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Research Article

AI Adoption Intensity and SME Innovation: A Configurational Perspective Based on Organizational Readiness and Learning Capability

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Abstract

This paper explores the configurations through which AI adoption intensity acts as a catalyst for innovation performance in SMEs. Based on configurational theory, a theoretical framework integrating AI adoption intensity, organizational readiness (IT infrastructure readiness, resource readiness, and culture readiness) and organizational learning capabilities (knowledge acquisition capability, knowledge integration and application capability) is developed. The findings of the fuzzy-set qualitative comparative analysis based on survey data collected from 196 SMEs in China indicate that none of the individual conditions is a necessary condition for achieving high levels of innovation performance. Three sufficient configurations are identified with a solution consistency score of 0.847 and a coverage score of 0.631. AI adoption intensity serves as a central condition in two configurations and a peripheral condition in one configuration, suggesting that its configurational role is context-dependent rather than uniform.

Keywords

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

1. Introduction

The use of artificial intelligence in SMEs has progressed from a simple binary choice about AI use to a more complex question about the extent of its penetration in different business activities and decisions. Although AI applications have been shown to offer promising potential for improving efficiency and fostering innovation in products, their success in SMEs varies greatly. Studies focusing on the influence of AI on large companies are predominant, but there is much less understanding about

how resource-limited SMEs use different levels of AI adoption to improve innovation outcomes (Mikalef & Gupta, 2021). This imbalance in the research literature is especially troubling since SMEs generally do not have the luxury of slack resources to cover unsuccessful investments in technology. Instead, understanding how AI triggers innovations at a relatively low cost is vital.

A number of studies have posited that the relationship between AI adoption intensity and innovation effectiveness is dependent on organizational context variables within the organization itself. Readiness of the organization, including technological capability, resource capability, and culture, will determine whether or not the organization has the capabilities necessary to embrace artificial intelligence technology. The capability of the organization to learn, meaning the ability to acquire and utilize new knowledge, will determine if the innovation outcomes can be achieved by the knowledge derived from artificial intelligence. Both of these capabilities can be complementary in certain organizations but substitute for each other in others, thus leading to various channels through which AI adoption intensity impacts innovation.

The current research mitigates this drawback using fuzzy-set qualitative comparative analysis, which is uniquely suited to determine a multitude of paths to a single destination (Pappas & Woodside, 2021). From an organizational design perspective, the three configurations identified in this study are best understood not as mere combinations of variables but as distinct structural archetypes through which resource-constrained firms organize their technological, cultural, and knowledge-based elements to enable innovation. Framing the findings in this way positions AI adoption within the broader question of how SMEs architect their internal organization for innovation, rather than treating it as an isolated technological input.

2. Literature Review

2.1. AI Adoption Intensity and SME Innovation Performance

AI adoption intensity is a broader notion that encompasses not just the use or non-use of AI technologies in organizations but also how deeply AI technologies are entrenched within the organization’s primary processes, including but not limited to product development and customer analysis. In research, firms that use AI in many processes have been found to produce better innovation results compared to firms that limit their use of AI technology to individual processes only (Chen et al., 2022). In the case of SMEs, however, the matter is complicated.

In contrast to larger organizations where resources are dedicated specifically for implementing artificial intelligence solutions, SMEs find themselves constrained by resource limitations, thus increasing risks as well as the possible rewards associated with any increase in AI intensity adoption. It has been previously established that technology adoption based on AI improves performance metrics, however, the impact is largely influenced by the absorptive capacity and strategy alignment of the

adopting firms (Chatterjee et al., 2023). Furthermore, Industry 4.0 technologies, including AI-based solutions, have been proposed as means through which sustainable innovations can be achieved; however, the linkages between the two factors have yet to be fully understood in the context of SMEs (Ghobakhloo et al., 2021). These knowledge gaps form the motivation behind the current research into AI adoption intensity.

2.2. Theoretical Foundations of Organizational Readiness and Learning Capability

Readiness in the organizational context indicates the degree to which the organization's internal context is ready to facilitate the adoption of the new technology. The concept of readiness takes into account issues such as technological infrastructure, availability of resources, and the openness of organizational leaders and personnel to changes. An organization that has higher readiness for change will have no problems incorporating AI technology since the foundations will be already laid down. Learning capability within the organizational setting refers to another aspect of organizational readiness that concerns the acquisition of external knowledge and application of such knowledge to produce new products or services.

Previous studies examining manufacturing SMEs have shown that organizational learning contributes effectively to improving sustainability in firm performance via the effect it has on innovation practices (Inthavong et al., 2023). In this regard, when these two variables are put into consideration, there appears a critical contradiction in terms of theory since readiness creates the conditions required for technology absorption, whereas learning capability acts as the process by which absorbed technologies become innovation. Various configurations of organizational learning types coupled with external collaboration have been shown to result in different innovation impacts, indicating that the relationship between readiness and learning capability could be more complicated than just existing independently (Du et al., 2022).

Although cultural readiness, knowledge acquisition capability, and knowledge integration and application capability are conceptually related to the broader constructs of absorptive capacity (Bedoya-Villa et al., 2023) and organizational learning, they are treated as distinct conditions in this study. Cultural readiness captures the normative dimension of preparedness, namely whether shared values and leadership support encourage AI-related change, which is conceptually separate from knowledge processes. Knowledge acquisition capability reflects the exploratory dimension of learning, corresponding to the identification and absorption of external knowledge, whereas knowledge integration and application capability reflects the exploitative dimension, corresponding to the conversion of acquired knowledge into innovation. Maintaining this distinction is essential in a configurational analysis, whose purpose is precisely to reveal how qualitatively different elements

combine; collapsing them into a single construct would obscure the combinatorial patterns that are central to this study.

2.3. Configurational Perspective and fsQCA Methodology

From an organizational design standpoint, treating AI adoption, readiness, and learning capability as interdependent elements of a firm's internal architecture requires an analytical approach that captures how these elements combine rather than how they act in isolation. The traditional variance-based techniques, like regression analysis, calculate the average effect of each independent variable while controlling for others, making assumptions about causal symmetry and independence of variables. Such assumptions rarely occur in organizational research, where the result is a product of multiple conditions' interaction. Instead, the configurational perspective can provide an insight into the matter by means of its three fundamental tenets, which include equifinality, implying that there can be multiple ways of arriving at the same result; causal asymmetry, meaning that the set of conditions leading to high output cannot simply be the opposite to those leading to low output; and conjunctural causation, whereby conditions interact with one another.

Qualitative Comparative Analysis with fuzzy sets has been widely used in business studies as the foremost method that embodies this approach (Kumar et al., 2022). It uses thresholds for calculating set membership scores, creates a truth table by combining all possible logical conditions, and then applies Boolean reduction to find both sufficient and necessary conditions. In the realm of digital transformation, fsQCA has already been used for analyzing how a combination of digital capabilities results in different levels of SME performance (Karadağ et al., 2024).

Another contemporary study has also made use of a two-stage model consisting of PLS-SEM and fsQCA to analyze the role played by AI capability in configuring with data-driven organizational culture to affect the performance of firms, demonstrating the appropriateness of the two-stage approach in modeling the complex interaction between AI and its performance effects (Fosso Wamba et al., 2024). The ability of fsQCA to uncover equifinality and asymmetry makes it an ideal choice for analyzing the complex relationship between AI adoption, organizational preparedness, learning capability, and innovation performance in SMEs.

3. Research Design

3.1. Construction of Configurational Analytical Framework

Based on the theoretical background provided by the literature review, this research develops a configurational analysis model that integrates AI adoption intensity, organizational readiness, and organizational learning capacity in the context of SME innovation performance. Rather than proposing unidirectional hypotheses between individual variables and the outcome, the model treats the six

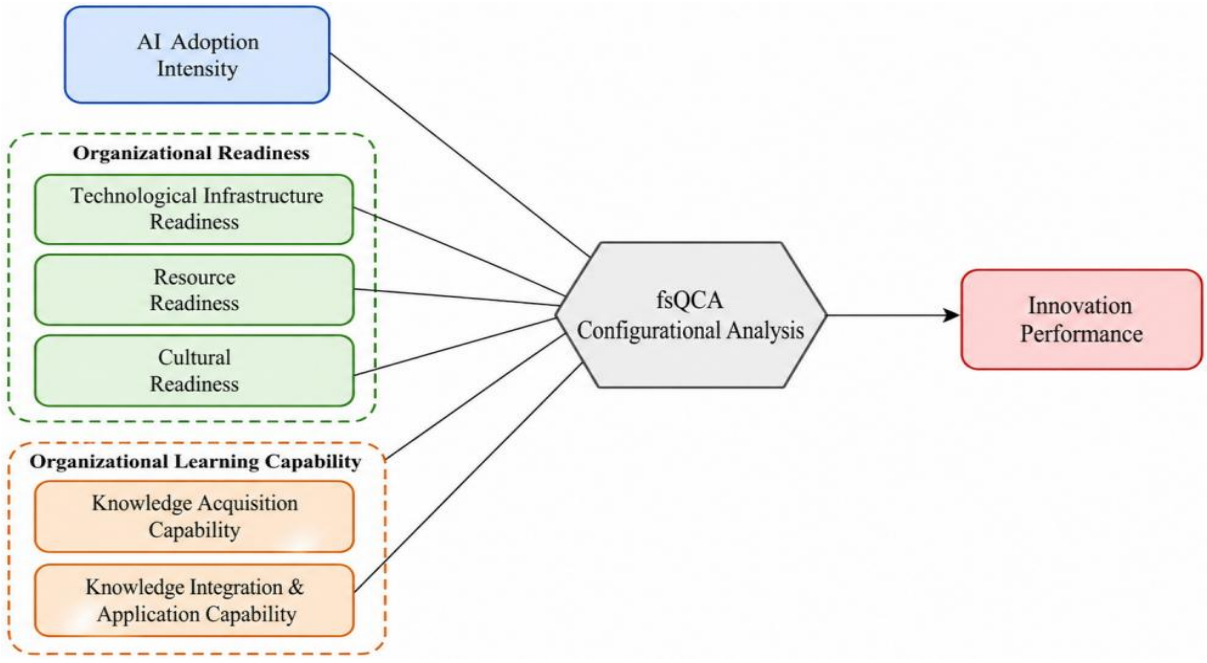
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elements as antecedent conditions, that is, the input building blocks of the analysis. These conditions are not themselves configurations; configurations refer to the specific combinatorial patterns of present and absent conditions that fsQCA identifies, through truth-table analysis and Boolean minimization, as sufficient pathways to high innovation performance. Organizational readiness is further subdivided into three components: technological readiness, resource readiness, and cultural readiness.

The capability for organizational learning is measured using two sub-dimensions, which include: knowledge acquisition capability and knowledge integration and application capability. Both adoption intensity of artificial intelligence and innovation performance are viewed as holistic variables. The six condition variables, as shown in Figure 1, are placed on the left side of the framework and are linked via a logic gate to the output variable, which is found on the other end of the framework. This framework deliberately focuses on internal organizational conditions. External environmental factors, such as competitive pressure, regulatory pressure, customer demand, and government support, which feature in broader technology adoption frameworks such as the TOE framework (Badghish & Soomro, 2024), are not included for two reasons. First, the research question concerns how SMEs internally organize their resources and capabilities to achieve innovation through AI, which is fundamentally a matter of organizational design rather than environmental adaptation. Second, fsQCA constrains the number of conditions relative to the number of cases; with 196 cases and six conditions, the model already approaches the limit of analytical tractability, and adding external conditions would increase truth-table sparsity and reduce interpretive clarity (Nikou et al., 2022). Incorporating external conditions remains an important direction for future research.

Figure 1

Configurational Analytical Framework



3.2. Variable Definition and Measurement

All of the variables used in this study were measured on a scale of one to five using Likert-type questions, as summarized in Table 1. The level of intensity of AI technology adoption was measured by assessing how much of the AI technology was integrated within the organization's activities, and this was done by asking three questions regarding the variety of AI technology utilized, the number of business processes involved, and the frequency of AI technology usage within the organization's operations. Organizational readiness, on the other hand, was measured according to its three dimensions, with each dimension being gauged using two questions.

Table 1

Variable Definitions and Measurement Items

Variable	Sub-dimension	Items	Scale
AI Adoption Intensity	—	AI tool variety; Business function coverage; Usage frequency	5-point Likert
Organizational Readiness	Technological Infrastructure Readiness	IT system maturity; Data management capability	5-point Likert
	Resource Readiness	Financial investment adequacy; Skilled personnel availability	5-point Likert
	Cultural Readiness	Leadership support for AI; Employee openness to change	5-point Likert
Organizational Learning Capability	Knowledge Acquisition	External knowledge identification; New knowledge absorption	5-point Likert
	Knowledge Integration & Application	Cross-departmental knowledge sharing; Knowledge-to-innovation conversion	5-point Likert
Innovation Performance	—	New product/service launches; Product/service improvement; Process optimization; Operational efficiency improvement	5-point Likert

Organizational learning capacity was assessed using two sub-factors, where knowledge acquisition was used to assess the organization's capacity to detect and acquire external knowledge, while knowledge integration and utilization was utilized to measure the efficiency with which acquired knowledge was used to develop innovation input. Innovation performance served as the outcome variable and was measured with four items that capture both product/service and process dimensions of innovation, consistent with the multidimensional conceptualization of product and process innovation in SMEs (Keelson et al., 2024). The items covered new product/service launches and product/service improvement, reflecting exploratory and incremental product innovation respectively, as well as process optimization and operational-efficiency improvement achieved through new technologies, methods, or organizational practices, reflecting process innovation. Defining the latter two items in terms of newly adopted methods distinguishes innovation-driven gains from routine

operational improvement. This breadth is appropriate for SMEs, where formal outputs such as patents often understate actual innovation activity (Athreye et al., 2021).

The reliability and validity of the measurement model were assessed prior to calibration. As reported in Table 2, all constructs exhibited Cronbach's α values above 0.70 and composite reliability (CR) values above 0.70, indicating adequate internal consistency. The average variance extracted (AVE) for each construct exceeded 0.50, and the square root of each construct's AVE exceeded its correlations with other constructs, supporting convergent and discriminant validity.

Table 2

Reliability and Validity of Constructs

Construct	Cronbach's α	CR	AVE
AI Adoption Intensity	0.86	0.91	0.71
Technological Infrastructure Readiness	0.81	0.87	0.66
Resource Readiness	0.79	0.85	0.62
Cultural Readiness	0.83	0.88	0.68
Knowledge Acquisition Capability	0.84	0.89	0.69
Knowledge Integration & Application Capability	0.87	0.92	0.73
Innovation Performance	0.85	0.90	0.70

3.3. Data Collection and Calibration

The data collection was done using an online survey administered to middle and senior level managers from SMEs operating in manufacturing, technology service, and retail industries in China. Respondents were chosen according to two parameters; the business should be employing less than 300 people and should be using at least one form of AI technology or tool in the last three years. A total of 280 surveys were administered, out of which only 196 could be included in the analysis due to non-response and inattention to some questions, resulting in a valid response rate of 70.0%.

Prior to calibration, each multi-item construct was aggregated into a single composite score by computing the arithmetic mean of its constituent items, an approach widely adopted in fsQCA studies using Likert-scale data because it preserves the original scale range and supports meaningful anchor assignment (Pappas & Woodside, 2021). The aggregated mean scores were then used as inputs for direct calibration. There are three qualitative anchors defined for each variable: the 95th percentile of the sample distribution is the cut-off point for full membership, the 50th percentile is the cut-off point for crossover, and the 5th percentile is the cut-off point for full non-membership. Because the raw data derive from a discrete 5-point Likert scale, the 50th-percentile crossover anchor can yield calibrated

membership scores of exactly 0.5, which fsQCA software automatically excludes from the truth table (Nikou et al., 2022). To avoid unintentional case loss, a constant of 0.001 was added to all scores that equaled precisely 0.5, a standard adjustment in configurational research (Furnari et al., 2021).

The percentile method of calibrating variables ensures that the qualitative anchors are not arbitrarily set but are grounded in reality through empirical evidence. The raw consistency threshold for determining sufficient conditions was set at 0.80, exceeding the minimum recommended value of 0.75 (Cangialosi, 2023) and corresponding to a natural breakpoint observed in the distribution of consistency scores across truth-table rows. The PRI consistency was additionally inspected, and all retained configurations exceeded a PRI value of 0.70. Given the moderate sample size of 196 cases distributed across the truth table, the frequency threshold was set at 1 to retain all empirically observed configurations; the subsequent robustness checks indicate that the solution remains stable under stricter parameter settings.

3.4. Common Method Bias Assessment

Because all variables were collected from single informants through a one-time online survey, common method bias (CMB) was assessed using Harman's single-factor test. All measurement items were entered into an exploratory factor analysis with unrotated principal component extraction. The first factor accounted for 28.6% of the total variance, well below the 50% threshold indicative of a dominant method factor (Podsakoff et al., 2024). In addition, procedural remedies were applied during data collection, including guaranteeing respondent anonymity and randomizing item order across construct blocks. Together, these results suggest that CMB does not pose a serious threat to the validity of the findings.

4. Results

4.1. Necessity Testing of AI Adoption Intensity and Organizational Conditions

Before conducting configurational analysis, all conditions and their negations have been analyzed separately for their necessity in relation to high innovation performance. If the consistency value of a condition is equal to or greater than 0.90, then the condition can be identified as necessary. According to Table 3 below, none of the conditions reached this consistency level. The conditions with the highest consistency levels include Knowledge Integration and Application Capability (0.851), AI Adoption Intensity (0.847), and Knowledge Acquisition Capability (0.835). These results imply that even though there may be some conditions which approach necessity, none of them individually qualifies as a necessary requirement in order to achieve high innovation performance. This result highlights the importance of the concept behind this research, in which conditions work together to influence an outcome rather than any one condition on its own.

Table 3

Necessary Condition Analysis for High Innovation Performance

Condition	Consistency	Coverage
AI Adoption Intensity	0.847	0.791
~AI Adoption Intensity	0.412	0.503
Technological Infrastructure Readiness	0.823	0.768
~Technological Infrastructure Readiness	0.439	0.528
Resource Readiness	0.786	0.742
~Resource Readiness	0.471	0.554
Cultural Readiness	0.812	0.773
~Cultural Readiness	0.448	0.519
Knowledge Acquisition Capability	0.835	0.784
~Knowledge Acquisition Capability	0.426	0.511
Knowledge Integration & Application Capability	0.851	0.802
~Knowledge Integration & Application Capability	0.407	0.498

Note. "~" denotes the negation (absence) of a condition. Necessity threshold: consistency ≥ 0.90.

4.2. Configurational Paths to High Innovation Performance Driven by Organizational Readiness and Learning Capability

With the consistency criterion set at 0.80 and the frequency criterion set at 1, the results of fsQCA revealed three configurations sufficient to create innovation performance, as illustrated in Table 4. The first configuration, entitled "Technology-Resource Synergy," consists of high intensity of AI adoption along with high technological infrastructure readiness and resource readiness as key factors, but not cultural readiness and knowledge acquisition ability. This result implies that companies with solid technological infrastructure and sufficient resources can benefit from innovation by incorporating AI technology deeply into their operations without cultural encouragement and external knowledge.

The overall solution consistency is 0.847, and the overall solution coverage is 0.631, indicating that these three paths collectively explain a substantial proportion of high innovation performance cases.

Table 4

Configurational Paths to High Innovation Performance

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Condition	Path 1: Technology-Resource Synergy	Path 2: Learning-Driven	Path 3: Comprehensive Collaboration
AIAdoptionIntensity	●	●	•
TechnologicalInfrastructureReadiness	●		
ResourceReadiness	●		•
CulturalReadiness	⊗	•	●
KnowledgeAcquisitionCapability	⊗	●	
KnowledgeIntegration&ApplicationCapability		●	●
RawCoverage	0.358	0.327	0.289
UniqueCoverage	0.087	0.063	0.051
Consistency	0.891	0.874	0.856
OverallSolutionCoverage		0.631	
OverallSolutionConsistency		0.847	

Note. ● = core condition present; • = peripheral condition present; ⊗ = core condition absent; blank = irrelevant.

4.3. Analysis of the Configurational Role of AI Adoption Intensity in Configurational Paths

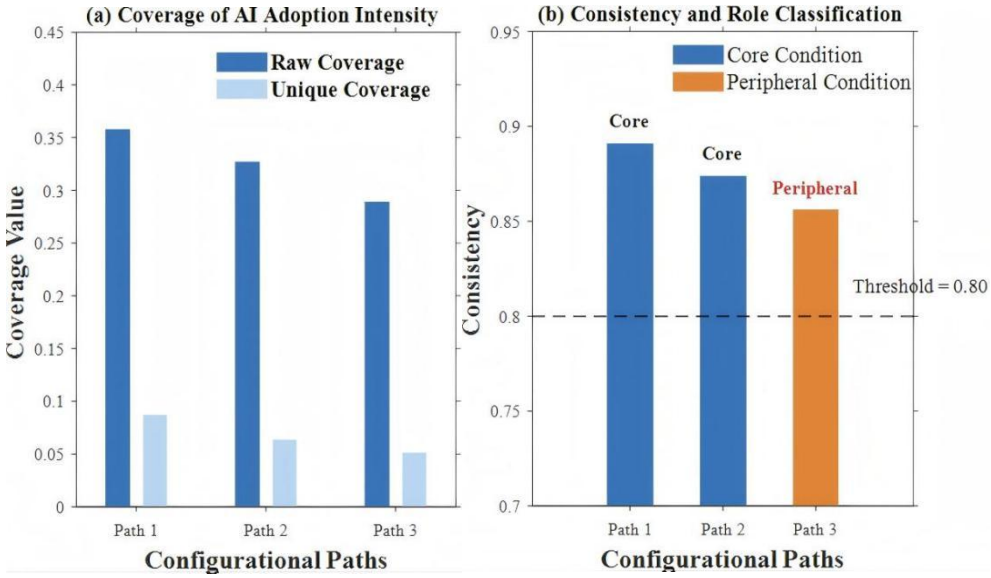
It should be noted that the following analysis describes the configurational role of AI adoption intensity as a set-theoretic association rather than a direct causal effect. Through the analysis of cross-paths, it becomes clear that the intensity of AI adoption is found in all three paths, albeit with a great variation in terms of the function performed by AI adoption intensity. In Paths 1 and 2, AI adoption intensity assumes the form of a core condition, implying that the presence of AI adoption intensity is vital and indispensable for the realization of high innovation performance in those particular configurations. In Path 3, AI adoption intensity takes a periphery position, acting as a supporting factor for the attainment of the end result.

In case of a supportive technological infrastructure and adequate resources, AI becomes the key mover. In combination with efficient learning processes, AI functions as a core condition in a completely different way. With efficient organizational culture and knowledge use, AI operates as a peripheral condition in an auxiliary capacity. As depicted in Figure 2, the gross extent of configurational paths with the intensity of AI implementation as a core antecedent (Paths 1 and 2: 0.358 and 0.327) is clearly greater than the one with an auxiliary role played by AI (Path 3: 0.289).

However, consistency is high above 0.80 for all paths, and thus, this role performed by AI is important for innovation performance.

Figure 2

Role Distribution of AI Adoption Intensity Across Configurational Paths. (a) Raw and unique coverage; (b) Solution consistency and core/peripheral role classification.



4.4. Robustness Tests

For a stability analysis of the results generated via the configurational approach, the analysis was conducted again after applying two adjustments to the analysis. The threshold value for consistency was increased from 0.80 to 0.85, while the calibration anchors were moved from 95th/50th/5th to 90th/50th/10th percentiles. In addition, the frequency threshold was raised from 1 to 2 as a further robustness check, and the same three configurations were retained with only minor changes in coverage. In either case, the three basic configurational paths identified earlier remained consistent with respect to their elements. The importance of adopting AI technology in terms of being a core and peripheral condition for Paths 1, 2, and 3, respectively, was consistently found in all robustness checks. Small differences might have occurred with respect to coverage values; however, none of the paths was lost, and no additional path has emerged.

5. Discussion

From the findings of the configurational analysis, it can be concluded that none of the organizational conditions are necessary on their own to realize innovation success, but there are three different combinations of organizational conditions that are sufficient. These results refute the existing belief in the AI adoption literature that higher technology integration necessarily results in innovation success. In the case of Technology-Resource Synergy and Learning-Driven configurations, although

the intensity of adopting AI is considered an important organizational condition, the way in which it combines with other conditions to form a sufficient pathway differs across configurations.

The other "Comprehensive Collaboration" path also shows that high levels of innovation are still achievable even if the adoption intensity of artificial intelligence only has a tangential impact on the organizations, given that their readiness and ability to integrate knowledge is very high. This substitution between organizational readiness and learning capability is consistent with the principle of equifinality in configurational theory. The mechanism can be further explained through the Resource-Based View (Kero & Bogale, 2023): when cultural readiness and knowledge integration capability are sufficiently high, they constitute valuable and difficult-to-imitate resources that generate innovation through tacit knowledge mobilization and cross-departmental collaboration, mechanisms that operate independently of AI-driven automation. From a dynamic capabilities perspective (Cimino et al., 2025), the sensing and reconfiguring capacities embedded in a mature learning system can functionally replicate the knowledge-synthesis role otherwise played by AI, allowing resource-constrained SMEs to reach comparable innovation outcomes through human-centered rather than technology-centered pathways. For small and medium-sized enterprises, this means that increased learning capability can be a substitute for poor infrastructure capabilities.

These configurational differences translate into path-specific strategic guidance. Firms positioned on the Technology-Resource Synergy path should concentrate investment on deepening AI integration within existing technological infrastructure and ensuring adequate resource allocation, since their innovation gains derive primarily from technology-resource complementarity rather than from cultural or learning mechanisms. Firms on the Learning-Driven path should prioritize external knowledge acquisition and the cultivation of an open, change-oriented culture, using AI specifically as a tool to accelerate knowledge absorption rather than as a standalone driver. Firms on the Comprehensive Collaboration path, where AI plays only a supporting role, should invest in cross-departmental knowledge integration and collaborative routines, treating AI as a complement to, rather than a substitute for, their human-centered learning capabilities. This differentiated roadmap allows managers to align their innovation strategy with their firm's existing organizational profile.

6. Conclusion

In this study, fsQCA is used to explore the effects of intensity of AI adoption, organizational readiness, and learning ability on the configuration of innovation performance in SMEs. The results show three alternative configurational pathways to high innovation performance in SMEs, indicating that the role of AI adoption intensity is configurationally associated with innovation and varies depending on the organizational context. Because the design is cross-sectional, these configurations should be interpreted as relationships of sufficiency rather than as causal effects. This study provides

an important contribution to configurational theory, showing that the relationship between AI and innovation performance in SMEs is configurationally complex. There are several limitations that need to be pointed out; for example, the cross-sectional research design makes causal inference impossible, and the sample is restricted to SMEs from China. Future research could also complement these perceptual measures with more formal innovation outputs, such as patents, new-product revenue share, or R&D commercialization rates.

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Data availability

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The authors declare that there is no conflict of interest.

Ethics approval

Not applicable.

Consent to participate

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Consent for publication

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