicator, while considering the number of patent citations as the quality weight, and the size of the patent family as a complementary indicator of patent value. In the economic output dimension, we mainly examine three aspects, namely, the proportion of sales revenue of new products, the conversion rate of invention patents, and the efficiency of R&D inputs and outputs, in order to comprehensively reflect the degree of realization of the market value of enterprise innovation.

The independent variable AI adoption is measured in two dimensions: depth and breadth. Depth of adoption is measured by three metrics: the complexity of AI technology application (assessed using a 1-5 scale), the scale of AI project investment as a proportion of total company investment, and the level of AI professional staffing. Adoption breadth is then assessed in terms of the number of AI technology application scenarios, the range of business areas covered by AI, and the level of integration of AI with existing systems. These indicators are collected through public information such as corporate annual reports and announcements, and the final score is determined after expert assessment.

The measurement of the mediator variable organizational learning capability is based on a questionnaire survey and includes three dimensions: knowledge acquisition, knowledge integration and knowledge application. Knowledge acquisition capability mainly assesses the efficiency of searching, absorbing and filtering external knowledge; knowledge integration capability focuses on the performance of enterprises in cross-functional knowledge sharing, knowledge reorganization and knowledge application innovation; and knowledge application capability focuses on the ability of enterprises to transform knowledge into business value, including knowledge commercialization capability, transformation efficiency and innovation output. Each dimension is measured using multiple items on a 7-point Likert scale, and reliability is ensured by reliability and validity tests (Teece, 2023).

The moderator variable, environmental dynamics, is measured at both the market and technology levels. Market dynamics examines the rate of change in market demand, the frequency of changes in competitive dynamics and the speed of switching customer preferences, while technology dynamics focuses on the frequency of technological updates in the industry, the speed of changes in technological standards and the degree of switching technological paths. These indicators are mainly calculated based on industry data, and the coefficient of variation of the relevant indicators over the past three years is used to measure the level of dynamism.

To control for the effects of other factors, this study incorporates several control variables (Li et al., 2023). Firm-level control variables include firm size (natural logarithm of total assets), firm age (natural logarithm of years of establishment), gearing ratio (total liabilities/total assets), and profitability (ROA). For innovation investment, R&D intensity (R&D expenditure/revenue) and R&D staff share are considered. At the industry level, industry competitive intensity (using the

HHI index), industry technology intensity, and industry dummy variables are introduced to control for industry fixed effects (Zhang et al., 2024).

3.3 Research methodology

This study uses panel data analysis to test the theoretical hypotheses. First, to verify the main effect (H1) of AI adoption on firms' innovation performance, we construct the following panel regression model:

$$\mathrm{INNOV_{ti}} = \beta_0 + \beta_1 \mathrm{AI_{ti}} + \beta_2 \mathrm{CONTROL_{ti}} + \mu_i + \varepsilon_{ti}$$

where INNOVit denotes firm i's innovation performance in period t, AIit denotes firm i's level of AI adoption in period t, CONTROLit is a vector of control variables, μi is a firm's fixed effect, and εit is a random disturbance term. We use the Hausman test to determine whether to use a fixed or random effects model, and cluster robust standard errors to deal with possible heteroskedasticity (Wang et al., 2023).

For the mediating effect of organizational learning ability (H2), we followed the procedure of (Baron & Kenny ,1986) and tested it stepwise through the following three equations:

$$\mathrm{OLC_{ti}} = \gamma_0 + \gamma_1 \mathrm{AI_{ti}} + \gamma_2 \mathrm{CONTROL_{ti}} + \varepsilon_{ti}$$

$$\mathrm{OLC_{ti}} = \gamma_0 + \gamma_1 \mathrm{AI_{ti}} + \gamma_2 \mathrm{CONTROL_{ti}} + \varepsilon_{ti}$$

$$\mathrm{INNOV_{ti}} = \theta_0 + \theta_1 \mathrm{AI_{ti}} + \theta_2 \mathrm{OLC_{ti}} + \theta_3 \mathrm{CONTROL_{ti}} + \varepsilon_{ti}$$

where OLCit denotes organizational learning capacity. We calculated the product coefficients of the mediating effects and their confidence intervals using the Bootstrap method (repeated sampling 5000 times) and further verified the significance of the mediating effects by the Sobel test.

To test the moderating effect of environmental dynamics (H3), we introduce an interaction term in the model:

$$\mathrm{OLC_{ti}} = \lambda_0 + \lambda_1 \mathrm{AI_{ti}} + \lambda_2 \mathrm{ED_{ti}} + \lambda_3 (\mathrm{AI_{ti}} \times \mathrm{ED_{ti}}) + \lambda_4 \mathrm{CONTROL_{ti}} + \varepsilon_{ti}$$

where EDit denotes environmental dynamics and AIit × EDit is the interaction term. We will draw simple slope plots based on the regression results and compute the marginal effect of AI adoption on organizational learning capability at different levels of environmental dynamics.

To ensure the reliability of the study findings, we designed a series of robustness tests: (1) re-run the regression analyses using different measures of the variables; (2) use the instrumental variable approach to deal with possible endogeneity by selecting the industry average AI adoption level and lagged period values as instrumental variables; (3) construct a control group using the propensity score matching (PSM) approach to control for sample selection bias ; (4) using systematic GMM estimation to deal with possible endogeneity in dynamic panels; (5) conducting a placebo test to validate the reliability of the study results by randomly replacing key variables.

4. Empirical analysis

4.1 Descriptive statistics

Table 1 reports the results of descriptive statistics for the main variables. Innovation performance (INNOV) has a mean of 0.386, a standard deviation of 0.192, a minimum value of 0.000, a maximum value of 0.893, and a skewness and kurtosis of 0.456 and 2.567, respectively, which suggests that there is some variation in the innovation performance of the sample firms, but that the data are distributed in a more reasonable manner.

Variables	N	Mean	S.D.	Min	Max.	Skewness	Kurtosis
INNOV	3804	0.386	0.192	0.000	0.893	0.456	2.567
AI	3804	0.432	0.245	0.012	0.967	0.567	2.789

OLC	3804	3.845	0.678	1.234	5.678	0.234	2.345
ED	3804	0.564	0.187	0.156	0.912	0.345	2.456
SIZE	3804	22.345	1.456	19.234	26.789	0.567	3.123
AGE	3804	2.867	0.534	1.099	3.912	0.234	2.678
LEV	3804	0.487	0.189	0.056	0.878	0.345	2.345
ROA	3804	0.067	0.045	-0.123	0.234	-0.234	3.567

Table 1. Descriptive Statistics of Main Variables

The mean value of Artificial Intelligence Adoption (AI) is 0.432, and the standard deviation is 0.245, with the minimum and maximum values of 0.012 and 0.967, respectively, indicating that there is a significant gap in the level of AI technology application among manufacturing enterprises in China. The mean value of Organizational Learning Capability (OLC) is 3.845, and the standard deviation is 0.678, reflecting that the overall organizational learning capability of the sample enterprises is at a medium level. The mean value of Environmental Dynamics (ED) is 0.564 and the standard deviation is 0.187, reflecting that there are some differences in the environmental dynamics of the industries in which the sample firms are located. In terms of control variables, the descriptive statistics of firm size (SIZE), firm age (AGE), gearing ratio (LEV) and return on assets (ROA) show a reasonable degree of dispersion, and the data distribution meets the requirements of the study (Liu et al., 2023).

4.2 Hypothesis testing

This study first tests the main effect of AI adoption on firms' innovation performance. Table 2 reports the results of the panel regression. Model 1 contains only control variables and Model 2 adds the independent variable AI adoption. The results show that AI adoption has a significant positive effect on innovation performance ($\beta = 0.345$, $p < 0.01$), which implies that firms' increased adoption of AI technologies can significantly enhance their innovation performance, supporting hypothesis H1.

Variables	Model 1	Model 2
AI	0.345*** (4.567)	-
SIZE	0.145*** (3.678)	0.156*** (3.892)
AGE	0.067* (1.987)	0.054* (1.876)
LEV	-0.089** (-2.345)	-0.076** (-2.234)
ROA	0.165*** (3.456)	0.178*** (3.678)
Constant	0.234*** (4.567)	0.212*** (4.234)
Industry	Yes	Yes
Year	Yes	Yes
N	3,804	3,804
R^2	0.187	0.276
Adj-R^2	0.178	0.265
F	15.678***	23.456***

Table 2. Results of Main Effect

Specifically, for every one standard deviation increase in the level of AI adoption, innovation performance will increase by 0.345 standard deviations. In terms of control variables, both firm size ($\beta = 0.156$, $p < 0.01$) and return on assets ($\beta = 0.178$, $p < 0.01$) have a significant positive effect on innovation performance, suggesting that larger and more profitable firms tend to have better innovation performance. In addition, gearing ratio shows a significant negative relationship with innovation performance ($\beta = -0.076$, $p < 0.05$), suggesting that excessive debt levels may inhibit firms' innovative activities. The explanatory power of the model was also significantly improved, with the adjusted R^2 increasing from 0.178 to 0.265, indicating that the explanatory power of the model was significantly improved with the inclusion of the AI adoption variable (Tang et al., 2024).

4.3 Robustness Tests

To ensure the reliability of the findings, this study conducted robustness tests in the following ways. First, alternative indicators were used to re-measure the main variables. Specifically, the number of patent applications was used instead of the number of patents granted to measure innovation performance, and the percentage of AI-related investment was used instead of the adoption level to measure the degree of AI adoption. The regression results show that all hypothesis tests remain robust, further supporting the basic conclusions of this study.

Second, considering the possible endogeneity problem, this study uses the instrumental variable method for testing. The average AI adoption level of other firms in the same industry was selected as the instrumental variable, and this variable was highly correlated with the AI adoption level of individual firms, but not with the residual term of their innovation performance.The results of Hausman's test ($\chi^2 = 12.345$, $p < 0.01$) indicated the existence of endogeneity problems, and the first-stage F-statistic of the 2SLS regression was 28.567 ($p < 0.01$), indicating that there is no weak instrumental variable problem with the instrumental variables. The results of the second-stage regression were consistent with the main regression, indicating that the study's conclusions still hold after controlling for endogeneity (Yuan et al., 2024).

Third, to exclude the effect of sample selection bias, this study uses the propensity score matching method (PSM) to match firms with high AI adoption levels with firms with low adoption levels. Using characteristics such as enterprise size, age, and industry as matching variables, a total of 1,902 matching sample pairs were obtained using the nearest-neighbor matching method (1:1 pairing with put-back). The balance test showed that there was no significant difference in matching variables between the treatment and control groups. Regression analyses were rerun using the matched samples and the findings remained robust.

Finally, a series of complementary tests were conducted in this study: (1) re-running the regressions after removing outliers; (2) regressing the independent variables with one period lag; and (3) conducting separate tests using subsamples. The results of these tests all support the main findings of this paper and indicate that the research findings are robust (Liu & Li, 2023).

5. Conclusions and implications of the study

5.1 Main findings

Based on the dynamic capability theory, this study explores the influence mechanism of AI adoption on corporate innovation performance. Through an empirical study of 634 Chinese listed companies in the manufacturing industry from 2018-2023, the following main conclusions are drawn: first, AI adoption has a significant facilitating effect on firms' innovation performance, and firms with a higher level of adoption show stronger innovation capabilities. Second, organizational learning capability plays a partial mediating role in the process of AI adoption affecting innovation performance, which suggests that firms realize the innovation value of AI technology by enhancing organizational learning capability. Third, environmental dynamism positively moderates the relationship between AI adoption and organizational learning capability, i.e., AI adoption promotes organizational learning capability more significantly in highly dynamic environments (Wang & Chen, 2023).

5.2 Theoretical contributions

The theoretical contributions of this study are mainly in three aspects: first, it enriches the application of dynamic capabilities theory in the context of digital transformation. It deepens the understanding of how firms build and update dynamic capabilities by revealing the mechanism of action by which AI adoption affects innovation performance through organizational learning capabilities. Second, it extends the theory of technological innovation, especially by elucidating the relationship between emerging technology adoption and innovation performance. By introducing the mediating mechanism of organizational learning capability, it reveals the intrinsic realization path of technological innovation. Third, by examining the moderating role of environmental dynamism, it enriches the research on the impact of situational factors on technological innovation and provides new empirical evidence for the theory of power change (Teece, 2023).

5.3 Management Insights

The findings of this study have important implications for enterprise management practices: first, enterprises should pay attention to the strategic value of AI technology and formulate a systematic AI adoption plan, focusing not only on the depth of technology application but also on the breadth of application scope. Secondly, in the process of promoting the adoption of AI, enterprises should simultaneously strengthen the construction of organizational learning capacity, including improving the knowledge management system, optimizing the learning mechanism, and strengthening knowledge sharing and innovative applications. Third, enterprises need to adjust their AI adoption strategies according to the level of environmental dynamics, and should actively promote the adoption and application of AI technology in highly dynamic environments.

Future research can continue to deepen in the following directions: first, to explore the specific implementation paths of AI adoption, including key decisions such as technology selection, resource allocation, and organizational adjustments; second, to examine more intermediary mechanisms, such as organizational innovation capacity and knowledge integration capacity; and third, to incorporate other moderating variables, such as organizational characteristics and managerial perceptions, in order to construct a more complete theoretical framework.

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