BEM Quaterly
WISDOM ACADEMIC https://doi.org/10.63808/bem.v2i1.401 Volume 2 , Issue 1

Conceptual Paper

Government Support, AI Adoption, and SME Innovation Performance: An Institutional Theory Perspective

Jubo Jin[1], Syaharizah Binti Abdul Aziz[1,*]
[1]City Graduate School, City University Malaysia, Kuala Lumpur 46100, Malaysia
[*]**Correspondence:** Syaharizah Binti Abdul Aziz, syaharizah@city.edu.my

© The Author(s) 2026.
This article is published by Wisdom Academic Press Ltd. under a Creative Commons Attribution 4.0 International License. The license permits use, sharing, adaptation, distribution, and reproduction in any medium or format, provided that appropriate credit is given to the original author(s) and the source, a link to the license is supplied, and any modifications are indicated. Unless otherwise stated, all images and third-party materials included in this article are also covered by the same license. For any material not covered by this license, if the intended use is neither permitted by applicable law nor allowed under the license terms, direct permission must be obtained from the copyright holder. To view a copy of this license, please visit http://creativecommons.org/licenses/by/4.0/.

Abstract

Artificial intelligence (AI) is increasingly central to innovation in small and medium-sized enterprises (SMEs), yet resource constraints limit their ability to exploit it. Governments worldwide provide institutional support to encourage SME AI adoption, but whether such support translates into innovation depends on internal organizational conditions that remain poorly understood. Drawing on institutional theory, this study treats government support as a source of coercive, normative, and mimetic pressure and develops an integrative conceptual model in which it influences SME innovation performance through AI adoption intensity, with organizational learning capability as a mediator and organizational readiness as a moderator. The model specifies that government support raises adoption intensity, which in turn enhances innovation performance; that organizational learning capability partially mediates this effect; and that organizational readiness strengthens the link between government support and adoption intensity. A quantitative, cross-sectional design is proposed: structured questionnaires will collect no fewer than 200 valid responses from SMEs, analyzed using partial least squares structural equation modeling (PLS-SEM). Theoretically, the study is expected to extend institutional theory from the adoption/non-adoption dichotomy to a continuous adoption-intensity construct and to position organizational learning as the channel transmitting adoption into innovation. Practically, it can inform the design of differentiated government policy and SME capability building.

Keywords

AI adoption intensity, SMEs, Innovation performance, Organizational learning capability, Organizational readiness

1. Introduction

The unprecedented growth of artificial intelligence (AI) technology is fundamentally changing the competitive structure and innovation models of firms around the world (Kraus et al., 2022; Rahman et al., 2025). On one hand, large firms, with rich resources and sophisticated technology infrastructure, have made great strides in implementing AI technology, whereas small and medium-sized enterprises (SMEs) encounter much tougher obstacles in the process of adoption due to their resource constraints (Kinkel et al., 2022; Schwaeke et al., 2024). Because SMEs lack the internal resources to absorb adoption costs and risks on their own, external institutional support becomes the decisive lever for their AI adoption, placing the institutional environment rather than firm-internal factors alone at the centre of explaining SME outcomes.

On the other hand, in order to address this gap, governments around the world have launched policies such as fiscal subsidies, taxation incentives, technology service platforms, and digital education initiatives designed to facilitate their adoption of AI technology and unleash their innovative capacity (Xiao et al., 2023). An interesting observation, however, is that although government policies are becoming increasingly supportive, adoption results of SMEs still vary greatly, with some experiencing great success, and others failing to do more than scratch the surface of AI technology applications despite the equal level of support.

Prior research on technology adoption has largely relied on the technology acceptance model (TAM; Davis, 1989) and the technology–organization–environment (TOE) framework (Bhuiyan, 2024), which emphasize users' internal perceptions and firm-level conditions and are therefore less equipped to explain how an external institutional actor such as government drives SME adoption. Three significant gaps are identified in the current literature regarding this issue. First, most of the prior literature focusing on AI adoption has been dominated by large organizations and an approach that considers "adoption versus non-adoption," whereas no attention has been paid to differences in AI adoption depth among SMEs – specifically, the intensity of adoption and the impact on innovation performance (Chatterjee et al., 2022; Enholm et al., 2022). Because the binary "adopt or not" view masks how deeply and broadly AI is actually used, it cannot explain why SMEs receiving comparable support diverge so sharply in innovation outcomes, making adoption intensity rather than the adoption decision alone the decisive variable.

Second, while the positive relationship between AI adoption and innovation performance has been proved, AI only offers potential technological opportunities but does not create any innovations. The organizational processes through which technological opportunities are translated into innovation results are under-researched. Organizational learning capability can be considered one of the mechanisms for such translation, but whether it mediates the relationship between AI adoption and

innovation performance still needs further research (Han et al., 2025; Jarrahi et al., 2023). Third, there is a notable difference in the effectiveness of government support among various organizations, indicating that certain organizational factors moderate the effectiveness. However, what specific organizational factors affect the effectiveness of the transformation process from institutional pressure to AI adoption behaviors is under-researched (Faiz et al., 2024; Jewapatarakul & Ueasangkomsate, 2024).

In order to bridge these gaps, the current study uses institutional theory as its fundamental perspective and constructs an integrative conceptual model linking government support, AI adoption intensity, organizational learning capability, organizational readiness, and innovation performance. Addressing the first gap, it conceptualizes adoption as a matter of intensity and examines how government support raises that intensity and how intensity, in turn, drives innovation (H1, H2). Addressing the second gap, it incorporates organizational learning capability as the mediator that opens the translation black box (H3). Addressing the third gap, it incorporates organizational readiness as the moderator defining the boundary condition under which government support converts into adoption (H4). Theoretically, organizational learning capability is pivotal because institutional theory implies that external pressure must be internally absorbed before it yields outcomes, while organizational readiness is pivotal because organizations enact heterogeneous responses to identical pressures according to their internal conditions. In doing so, the study extends institutional theory in two ways: it shifts the theory's outcome from the binary adoption decision to a continuous adoption-intensity construct, and it specifies the internal conditions (readiness) and processes (learning) that govern how institutional pressure is converted into innovation. Meanwhile, this study explores the under-researched organizational learning black box concerning the impact of AI adoption on innovation performance.

2. Literature Review

2.1. Institutional Pressures and Government Support for AI Adoption

The fundamental thesis of institutionalism indicates that organizational activity does not only rely on efficiency-based considerations but rather depends significantly on the institutional context outside the organization (DiMaggio & Powell, 1983). In this regard, there exist three isomorphism mechanisms of the institutional impact on technology adoption choices: coercive isomorphism based on legal requirements and directives from authorities, normative isomorphism relying on behavioral norms promoted by industries' associations and professional societies, and mimetic isomorphism due to imitating role models under uncertain conditions (DiMaggio & Powell, 1983). All these mechanisms represent an external pressure system that drives organizations toward adopting technologies. In the SME AI-adoption context, these mechanisms operate mainly through the firm's

external resource and policy environment, in which government is the dominant institutional actor.

Government support operates as a multidimensional vector of institutional pressure that spans all three mechanisms (DiMaggio & Powell, 1983). Coercive pressure arises where digitalization mandates, regulatory compliance requirements, or the eligibility conditions attached to public support oblige resource-dependent SMEs to act. Fiscal instruments such as subsidies and tax allowances do not constitute coercion in themselves; rather, they lower the cost and risk of adoption, operating as regulative inducements that reinforce the adoption decision. Normative pressure stems from government- and association-promoted digitalization guidelines and standards. Mimetic pressure arises as SMEs, under uncertainty, imitate government-endorsed exemplar adopters. By simultaneously lowering adoption costs and exerting these pressures, government support not only induces adoption but also encourages SMEs to embed AI across business functions, thereby raising adoption intensity (Xiao et al., 2023).

2.2. AI Adoption Intensity and Innovation Performance

AI adoption intensity, being a continuous variable, extends beyond the conventional dichotomy of 'adoption vs. non-adoption' and measures not only the depth but also the breadth of AI integration in business operations (Enholm et al., 2022). The former refers to whether the AI technology has reached the core processes responsible for value creation or is used in peripheral areas, while the latter relates to multi-scenario AI application throughout different functional areas.

AI adoption intensity facilitates innovation via several channels. When deeply integrated into marketing and customer research, demand discovery based on data leads to quick innovation in products or services offered. When widely implemented in operations management, process automation frees up human power for creative activity. More critically, cross-functional integration allows combining knowledge accumulated by the firm in various business fields, resulting in innovation of its business model and value offering (Liu et al., 2025; Chatterjee et al., 2022). Adoption intensity, thus, leads to higher innovation capability, with superficial use resulting merely in improvement of operations, while intense and widespread use leading to actual innovation. A competing view cautions that adoption intensity alone is insufficient and that performance gains depend on complementary organizational capabilities (Amin et al., 2024), an argument developed in H3.

2.3. The Mediating Role of Organizational Learning Capability

While AI adoption intensity may directly affect innovation performance, the internal transmission mechanism is yet to be clarified. Being a general-purpose technology, the insights derived from AI, including the outcomes from data analysis and pattern recognition, and even prediction, can only be regarded as possibilities at the technical level. To turn them into tangible innovation outcomes,

organizational absorptive, interpretative, and decision-making capabilities must be leveraged. Organizational learning capability plays the central role in this transformation process (Han et al., 2025; Jarrahi et al., 2023). This is consistent with institutional theory's premise that external pressure must be internally absorbed before producing outcomes; a competing resource-based reading would cast learning capability as a direct driver of innovation rather than a mediator—addressed here by hypothesizing partial mediation.

Organizational learning capability can be enhanced by four different aspects of AI adoption intensity. The first aspect concerns information access and acquisition from the outside market and technical environment that is facilitated by the use of AI technology. The second aspect is the speed of knowledge distribution enabled by information technology. The third aspect is the depth of organizational sense-making capability supported by human-machine interaction for complex data analysis. The fourth aspect is organizational knowledge retention guaranteed by systematic knowledge management enabled by artificial intelligence.

2.4. The Moderating Role of Organizational Readiness

A major assumption of institutional theory is that the efficiency of transformation of institutional pressure into organizational action is variable based on the degree to which organizations are able to receive and process the signals provided by institutional pressures. Absorptive capacity of institutional signals is reflected in organizational readiness. Contrasted against moderating the impacts of AI adoption, the concept of organizational readiness moderates if institutional pressures are able to translate into AI adoption through adoption actions, a moderation locus rooted in institutional theory (Jewapatarakul & Ueasangkomsate, 2024; Faiz et al., 2024). Institutional theory holds that organizations facing identical pressures enact heterogeneous strategic responses according to their internal conditions (Oliver, 1991; Clemens & Douglas, 2005); organizational readiness is the internal condition determining whether government-generated pressure is translated into actual adoption.

Organizational readiness can be categorized according to three related factors. Technology infrastructure readiness refers to an enterprise's readiness with respect to having data systems and computing power to deploy AI. Human capital readiness is determined by whether workers have the necessary technical competencies for the deployment of AI. Management process readiness pertains to decision-making processes and the receptivity of organizational culture to technology.

3. Hypotheses Development

Because the coercive, normative, and mimetic mechanisms jointly direct SMEs toward deeper and broader AI use, government support is expected to increase AI adoption intensity. Accordingly: H1: Government support positively influences AI adoption intensity in SMEs.

Within the institutional logic of this study, H2 captures the downstream stage in which institutionally induced adoption is converted into innovation outcomes. Based on the channels discussed in the literature review, the following hypothesis is formulated. H2: AI adoption intensity positively influences innovation performance in SMEs.

By enhancing organizational learning capability, AI adoption intensity exerts an indirect effect on innovation performance. It is anticipated that this relationship will be partially mediated, as AI adoption may also have a direct effect on innovation performance through increasing efficiencies through process automation. Nevertheless, organizational learning capability is the most important mediation mechanism. Therefore, the following hypothesis is proposed. H3: Organizational learning capability mediates the relationship between AI adoption intensity and innovation performance.

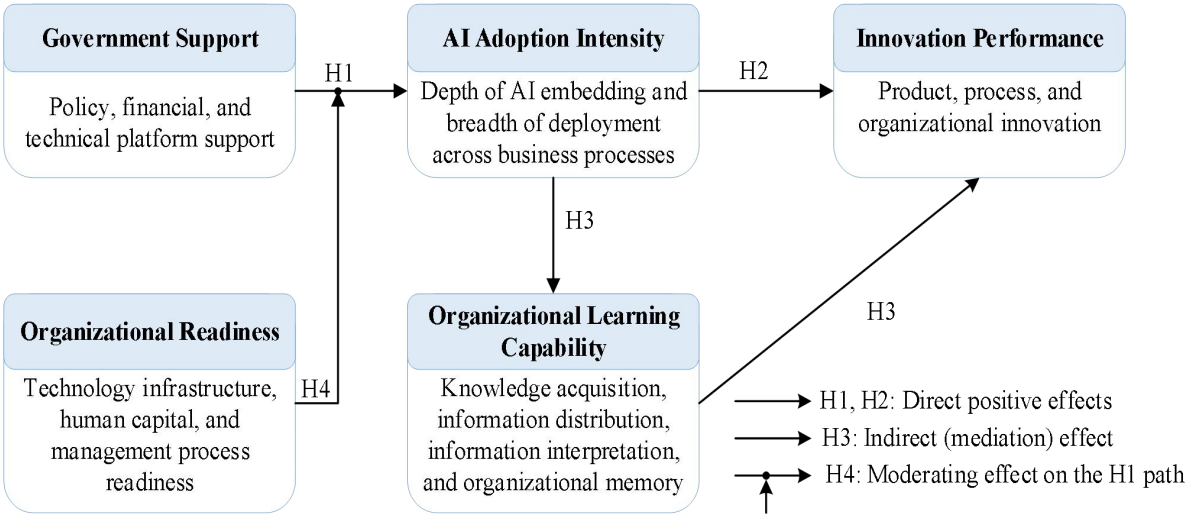
SMEs with high organizational readiness will be able to convert institutional signals into concrete actions, thereby embedding AI deeply into core operations and achieving high-intensity adoption. Organizations with low organizational readiness will continue to face constraints in overcoming the adoption barrier as a result of poor technological preparation, lack of skilled personnel, or rigid management processes, leading to shallow and fragmented AI deployment despite receiving identical levels of institutional support. Therefore, this study will propose the following hypothesis. H4: Organizational readiness positively moderates the relationship between government support and AI adoption intensity, such that the positive effect is stronger when organizational readiness is higher.

4. Conceptual Framework

Drawing upon the foregoing literature review and hypotheses development, this study constructs an integrative conceptual model (see Figure 1).

Figure 1

Conceptual Research Model



Drawing on institutional theory, the model takes government support as the institutional driver for

AI adoption and treats AI adoption intensity as the key mediating variable connecting institutional factors with innovation outputs from the firm. There are three key paths in the model. First, the direct path describes the path from government support to improved innovation performance by way of increased AI adoption intensity (H1→H2). Second, the mediation path shows the internal process through which AI adoption intensity has an indirect effect on innovation performance by way of the learning capability of organizations, which is to say, enhanced AI adoption increases learning capability concerning acquiring information, disseminating information, interpreting information, and remembering information for innovation outputs (H3). Third, the moderation path shows the influence of organizational readiness as a contextual factor on how effectively institutions impact on AI adoption intensity in enterprises so that greater readiness will enable full translation of institutional forces into actions for deep adoption (H4). Here the reasoning of the model is that institutional theory accounts for the source of the outside drive, organizational readiness determines whether institutionally generated pressure could be rooted successfully, while organizational learning capability accounts for the process of technological adoption into innovation output. Institutional theory is adopted as the core lens because, unlike adoption models centred on internal perceptions (TAM) or on technology–organization–environment factors (TOE), it directly theorizes how an external actor—government—drives SME adoption, which is this study's central question. Each path is consistent with prior evidence: government support raising SME digital adoption (Xiao et al., 2023; Faiz et al., 2024), adoption intensity advancing innovation (Liu et al., 2025; Amin et al., 2024), and learning capability transmitting AI effects to innovation (Han et al., 2025). Table 1 provides an overview of the relationship between the paths and hypothesis directions.

Table 1

Summary of Research Hypotheses

Hypothesis	Path	Predicted Direction
H1	Government Support → AI Adoption Intensity	Positive (+)
H2	AI Adoption Intensity → Innovation Performance	Positive (+)
H3	AI Adoption Intensity → Organizational Learning Capability → Innovation Performance	Positive mediation
H4	Organizational Readiness × Government Support → AI Adoption Intensity	Positive moderation

5. Proposed Methodology

5.1. Research Design

This paper will adopt a quantitative research methodology where cross-sectional data will be gathered via structured questionnaires in order to verify the hypothesized conceptual framework as well as test the associated research hypotheses. It is important to emphasize that such research design adheres to the common paradigmatic approach in SME technology adoption literature and is able to efficiently reveal relational patterns among several constructs. A cross-sectional design is appropriate because the study aims to test the hypothesized structural relationships among constructs rather than their evolution over time. The target population includes SMEs belonging to the manufacturing and services industries who have introduced or are in the process of introducing AI technologies into their operations. The sampling procedure will involve stratified random sampling with industry sector and firm size used as the strata. These two strata are chosen because AI adoption propensity differs systematically across industries and firm sizes, so stratified random sampling ensures the sample proportionally represents these segments and improves representativeness. Data will be collected from senior and mid-level management representatives or other individuals involved in decision making pertaining to adoption of AI technologies whose responses can serve as valid proxies for organizational views on the matter in question. The minimum sample size will be determined using the inverse square root method recommended for PLS-SEM (Kock & Hadaya, 2018) rather than the ten-times rule. Assuming a minimum detectable path coefficient of 0.2 at a 5% significance level and 80% statistical power, this method yields a required minimum of approximately 155 responses; a target of at least 200 valid responses will therefore be collected to provide an adequate margin and to accommodate potential incomplete returns.

5.2. Measurement of Constructs

All constructs used in the present paper will be adapted from well-established scales in the literature to achieve the content validity of the measurement tools. Where necessary, item wording will be adapted to the SME AI-adoption context to preserve content validity, while retaining the original constructs' meaning. Information about operationalization, dimensions and sources of the scales used to measure different constructs is presented in Table 2. Government support includes policy, financial and technical platform support for the use of artificial intelligence technology as an instrument for enhancing organizational innovativeness. AI adoption intensity can be assessed according to two dimensions: embedding depth – level of integration of AI into the essential business processes, and deployment breadth – extent of deployment of AI applications throughout different functions within the organization. Organizational learning capability includes such dimensions as knowledge

acquisition, information distribution, information interpretation and organizational memory, all derived from the recent empirical studies on the relation between adoption of AI technology and organizational learning capabilities. Organizational readiness includes three dimensions: technology infrastructure readiness, human capital readiness and management process readiness. Innovation performance is evaluated according to three dimensions: product, process and organizational innovations, all of which are measured by means of subjective perception performance scales common in previous research. Subjective performance measures are appropriate here because objective archival performance data are seldom available for SMEs, and managerial perceptual assessments are a widely accepted proxy in SME and innovation research. Apart from that, the model employs some control variables, namely firm size, firm age, industry type and CEO digital literacy, to rule out their potentially confounding influence on the research outcomes. All constructs' measures will be measured using a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Table 2

Construct Operationalization and Measurement Sources

Construct	Dimensions	Adapted From
Government Support	Policy support; Financial support; Technical platform support	Xiao et al. (2023); Faiz et al. (2024)
AI Adoption Intensity	Depth of AI embedding; Breadth of AI coverage	Kinkel et al. (2022); Chatterjee et al. (2022)
Organizational Learning Capability	Knowledge acquisition; Information distribution; Information interpretation; Organizational memory	Han et al. (2025)
Organizational Readiness	Technology infrastructure; Human capital; Management process	Jewapatarakul & Ueasangkomsate (2024)
Innovation Performance	Product innovation; Process innovation; Organizational innovation	Chatterjee et al. (2022)
Controls	Firm size; Firm age; Industry type; CEO digital literacy	—

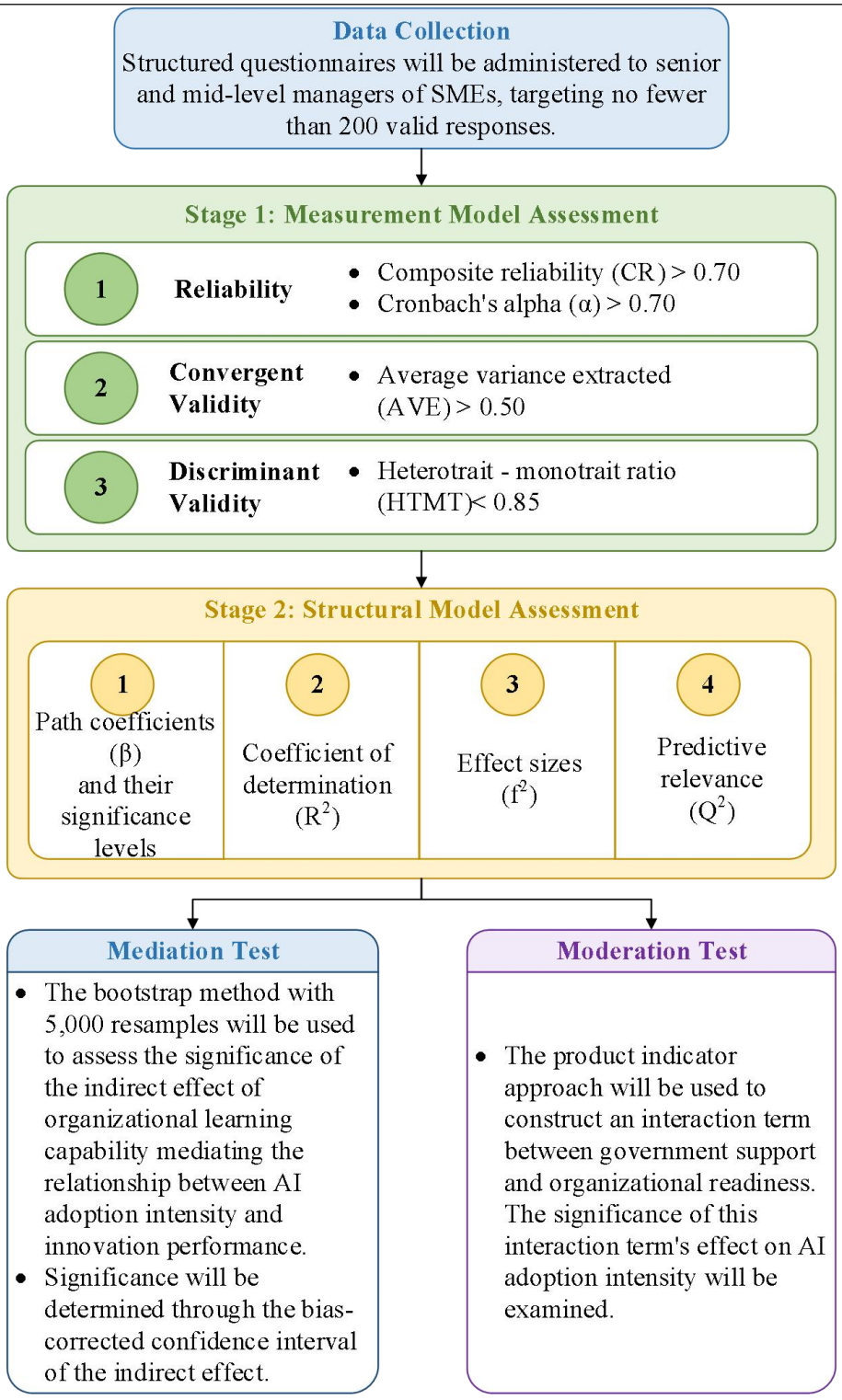
5.3. Data Analysis

Analysis will be conducted via partial least squares structural equation modeling (PLS-SEM). The choice of PLS-SEM in lieu of the covariance-based CB-SEM is justified by several factors as mentioned below. First, PLS-SEM is well suited to exploratory research on relatively new theoretical

constructs and is more robust than CB-SEM with small-to-medium samples, although an adequate sample size is still required to ensure sufficient statistical power (Hair et al., 2021). Moreover, the use of PLS-SEM is not contingent upon certain data distributional assumptions such as data normality. The analysis procedure involves two stages – measurement model and structural model assessments. At the first stage, reliability will be assessed by means of composite reliability (CR) and Cronbach's alpha measures, both having to be larger than 0.70. Convergent validity will be measured by average variance extracted (AVE) measure, the threshold being above 0.50. At the same time, discriminant validity will be tested with the help of heterotrait-monotrait ratio (HTMT), having to be less than 0.85 (Hair et al., 2021). In the second stage, path coefficients, their significance level, R^2, effect size f^2, and Q^2 measure of predictive relevance will be reported. For assessing the mediation effect, bootstrapping approach with 5,000 resamples will be applied. The mediating effect of organizational learning capability will be confirmed or rejected based on the confidence interval for indirect effects. The moderation effect will be examined by means of product indicator method, where the interaction term between government support and organizational readiness will be formed to study its impact on AI adoption intensity. All of the above are illustrated in Figure 2.

Figure 2

Proposed PLS-SEM Analytical Framework



6. Discussion

6.1. Expected Theoretical Contributions

The study's expected theoretical contributions correspond to the three research gaps stated in the introduction. First, studies on technology adoption that have taken an institutional perspective have mostly used the "adoption versus non-adoption" dichotomy to examine organizational behavior. By

introducing the concept of "adoption intensity"—the depth of AI embedding and the breadth of its deployment across business processes—the study is expected to reveal the influence of institutional factors on organizational adoption behavior in finer detail and thereby to enrich institutional theory in explaining firms' digital transformation. Second, incorporating organizational learning capability as a mediator is expected to open up the black box left unexamined in previous research and to articulate the mechanisms through which firms turn AI-derived capabilities into innovation outputs via organizational learning—namely the acquisition, dissemination, interpretation, and storage of information. This would clarify the mediating mechanism more thoroughly and move beyond the simplistic direct-effect relationships typical of previous studies. Finally, positioning organizational readiness as a moderator is expected to show that institutional pressures lead to technology adoption only when an organization meets specific boundary conditions, suggesting that institutional theory should be enriched to address the organizational microlevel.

6.2. Anticipated Practical Implications

The anticipated practical implications concern two major stakeholder groups. If the moderating role of organizational readiness is supported, the framework implies that AI policies for promoting SMEs should avoid a one-size-fits-all design and instead adopt differentiated or tiered policies according to firms' organizational readiness. For those more ready firms, the policy efforts should focus on the issue of integrating technology into its business practices and application at higher levels. For the less ready firms, the policy efforts should focus on developing basic organizational capabilities, such as improved digital infrastructure, digital literacy of the workforce, and management process optimization in order to improve resource allocation efficiency from government spending. For SME managers, the study suggests that the success of AI-related innovation is likely to depend less on AI technologies themselves than on organizational learning capability. The problem with many companies is that while acquiring innovative technology, they have failed to develop an organization's ability to learn and make use of its knowledge. Hence, what SME managers need to do is to pursue both AI adoption and organizational learning capability development.

6.3. Limitations and Future Research

However, several limitations should be noted and considered for future research. First, the cross-sectional design restricts the potential for causality inference, even though the use of structural equation modeling may enable researchers to test the causality direction among different constructs. In contrast, longitudinal tracking studies or quasi-experimental designs can be used to examine how policies dynamically affect changes in the evolution of AI intensity. Second, the sample may be recruited from a particular country or region, but different countries or regions may have distinct institutional settings, cultures, and markets that may shape not only the way institutional pressure

works but also the learning process of organizations. Future studies could employ cross-national comparative designs to validate the theoretical framework in different institutional settings. Third, all variables will be assessed through subjective measures, which may bring about common method variance. Future research could incorporate subjective ratings with objective measures of innovation, such as the number of patents awarded, revenue from innovation products, or investments in R&D as a percentage of total expenditures.

7. Conclusion

With the rapid expansion of AI implementation within industrial production processes, one of the crucial questions of common interest to both academic scholarship and policy practice is how SMEs should implement AI through the use of government support and transform it into innovation performance. Building on institutional theory, this study develops an integrative theoretical framework comprising government support, AI adoption intensity, organizational learning capability, organizational readiness, and innovation performance, from which four interrelated hypotheses are derived for future empirical testing.

The model rests on two mutually supporting propositions. First, government support is expected to be an important institutional driver of SMEs' AI adoption, yet a necessary rather than a sufficient condition, with its effectiveness conditioned by organizational readiness: enterprises with advanced technology, adequate talent, and efficient management processes would convert policy signals into actual adoption more readily than firms lacking such readiness, even under equal government support. Second, the conversion of AI adoption intensity into innovation performance is not expected to be automatic but to require organizational learning capability. Only after obtaining knowledge and distributing information through organizational processes will enterprises truly transform the output of AI-based data insights and pattern recognition into innovation results at all three levels of products, processes, and business models.

More generally, the model conceptualizes a synergy between the institutional environment and internal organizational capabilities. The pressure exerted by the external environment serves as the direction and motivation for innovation adoption, whereas the organization's internal readiness and capability for learning determine its ability to absorb the motivation and eventually transform it into innovation results. In the context of fast iteration of artificial intelligence technologies and increasing number of application areas, the matching effect between the two will play an increasingly important role in the management of innovation activities in SMEs in the years ahead. In other words, when formulating policies and strategies for innovation activities, policymakers and enterprises alike need to think beyond the use of technological instruments per se, and consider the precision of institutional support and the synergy of organizational capabilities.

Acknowledgments

The authors declare that no specific acknowledgments are required.

Author contributions

Not applicable.

Funding

This research received no external funding.

Data availability

No data availability statement is required.

Declarations

Conflict of interest

The authors declare that there is no conflict of interest.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Additional information

Received: 9 May 2026

Accepted: 31 July 2026

Published online: 13 October 2026

Publisher's Note

Wisdom Academic Press Ltd. remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

[1] Amin, A., Bhuiyan, M. R. I., Hossain, R., Molla, C., Poli, T. A., & Milon, M. N. U. (2024). The adoption of Industry 4.0 technologies by using the technology organizational environment framework: The mediating role to manufacturing performance in a developing country. *Business Strategy & Development*, *7*(2), Article e363.

[2] Bhuiyan, M. R. I. (2024). Industry readiness and adaptation of fourth industrial revolution: Applying the extended TOE framework. *Human Behavior and Emerging Technologies*, *2024*, Article 8830228.

[3] Chatterjee, S., Chaudhuri, R., Vrontis, D., & Basile, G. (2022). Digital transformation and entrepreneurship process in SMEs of India: A moderating role of adoption of AI-CRM capability and strategic planning. *Journal of Strategy and Management*, *15*(3), 416–433. https://doi.org/10.1108/JSMA-02-2021-0049

[4] Clemens, B. W., & Douglas, T. J. (2005). Understanding strategic responses to institutional pressures. *Journal of Business Research*, *58*(9), 1205–1213.

[5] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.

[6] DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, *48*(2), 147–160.

[7] Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers*, *24*(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

[8] Faiz, F., Sharma, A., Torabi, T., & Li, S. (2024). Determinants of digital technology adoption in innovative SMEs. *Journal of Innovation & Knowledge*, *9*(4), Article 100595.

[9] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

[10] Han, S., Zhang, D., Zhang, H., & Lin, S. (2025). Artificial intelligence technology, organizational learning capability, and corporate innovation performance: Evidence from Chinese specialized,

refined, unique, and innovative enterprises. *Sustainability*, *17*(6), Article 2510. https://doi.org/10.3390/su17062510

[11] Jarrahi, M. H., Askay, D., Eshraghi, A., & Smith, P. (2023). Artificial intelligence and knowledge management: A partnership between human and AI. *Business Horizons*, *66*(1), 87–99. https://doi.org/10.1016/j.bushor.2022.03.002

[12] Jewapatarakul, D., & Ueasangkomsate, P. (2024). Digital organizational culture, organizational readiness, and knowledge acquisition affecting digital transformation in SMEs from food manufacturing sector. *SAGE Open*, *14*(4). https://doi.org/10.1177/21582440241297405

[13] Kinkel, S., Baumgartner, M., & Cherubini, E. (2022). Prerequisites for the adoption of AI technologies in manufacturing: Evidence from a worldwide sample of manufacturing companies. *Technovation*, *110*, Article 102375. https://doi.org/10.1016/j.technovation.2021.102375

[14] Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, *28*(1), 227–261.

[15] Kraus, S., Durst, S., Ferreira, J. J., Veiga, P., Kailer, N., & Weinmann, A. (2022). Digital transformation in business and management research: An overview of the current status quo. *International Journal of Information Management*, *63*, Article 102466. https://doi.org/10.1016/j.ijinfomgt.2021.102466

[16] Liu, H., Wang, P., & Li, Z. (2025). Artificial intelligence and innovation capability: A dynamic capabilities perspective. *International Review of Economics & Finance*, *99*, Article 103880. https://doi.org/10.1016/j.iref.2025.103880

[17] Oliver, C. (1991). Strategic responses to institutional processes. *Academy of Management Review*, *16*(1), 145–179.

[18] Rahman, M. M., Islam, M., Islam, M. A., Saha, R., & Hossain, D. (2025). Emerging trends in digital transformation and information systems by bibliometric analysis in the United States. *Journal of Information Systems and Informatics*, *7*(4), 3792–3825.

[19] Schwaeke, J., Peters, A., Kanbach, D. K., Kraus, S., & Jones, P. (2024). The new normal: The status quo of AI adoption in SMEs. *Journal of Small Business Management*. Advance online publication. https://doi.org/10.1080/00472778.2024.2379999

[20] Xiao, J., Li, G., Zhu, B., & Xie, L. (2023). Evaluating the impact of government subsidies on the digital transformation of SMEs: Evidence from China. *Humanities and Social Sciences Communications*, *10*, Article 751.