# The Driving Mechanism of Artificial Intelligence Applications on Firm Ambidextrous Innovation: The Mediating Role of Organizational Learning and the Moderating Effect of Knowledge Integration Capability

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**Abstract.** This study investigates how artificial intelligence (AI) applications drive firm ambidextrous innovation, focusing on the mediating role of organizational learning and the moderating effect of knowledge integration capability. Drawing on organizational learning theory and the knowledge-based view, we develop a moderated mediation model that conceptualizes AI as cognitive infrastructure reshaping organizational learning pathways. Based on two-phase survey data from 414 Chinese firms, we employ structural equation modeling to test our hypotheses. The results reveal that AI applications positively influence both exploitative innovation ($\beta = 0.347$, $p < 0.001$) and exploratory innovation ($\beta = 0.346$, $p < 0.001$). Organizational learning partially mediates these relationships with indirect effects, accounting for 31.5% of AI's total effect on ambidextrous innovation. Furthermore, knowledge integration capability positively moderates the relationship between organizational learning and both innovation types, with stronger moderating effects on exploratory innovation ($\beta = 0.202$, $p < 0.001$) than on exploitative innovation ($\beta = 0.146$, $p < 0.001$). These findings contribute to the literature by reconceptualizing AI as cognitive enhancement technology and identifying knowledge integration as a critical boundary condition. For managers, our results emphasize the need for balanced investment in AI technologies, learning infrastructure, and knowledge integration capabilities.

**Keywords:** Artificial Intelligence Applications, Organizational Learning, Firm Ambidextrous Innovation, Knowledge Integration Capability, Structural Equation Modeling

## 1 Introduction

The integration of artificial intelligence into organizational processes has raised scholarly interest in its impact on innovation. While prior research confirms positive links between AI adoption and innovation outcomes[1][2], the mechanisms through which AI


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enables tangible innovation remain unclear, particularly for ambidextrous innovation—the simultaneous pursuit of exploratory and exploitative innovation[3].

This study addresses this void by proposing a framework that conceptualizes AI applications as a "cognitive infrastructure" reshaping organizational knowledge systems and learning pathways. Specifically, we develop a theoretical model wherein AI applications influence firm ambidextrous innovation through the mediating mechanism of organizational learning, while this relationship is contingent upon firms' knowledge integration capabilities.

The theoretical significance of this research is threefold. First, by introducing organizational learning as a mediating mechanism, we advance understanding of how AI applications transcend their instrumental functionality to reshape organizational cognition patterns. Second, by examining knowledge integration capability as a critical boundary condition, our contingency perspective explains the heterogeneity in ambidextrous innovation outcomes following AI implementation. Third, by integrating these perspectives within a moderated mediation framework, we offer a more nuanced understanding of the complex relationships between technologies and ambidextrous innovation outcomes.

Our empirical analysis draws on survey data from 414 firms, employing structural equation modeling to test our hypotheses. Preliminary results support the mediating role of organizational learning and the moderating role of knowledge integration capability, revealing the cognitive transformation pathway through which AI drives firm ambidextrous innovation.

## 2 Literature Review and Theoretical Development

### 2.1 Artificial Intelligence Applications and Organizational Transformation

Contemporary AI applications in organizational contexts extend beyond automation to include machine learning algorithms, natural language processing, computer vision, and predictive analysis that collectively enhance organizational sensing, processing, and decision-making capabilities[1]. This evolution has prompted scholars to reconceptualize AI not merely as efficiency-enhancing tools but as cognitive augmentation technologies that fundamentally transform how organizations perceive, interpret, and respond to their environments [5].

The theoretical foundations for understanding AI's organizational impact draw from multiple perspectives.Technology-Organization-Environment (TOE) framework scholars have examined contextual factors influencing AI adoption[6], while resource-based view proponents have analyzed AI capabilities as strategic resources[7]. However, these perspectives often treat AI as external to organizational cognition rather than as an integral component reshaping internal knowledge processes. Our research bridges this gap by conceptualizing AI applications as cognitive infrastructure that reconfigures organizational learning pathways.

## 2.2 Organizational Learning as a Mediating Mechanism

Building on organizational learning theory[8][9], we conceptualize organizational learning as the process through which firms transform information into knowledge and action, encompassing both exploratory and exploitative learning modes.

The mediating role of organizational learning between technology adoption and innovation outcomes has received empirical support[10]. Building on this foundation, we propose that AI applications enhance organizational learning processes, which subsequently drive firm ambidextrous innovation.

## 2.3 Firm Ambidextrous Innovation

Ambidextrous innovation refers to the simultaneous pursuit of exploratory innovation (creating new or enhanced value through novel products, services, processes, or business models) and exploitative innovation (refining and extending existing products, services, processes, or business models)[3][4]. This dual approach to innovation is characterized by its ability to balance short-term efficiency gains from exploitation with long-term growth opportunities from exploration[11].

The relationship between organizational learning and ambidextrous innovation has been theoretically established but empirically underexplored. Organizational learning enables firms to develop the cognitive flexibility required for ambidextrous innovation[12], while technologies provide the infrastructure that facilitates this learning[3]. However, the specific mechanisms through which AI applications enable ambidextrous innovation remain inadequately understood. This study addresses this gap by examining the mediating role of organizational learning in this relationship.

## 2.4 Knowledge Integration Capability as a Boundary Condition

Knowledge integration capability refers to an organization's ability to synthesize dispersed knowledge elements into coherent, actionable insights[10]. The knowledge-based view of the firm[13]posits that competitive advantage stems from organizational capabilities to create, transfer, and integrate knowledge.

In this context, knowledge integration capability functions as a critical boundary condition that determines whether AI-generated insights can be effectively transformed into 5ambidextrous innovation outcomes. Firms with high knowledge integration capability can more effectively process the complex knowledge outputs from AI systems, translating them into coherent ambidextrous innovation strategies[14].

While AI applications can enhance learning processes, the conversion of learning outcomes into ambidextrous innovation results depends on complementary organizational capabilities—particularly knowledge integration capacity. This boundary condition explains the heterogeneity in ambidextrous innovation outcomes observed across firms implementing similar AI technologies.

### 2.5 Hypotheses Development

**Hypothesis1**:Artificial intelligence applications positively influence firm ambidextrous innovation.

**Hypothesis2**: Organizational learning mediates the relationship between artificial intelligence applications and firm ambidextrous innovation.

**Hypothesis3**: Knowledge integration capability positively moderates the relationship between organizational learning and firm ambidextrous innovation, such that this relationship is stronger when knowledge integration capability is high.

## 3 Research Methodology and Results Analysis

### 3.1 Data Collection and Sample

This study employed a questionnaire survey method to collect data. Phase one collected data on independent variables, mediating variables, moderating variables, and control variables, while phase two gathered dependent variable data. The survey targeted middle and senior management or core R&D personnel from enterprises in Tianjin, Hebei, Shandong, and other regions. A total of 478 questionnaires were distributed across the two phases, with 414 valid matched questionnaires obtained after screening and matching, yielding an effective response rate of 86.6%. Table 1 show the sample covered diverse industries and enterprise scales, demonstrating strong representativeness.

### 3.2 Variable Explanation and Measurement

Items for each variable were assessed using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). ①The artificial intelligence application measurement adopted Li Xiaoyue's scale, referencing Lee et al. (2024)[15], comprising 3 measurement items. ②The firm's ambidextrous innovation drew on He and Wong (2004)[17] and Jansen et al. (2006)[16], including 7 items for exploratory innovation, 7 for exploitative innovation, and 8 for common issues of both, with He and Wong(2004)[17]adding the scores of exploratory and exploitative innovation to represent the ambidextrous innovation level. ③The organizational learning, referencing Tippins (2010)[18], totaling 4 items.④The knowledge integration capability measurement adopted Wang Rujun's scale, comprising 3 measurement items[19]. Additionally, this study controlled for three variables that might influence results: firm size, firm age, and industry type.

**Table 1.** Descriptive Statistical Analysis

| class | | frequency | Percentage(%) |
|---|---|---|---|
| Company establishment year | 3 years or less | 38 | 9.2 |
| | 4-6 years | 114 | 27.5 |
| | 6-8 years | 162 | 39.1 |

| | | | |
|---|---|---|---|
| | 8 years or more | 100 | 24.2 |
| Scale | 20 or fewer | 38 | 9.2 |
| | 21-300 people | 254 | 61.4 |
| | 300–1000 people | 80 | 19.3 |
| | 1,000 or more people | 42 | 10.1 |
| Form of ownership of enterprise | public enterprise | 62 | 15 |
| | non-public enterprise | 148 | 35.7 |
| | mixed ownership enterprise | 108 | 26.1 |
| | other | 96 | 23.2 |
| Industry of the enterprise | general equipment manufacturing industry | 46 | 11.1 |
| | Computer Communication and Electronic Equipment Manufacturing Industry | 56 | 13.5 |
| | automotive industry | 52 | 12.6 |
| | Pharmaceutical manufacturing industry | 56 | 13.5 |
| | Information transmission, software and information technology services | 42 | 10.1 |
| | Scientific research and technology services | 56 | 13.5 |
| | financial service industry | 54 | 13 |
| | Wholesale and Retail Trade | 32 | 7.7 |
| | other | 20 | 4.8 |
| Industry stage of the enterprise | initial stage | 148 | 35.7 |
| | growth stage | 126 | 30.4 |
| | maturity stage | 126 | 30.4 |
| | decline stage | 14 | 3.4 |

### 3.3 Normality Test

The assumption of multivariate normality is a prerequisite for employing Maximum Likelihood (ML) estimation in Structural Equation Modeling (SEM). Descriptive statistics indicate that the absolute values of the skewness coefficients for all variables range from [0.879, 1.114], and the absolute values of the kurtosis coefficients range from [0.028, 0.670]. These results satisfy the recommended criteria for normality (i.e., absolute skewness < 3 and absolute kurtosis < 10), suggesting that the sample data follows a normal distribution.

### 3.4 Reliability, Validity, and Common Method Bias Tests

The reliability analysis shows that both the Cronbach's α coefficients and the Composite Reliability (CR) for each scale exceed 0.8, demonstrating high internal consistency reliability.

Results from the Exploratory Factor Analysis (EFA) yielded a KMO value of 0.879, and Bartlett's Test of Sphericity reached statistical significance ($\chi^2 = 3096.352$, $p < 0.001$), indicating that the data is suitable for factor analysis. Furthermore, all factor loadings exceeded the 0.5 threshold, and the cumulative variance explained reached 61.318%, confirming robust construct validity.

To control for Common Method Bias (CMB), the study utilized anonymous surveys and incorporated reverse-coded items. Additionally, Harman's single-factor test was conducted for statistical control. The results revealed that the variance explained by the first unrotated factor was 26.288%, well below the 40% threshold, indicating that common method bias does not pose a serious threat to this study.

### 3.5 Correlation Analysis

Pearson correlation analysis was performed using SPSS 30.0 to examine the relationships, significance levels, and directions between variables. The results are summarized in **Table 2**.

**Table 2.** Correlation Analysis Results

| | AI Application | Common Issues | Exploratory Innovation | Exploitative Innovation | Organizational Learning | Knowledge Integration |
|---|---|---|---|---|---|---|
| AI Application | 1 | | | | | |
| Common Issues | 0.327** | 1 | | | | |
| Exploratory Innovation | 0.352** | 0.363** | 1 | | | |
| Exploitative Innovation | 0.139** | 0.348** | 0.361** | 1 | | |
| Organizational Learning | 0.154** | 0.225** | 0.336** | 0.271** | 1 | |
| Knowledge Integration | 0.223** | 0.289** | 0.242** | 0.470** | 0.449** | 1 |

Note: ** $p < 0.01$, * $p < 0.05$.

Common issue = exploratory innovation + exploitative innovation.

### 3.6 Hypothesis Testing

Following the theoretical framework, an SEM model was constructed with AI Application, Organizational Learning, Exploitative Innovation, and Exploratory Innovation as core variables. AMOS 21.0 was utilized to assess the model fit. As shown in **Table**

**3**, all fit indices met the recommended benchmarks, indicating a good model-to-data fit.

**Table 3.** SEM Model Fit Indices

| Category | $x^2/d_f$ | RMR | GFI | CFI | RMSEA |
|---|---|---|---|---|---|
| Recommended Criteria | 1~3 | <0.1 | >0.9 | >0.9 | <0.8 |
| Observed Values | 2.681 | 0.086 | 0.907 | 0.921 | 0.064 |

**3.6.1 Main Effects Test.**

Hierarchical regression analysis was first conducted with exploitative and exploratory innovation as dependent variables. After controlling for relevant covariates, the AI application was found to have a significant positive effect on both exploitative innovation (β= 0.347, $p < 0.001$) and exploratory innovation (β= 0.346, $p < 0.001$). The structural equation model further validated these results, showing that the standardized path coefficients for the effects of AI Application on exploitative innovation (β = 0.45, p < 0.001), exploratory innovation (β= 0.20, $p < 0.001$), and organizational learning (β = 0.22, $p < 0.001$) were all significantly positive. As showed in **Fig. 1** Thus, Hypothesis H1 is supported.

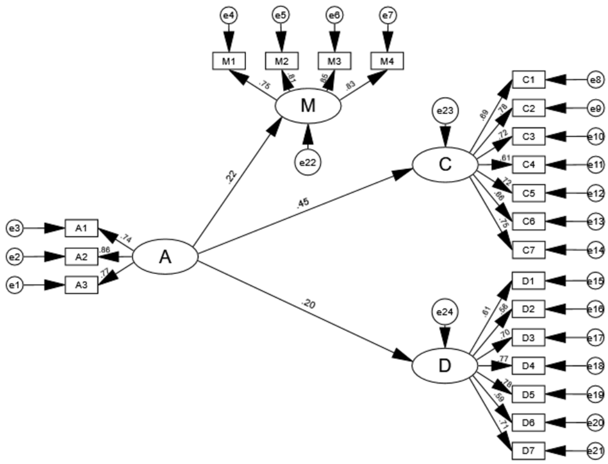


**Fig. 1.** Path diagram of the structural model(standardized coefficients)

**3.6.2 Mediation Effects Test.**

Upon establishing the main effects, the mediation analysis revealed that after incorporating Organizational Learning into the model, the direct effects of AI Application on both innovation types remained significant, although the coefficients decreased to β= 0.307 ($p < 0.001$) and β= 0.078 ($p < 0.001$), respectively. As showed in **Fig. 2**, **Table**

**4**, This suggests that Organizational Learning plays a partial mediating role in these relationships, supporting H2.

**Table 4.** Fit Indices of the Mediation SEM Model

| Category | $x^2/d_f$ | RMR | GFI | CFI | RMSEA |
|---|---|---|---|---|---|
| Recommended Criteria | 1~3 | <0.1 | >0.9 | >0.9 | <0.8 |
| Observed Values | 2.323 | 0.071 | 0.915 | 0.938 | 0.057 |

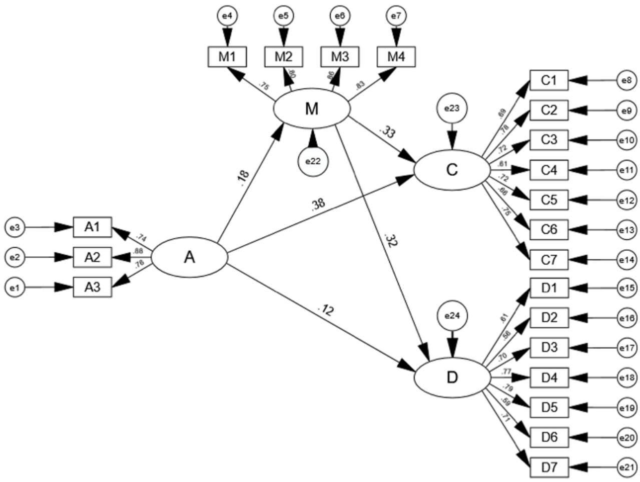


**Fig. 2.** Path diagram of the structural model(standardized coefficients)

A Bootstrapping procedure was further employed to verify the mediation. The model fit remained robust. Path analysis confirmed that AI Application significantly promotes Organizational Learning (β= 0.18, $p < 0.05$), which in turn significantly enhances both exploitative (β= 0.33, $p < 0.001$) and exploratory innovation (β= 0.32, $p < 0.001$). The indirect effects of Organizational Learning between AI Application and innovation were 0.267 and 0.084, as showed in **Table 5**, **Table 6**, respectively, with 95% confidence intervals excluding zero, further confirming the significance of the mediation.

**Table 5.** Mediating Effect of Organizational Learning between AI Application and Exploitative Innovation

| Path | Effect Type | Effect Size (r) | SE | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | LLCI | ULCI |
| AI Application→Organizational Learning→Exploitative Innovation | Direct | 0.301 | 0.011 | 0.221 | 0.381 |
| | Indirect | 0.267 | 0.007 | 0.190 | 0.344 |
| | Total | 0.034 | 0.015 | 0.008 | 0.641 |

**Table 6.** Mediating Effect of Organizational Learning between AI Application and Exploratory Innovation

| Path | Effect Type | Effect Size (r) | SE | 95% Confidence Interval LLCI | ULCI |
|---|---|---|---|---|---|
| AI Application→Organizational Learning→Exploratory Innovation | Direct | 0.088 | 0.039 | 0.102 | 0.165 |
| | Indirect | 0.084 | 0.039 | 0.012 | 0.140 |
| | Total | 0.172 | 0.010 | 0.095 | 0.249 |

**3.6.3 Moderation Effects Test.**

Hierarchical regression was employed to test the moderating effect of Knowledge Integration Capability. The interaction term between AI Application and Knowledge Integration Capability significantly predicted both exploitative innovation ($\beta= 0.146$, $p < 0.001$) and exploratory innovation ($\beta= 0.202$, $p < 0.001$). These findings indicate that Knowledge Integration Capability positively moderates the relationship between AI Application and digital innovation; specifically, the positive impact of AI Application becomes more pronounced as knowledge integration capability increases. Thus, H3 is supported.

# 4 Discussion and Theoretical Implications

## 4.1 Theoretical Contributions

First, we reconceptualize AI as cognitive enhancement technologies that reshape organizational knowledge systems beyond efficiency-focused perspectives. AI significantly enhances both exploitative ($\beta = 0.347$, $p < 0.001$) and exploratory innovation ($\beta = 0.346$, $p < 0.001$), revealing its cognitive value-creation mechanisms.

Second, knowledge integration capability serves as a critical boundary condition explaining heterogeneous AI innovation outcomes. It positively moderates the organizational learning–innovation relationship ($\beta = 0.146$ for exploitative, $\beta = 0.202$ for exploratory, both $p < 0.001$), with stronger effects on exploratory innovation.

Third, we advance ambidextrous innovation theory by demonstrating that AI fosters ambidexterity both directly and indirectly through organizational learning, with the indirect pathway accounting for 31.5% of the total effect.

## 4.2 Practical Implications

Our findings offer several important practical implications for managers implementing AI strategies.First, firms should view AI implementation as cognitive transformation, investing in both technology and knowledge creation capabilities.

Second, prioritize knowledge integration capability as complementary asset, with stronger moderating effect on exploratory innovation.

Third, our mediation analysis shows that organizational learning mediates 35.1% of AI's total effect on ambidextrous innovation. This suggests that firms cannot simply purchase AI technologies and expect innovation outcomes; they must also invest in learning infrastructure,particularly for firms with 21-300 employees.

## 5 Limitations and Future Research Directions

This study has several limitations. First, organizational learning was examined as a unitary construct—future research should distinguish exploratory and exploitative learning to reveal their differential mediating effects. Second, our knowledge integration capability measure focused on internal synthesis; future studies should examine external knowledge integration from partners and ecosystems, and test our model across different cultural contexts. Addressing these limitations through longitudinal designs, cross-cultural comparisons, and qualitative case studies would further validate our findings.

## 6 Conclusion

This study advances the understanding of how artificial intelligence applications drive firm ambidextrous innovation through the mediating role of organizational learning and the moderating effect of knowledge integration capability. By reconceptualizing AI as cognitive infrastructure reshaping organizational learning pathways, we explain how AI differentially influences exploitative and exploratory innovation.

Our findings demonstrate that organizational learning partially mediates the relationship between AI applications and firm ambidextrous innovation, with this indirect pathway accounting for 31.5% of the total effect. Furthermore, knowledge integration capability positively moderates the learning–innovation link, with a stronger effect on exploratory innovation ($\beta = 0.202$, $p < 0.001$) than on exploitative innovation ($\beta = 0.146$, $p < 0.001$).

These findings explain heterogeneous AI innovation outcomes and highlight the need for organizational learning and knowledge integration capabilities. Firms investing simultaneously in AI, organizational learning, and knowledge integration are better positioned to achieve ambidextrous innovation, particularly in exploratory domains.

By integrating AI research, organizational learning theory, and the knowledge-based view, this study provides a theoretical foundation for understanding digital-enabled cognitive transformation. Formalizing the mediating and moderating mechanisms offers both theoretical insights and practical guidance for leveraging AI in sustained innovation.

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As this text draws to a close, it also marks the conclusion of our nearly year-long research journey. From one spring to another, taking this spring as a starting point, we stride toward every promising spring in the wider world.

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