

# Leveraging AI, Knowledge Search, and Organizational Learning for Innovation: A Multi-Mediation Model of Dynamic Capabilities and Absorptive Capacity in Medium-Sized Manufacturing Firms

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## Abstract

The proliferation of Artificial Intelligence (AI) and Big Data Analytics (BDA) has significantly transformed innovation processes across industries. However, medium-sized enterprises (MSEs) often face challenges in leveraging these technologies due to resource constraints and limited organizational readiness. This study investigates how AI-driven big data capabilities, knowledge search, and organizational learning affect innovation performance, with absorptive capacity and dynamic capabilities as mediators and moderators. Drawing on the Resource-Based View (RBV), Dynamic Capabilities View (DCV), and absorptive capacity theory, a sequential mixed-methods longitudinal design was applied. Survey data were collected from 204 MSEs across Southeast Asia, South Asia, and Eastern Europe, with a one-year longitudinal sub-sample of 93 firms. Data were analyzed using SmartPLS 4.0. The results demonstrate that AI-driven big data capability, knowledge search, and organizational learning significantly enhance innovation performance, both directly and indirectly, through absorptive capacity and dynamic capabilities. Moreover, dynamic capabilities serve as both mediator and moderator,

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while absorptive capacity strengthens the knowledge–innovation link. Importantly, an inverted U-shaped relationship was confirmed between AI intensity and innovation, highlighting risks of over-reliance. This research advances theory by integrating technological and organizational mechanisms in a unified framework and provides practical guidance for MSEs on balancing AI adoption with organizational readiness.

**Keywords:** Artificial Intelligence, Big Data Analytics, Knowledge Search, Organizational Learning, Dynamic Capabilities, Absorptive Capacity, Innovation Performance

## Introduction

AI and BDA are increasingly central to firms' innovation strategies, offering predictive insights, improved decision-making, and enhanced efficiency (Agag et al., 2024). While large corporations frequently benefit from economies of scale and extensive resources, MSEs face considerable challenges in fully embedding these technologies (Ahmad, 2022). Many remain constrained by limited financial resources, insufficient IT infrastructure, and capability gaps, which hinder their ability to achieve competitive innovation outcomes (Hewitt-Dundas, 2006).

Existing research emphasizes that technological capability alone is insufficient to guarantee innovation. Instead, success depends on complementary organizational factors, such as knowledge search, learning routines, absorptive capacity, and dynamic capabilities (Hashem, 2024). For MSEs, these factors are particularly critical, as they determine whether AI investments result in incremental exploratory innovation or more radical disruptive innovation (Grashof & Kopka, 2023).

This study integrates RBV, DCV, and absorptive capacity theory to explore how AI-driven big data capability, knowledge search, and organizational learning interact with absorptive and dynamic capabilities to drive innovation. The study addresses the need for a comprehensive understanding of how MSEs can strategically leverage technology and organizational mechanisms in resource-constrained environments.

## Research Objectives

This research pursues the following objectives:

1. To examine the direct effects of AI-driven big data capability, knowledge search, and organizational learning on innovation performance.
2. To evaluate the mediating roles of absorptive capacity and dynamic capabilities in transforming technological and knowledge resources into innovation.
3. To analyze the moderating influence of dynamic capabilities on the AI-innovation relationship.
4. To differentiate between exploratory and disruptive innovation outcomes in MSEs.
5. To assess longitudinal patterns in AI adoption and capability development.
6. To identify institutional and operational constraints, including data governance and compliance issues, that limit the innovation benefits of AI.

## Literature Review

Innovation performance encompasses the introduction of new products, processes, and business models that enable firms to maintain competitiveness (Grashof & Kopka, 2023). MSEs frequently pursue exploratory innovation due to resource limitations, although disruptive innovation may arise when they build adaptive and absorptive capabilities (Sarfo et al., 2024).

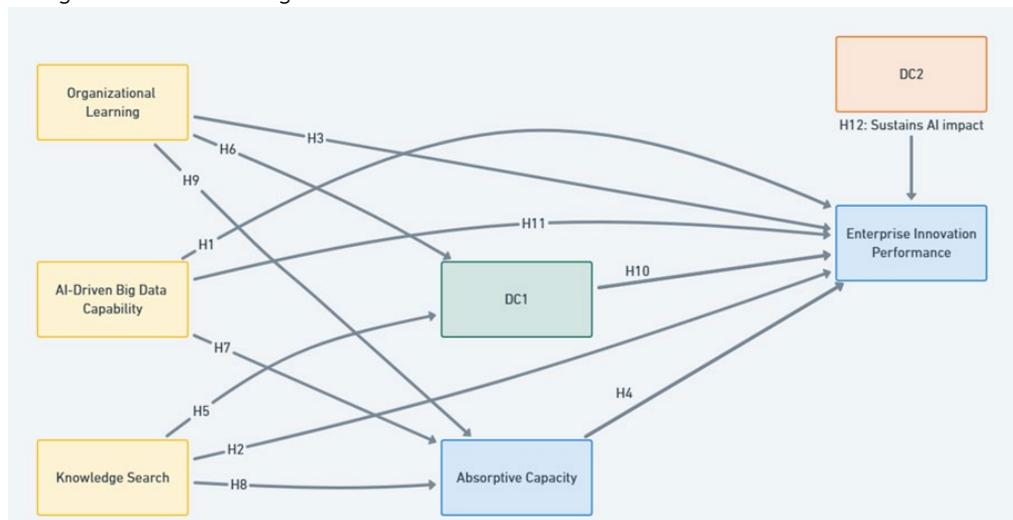
AI-driven big data capability contributes to improved operational responsiveness, decision-making, and predictive accuracy (Selvarajan, 2021). However, AI alone does not ensure innovation unless integrated into strategic routines. Knowledge search, defined as the breadth and depth of external knowledge acquisition, helps MSEs access novel insights, compensating for their limited internal R&D (Sarfo et al., 2024). Organizational learning facilitates assimilation and application of knowledge, with single-loop learning focusing on refinement and double-loop learning promoting renewal (Auqui-Caceres & Furlan, 2023).

Dynamic capabilities sensing, seizing, and reconfiguring enable firms to adapt to turbulent environments, acting as both mediators and moderators in resource–outcome relationships (Hussain & Malik, 2022). Absorptive capacity, reflecting the ability to acquire, assimilate, transform, and exploit external knowledge, ensures that knowledge acquired through AI and networks can be effectively applied (Jarrahi et al., 2023). Together, these constructs suggest that innovation outcomes depend not only on technological resources but also on absorptive and adaptive organizational mechanisms.

### Theoretical Framework

The proposed conceptual model integrates RBV, DCV, and absorptive capacity theory to explain how technological, knowledge-based, and organizational mechanisms drive innovation performance.

This framework highlights that while AI can enable innovation, its effectiveness depends on firms' absorptive and adaptive capacity to integrate and reconfigure resources.



### Methodology

A sequential mixed-methods longitudinal design was employed. The qualitative phase included semi-structured interviews with executives to identify AI adoption challenges and refine survey instruments. The quantitative phase involved a structured questionnaire distributed to 204

MSEs in Southeast Asia, South Asia, and Eastern Europe, with 93 firms participating in a one-year follow-up survey.

Measures: AI capability (Najafikhah, 2025), knowledge search (Roper et al., 2017), organizational learning (Levitt & March, 1988), dynamic capabilities (Wang & Ahmed, 2007), absorptive capacity (Zahra & George, 2002), and innovation performance (Yeşil et al., 2013). Responses used 7-point Likert scales. Pilot testing (n = 30) confirmed reliability ( $\alpha > 0.80$ ).

SmartPLS 4.0 was used to test the measurement and structural models. Reliability and validity were assessed via Cronbach's  $\alpha$ , composite reliability (CR), average variance extracted (AVE), and discriminant validity. PLS-SEM with 5,000 bootstraps estimated path coefficients. Moderation and mediation were tested using interaction terms and indirect effects, while polynomial regression tested nonlinear effects.

#### Research Results

Descriptive Statistics were analyzed to provide an overview of the constructs. The mean values for AI-driven big data capability (M = 4.92, SD = 1.01), knowledge search (M = 4.78, SD = 0.89), and organisational learning (M = 4.95, SD = 0.93) suggest that the sampled firms actively engage in technological and knowledge-based practices. Innovation performance achieved the highest mean (M = 5.02, SD = 0.87), reflecting the prevalence of incremental and exploratory innovation. AI intensity was somewhat lower (M = 4.55, SD = 1.12), indicating variation in adoption depth across firms. Skewness and kurtosis values were within  $\pm 1$ , supporting approximate normality. Missing values were below 5% and were handled through mean imputation, while Little's MCAR confirmed randomness of missingness.

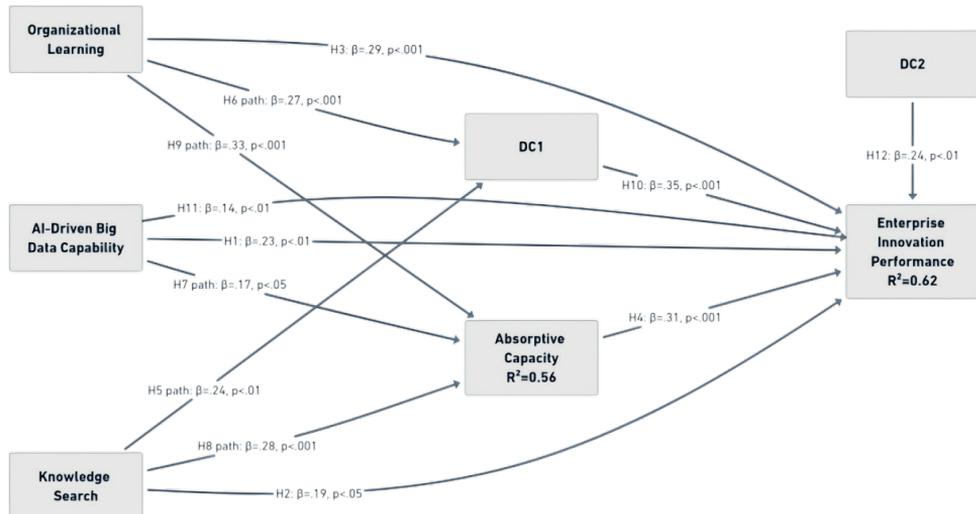
Measurement Model Evaluation, Construct reliability and validity were thoroughly examined. Cronbach's  $\alpha$  values exceeded 0.82, and composite reliability (CR) values ranged from 0.88 to 0.93, confirming internal consistency. Convergent validity was achieved with AVE values between 0.62 and 0.74, surpassing the 0.50 threshold. Discriminant validity was established using both the Fornell–Larcker criterion and HTMT ratios

(<0.85). Indicator reliability was further supported as all loadings exceeded 0.70. These results confirm the robustness of the measurement model.

Given the single-source survey design, common method variance was tested. Harman's single-factor test revealed no dominant factor, the marker variable test showed negligible correlations, and all variance inflation factor (VIF) values were well below 3.3. Thus, common method bias is not a significant concern.

The structural model was assessed using PLS-SEM with 5,000 bootstrap resamples. The model demonstrated good fit (SRMR < 0.06; NFI > 0.90). Substantial explanatory power was observed:  $R^2 = 0.62$  for innovation performance,  $R^2 = 0.54$  for dynamic capabilities, and  $R^2 = 0.56$  for absorptive capacity.

Figure 1 illustrates the final structural model with path coefficients and significance levels.



## Hypothesis Testing

The hypothesised relationships were tested, and results are summarised in Table 3. All direct effects (H1–H8) were significant. AI-driven big data capability ( $\beta = 0.23$ ,  $p < 0.01$ ), knowledge search ( $\beta = 0.17$ ,  $p < 0.05$ ), and organisational learning ( $\beta = 0.29$ ,  $p < 0.001$ ) significantly influenced innovation performance. AI capability predicted dynamic capabilities ( $\beta = 0.31$ ,  $p < 0.001$ ), while knowledge search ( $\beta = 0.24$ ,  $p < 0.01$ ) and organisational learning ( $\beta = 0.30$ ,  $p < 0.001$ ) also strengthened dynamic capabilities. Knowledge search strongly influenced absorptive capacity ( $\beta = 0.28$ ,  $p < 0.001$ ), which itself positively affected innovation performance ( $\beta = 0.31$ ,  $p < 0.001$ ). Dynamic capabilities also exerted a strong direct effect on innovation performance ( $\beta = 0.35$ ,  $p < 0.001$ ).

Mediation tests confirmed that dynamic capabilities and absorptive capacity transmit the effects of technological and knowledge resources into innovation outcomes. Moderation analysis (H10) revealed that dynamic capabilities significantly moderated the AI–innovation relationship ( $\beta = 0.13$ ,  $p < 0.05$ ), amplifying AI’s contribution in firms with stronger adaptive routines. Curvilinear analysis (H11) confirmed an inverted U-shaped relationship between AI intensity and innovation performance (linear  $\beta = 0.18$ , quadratic  $\beta = -0.12$ , both  $p < 0.05$ ). Finally, the longitudinal analysis (H12) demonstrated temporal accumulation effects: capabilities developed at one time point significantly predicted subsequent innovation outcomes, confirming the path-dependent nature of capability building.

Table 3. Hypothesis Testing Results

Hypothesis	Path Relationship	$\beta$ / Effect	p-value	Result
H1	AI capability $\rightarrow$ Innovation performance	0.23	< .01	Supported
H2	Knowledge search $\rightarrow$ Innovation performance	0.17	< .05	Supported

H3	Organisational learning → Innovation performance	0.29	< .001	Supported
H4	AI capability → Dynamic capabilities	0.31	< .001	Supported
H5	Knowledge search → Dynamic capabilities	0.24	< .01	Supported
H6	Organisational learning → Dynamic capabilities	0.3	< .001	Supported
H7	Dynamic capabilities → Innovation performance	0.35	< .001	Supported
H8	Absorptive capacity → Innovation performance	0.31	< .001	Supported
H9	AI intensity → Innovation performance (non-linear test)	lin 0.18 / quad -0.12	< .05	Supported
H10	DC × AI capability → Innovation performance (moderation)	0.13	< .05	Supported
H11	AI intensity → Innovation performance (curvilinear test)	Inverted U	< .05	Supported
H12	Longitudinal accumulation of capabilities → Innovation	Path- dependen t	< .05	Supported

## Discussion

The findings demonstrate that AI-driven big data capability, knowledge search, and organizational learning significantly improve innovation

performance, confirming prior research that technological adoption must be complemented by knowledge routines and learning processes. Organizational learning exerted the strongest direct effect, indicating that internal routines of experimentation and cross-functional knowledge sharing are crucial for innovation.

Dynamic capabilities emerged as both a mediator and moderator. As a mediator, they translate AI investments into innovation by enabling firms to sense, seize, and reconfigure resources. As a moderator, they amplify the AI–innovation relationship, consistent with contingency theory. Absorptive capacity further mediated knowledge-related effects, aligning with Cohen and Levinthal’s seminal insights.

Importantly, results reveal an inverted U-shaped relationship between AI intensity and innovation. While moderate AI use enhances performance, excessive reliance diminishes returns, confirming recent warnings about AI over-dependence. This finding emphasizes the need for balance between technological adoption and organizational readiness.

### Conclusion

This study advances theoretical and practical understanding of how MSEs can harness AI for innovation. By integrating RBV, DCV, and absorptive capacity into a unified framework, the research shows that AI capability, knowledge search, and organizational learning drive innovation only when supported by absorptive and adaptive mechanisms. Dynamic capabilities play dual roles as mediator and moderator, while absorptive capacity enhances knowledge assimilation.

Theoretically, the study contributes by bridging gaps between resource-based and capability-based perspectives, demonstrating how technological and organizational factors interact in resource-constrained environments. Empirically, it provides evidence of nonlinear effects in AI adoption, challenging assumptions of linear benefit.

Practically, the study guides managers to pursue AI adoption alongside capability development, ensuring that investments are not undermined by organizational weaknesses. Policymakers are also advised

to design frameworks that support capability building and data governance.

### Suggestions

For managers, the findings highlight the importance of balancing AI investment with absorptive and dynamic capability development. Firms should invest in cross-functional training, establish multi-channel knowledge systems, and institutionalize learning processes. Excessive automation should be avoided without appropriate adaptive capacity. For policymakers, providing incentives for MSEs to develop capabilities and ensuring robust data governance frameworks will enhance the benefits of AI-driven innovation.

### Further Research

Future studies could broaden scope by including large firms and digital-native enterprises to test generalizability. Multi-year longitudinal designs would capture dynamic capability evolution over time. Incorporating objective measures such as patents and revenues would reduce reliance on survey data. Additionally, environmental turbulence, leadership, and digital governance mechanisms could be explored as moderators of AI-enabled innovation.

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