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AI in strategic management and organizational agility of SMEs: leadership, policy environment, and adaptive capability

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ABSTRACT

This study investigates how artificial intelligence strategic capabilities, transformational leadership, and policy environments collectively influence organizational agility in small and medium-sized enterprises through dynamic capability mechanisms. Employing a mixed-methods design, the research analyzes survey data from 300 SMEs across manufacturing, service, and technology sectors, complemented by qualitative case studies. Structural equation modeling reveals that AI strategic capabilities constitute the strongest predictor of organizational agility ($\beta=0.42$, $p<0.001$), with digital dynamic capabilities mediating 67% of this total effect. Technology-management fit emerges as a critical boundary condition, amplifying AI effectiveness by 123% under high alignment scenarios ($\beta=0.58$ versus $\beta=0.26$ in low alignment contexts). Transformational leadership exhibits dual mechanisms through direct positive effects on agility ($\beta=0.28$, $p<0.001$) and moderating influences on AI-agility relationships ($\beta=0.21$, $p<0.01$). Notably, AI capabilities demonstrate buffering properties against policy environment uncertainty ($\beta=0.12$, $p<0.05$), transforming institutional constraints into manageable strategic variables. Machine learning analyses reveal nonlinear effects with diminishing returns beyond the 75th percentile of AI adoption. The structural model explains substantial variance in organizational agility ($R^2=0.64$) and firm performance ($R^2=0.52$). These findings extend dynamic capability theory to digital contexts, reconceptualize AI as a strategic capability rather than an operational tool, and illuminate digital leadership dimensions, offering evidence-based guidance for SME managers, technology vendors, and policymakers navigating digital transformation challenges.

1. Introduction

The SME strategic environment is therefore undergoing a marked change due to the growing adoption of AI, which offers innovative opportunities to enhance efficiency and strategic competitiveness. Current trends indicate that the adoption of AI is a major factor in the sustainable development and growth of SMEs, enabling them to develop dynamic capabilities to navigate a dynamic environment and marketplace uncertainty [1]. Although SMEs constitute over 90% of all business entities worldwide, they face specific challenges in adopting AI due to limited technical knowledge and expertise in adapting to the latest AI technologies [2]. The modern business environment is characterized by high levels of volatility and uncertainty; consequently, SMEs need to be highly adaptable. The adoption and success of digital transformations depend not only on the implementation of

technology but also on their ability to provide supplemental organizational capacity to leverage it [3]. Alignment and agility in big data capabilities in the organization are now regarded as critical enablers in the ability to capitalize on the results of digital transformations in order to produce optimal outcomes in terms of innovation performance, given that technology investment returns are realized in an environment where agility and flexibility exist in the organization [4]. A principal need for the competitiveness of SMEs in digital economies is organizational agility—that is, the ability to monitor and respond to environmental changes instantly. The association among organizational agility, digital competencies, and management support is therefore identified as a critical success factor, given that empirical evidence shows that top management support significantly moderates the association between digital competencies and

success [5]. SMEs must develop dynamic capabilities to underpin continuous strategic change and agility, as dynamic capabilities encompass identifying opportunities and threats, exploring opportunities by seizing resources, and reshaping the organization's architecture [6]. Leadership plays a central role in integrating digital transformation and in creating conducive environments for AI adoption. However, leaders' power is mediated by broader institutional settings, shaped by policy environments that either enable or constrain the processes of digital transformation to varying extents. Cross-country studies show significant differences in AI adoption rates across organizations in policy environments shaped by regulations and investments in digital infrastructure, among other factors [7]. A policy environment comprises opportunities and constraints that may have negative effects or facilitate AI adoption.

Despite heightened scholarly interest in AI adoption among SMEs, existing studies have several fundamental limitations. Most existing studies have focused on AI adoption without considering the dynamic interaction between technological capabilities and institutional contexts. The dominance of analysis within large-scale organizations has led to limited exploration of SME-specific contexts. Furthermore, existing studies have not effectively examined the relationships between AI technology and organizational contexts in shaping strategic outcomes, such as organizational agility. In addition, the relationship between technological capabilities and performance outcomes remains unclear. Crucially, current studies have lacked empirical analysis of the influence of institutional contexts on effectiveness. The proposed study bridges the gap in the field by introducing an integrated framework to examine the collective effect of AI dimensions, leadership, and policies influencing agility outcomes in SMEs. The proposed work treats AI as a dynamic capability factor, drawing on dynamic capability theory, whereby the adoption of AI, in conjunction with effective leadership and appropriate policies, enables the organization to address adverse conditions in the business environment. The proposed work has three primary contributions in the field. Theoretically, it advances dynamic capability theory by conceptualizing how digital dynamic capabilities mediate the adoption of AI and its overall outcomes in SMEs. The proposed study would, in terms of methodology, contribute to the field of management science by employing mixed methods that combine SEM and machine learning to test the proposed framework. With regard to applicability, it would also provide concrete advice and guidance on the subject. The following sections will detail their analyses and conclusions.

2. Literature review and theoretical framework

2.1 Digital transformation in SME strategic management

The issues in strategic management in SMEs are related to scarcity, asymmetric information, and decision-making processes, which distinguish SMEs from large enterprises. The success of SMEs largely depends on remaining technology-friendly and adopting digital tools to enhance the effectiveness and efficiency of their business processes, despite the challenges of integrating a digital strategy into an adequate strategic framework [8]. In dynamic digital markets, where survival ultimately depends on adaptability, the

traditional strategic management approach relies on inflexible planning and hierarchical decision-making. These forces arise from increasing demand among the customer base, coupled with the intensifying pace and scope of technological advancements. Strategic agility in digital transformation enables SMEs to achieve a sustained competitive advantage through increased efficiency, enhanced customer knowledge, and innovative business models [9]. However, the relationship between expenditures on digital transformation and their outcomes is not always linear due to substantial variation in readiness and implementation. Here, the role of strategic agility is prominent in emphasizing the importance of improving performance in the international environment by enabling rapid strategy adjustments in response to environmental uncertainty [10].

However, there are significant barriers to SMEs' digital transformation. This is because technology acquisition is only one side of a complex challenge: talent development and adaptation to new cultures and processes. It appears that many SMEs have the necessary technology for their operations but lack the talent required to use it, thereby making digital transformation technology-dependent rather than technology-independent for SMEs [11]. This is particularly apparent for SMEs operating in emerging markets, given their limited resources, and is significant because digital business transformation is crucial for fostering frugal innovations and achieving sustainable resilience to operational disturbances amid economic upheavals [12].

2.2 AI and dynamic capability theory

The dynamic capabilities approach is one of the most powerful conceptual frameworks for understanding how organizations sustain their competitive advantages amid turbulent environments through effective strategic resource restructuring. The three-component framework consisting of sensing, seizing, and transforming defines the micro-foundations of processes through which organizations adapt to turbulent environments by capturing activities associated with sensing, seizing, and transforming. The roles of digital transformational leadership, digital capabilities, and the alignment between digital capabilities and strategy are of significant importance for successful SME digital transformation outcomes, as digital capabilities mediate the relationship between leadership and outcomes [13].

The development of AI technology constitutes a fundamental augmentation of these dynamic capabilities and thereby gives rise to what is conceptualized as digital dynamic capabilities. The need for digital transformation in any business entails building new capabilities for digital sensing for environmental scanning, digital seizing for exploring opportunities, and digital reconfiguration for sustained adaptation processes [14]. AI-enabled environmental sensing extends market intelligence by generating real-time information to identify unforeseen trends and threats with high precision, exceeding human capabilities. SMEs operating within the MOBILITY industry employ dynamic capability perspectives to identify pathways for digital transformation of capabilities related to sensing, seizing, and reconfiguring, despite limited resources [15].

Data-driven opportunity scanning is another area in which AI significantly impacts strategic management. Based on extensive data analysis, machine learning algorithms uncover market opportunities and inefficiencies that human analysts cannot possibly detect through their own capabilities. According to evidence provided by systematic literature reviews, five dimensions of capabilities are required for digital transformation: digital dynamic capabilities, digital innovation capabilities, digital technology capabilities, digital culture capabilities, and digital data analytics capabilities [16]. This is because AI-driven resource restructuring enables rapid responses to environmental changes by reallocating organizational resources, which is not possible with traditional management methods.

The theoretical positioning of AI is beyond instrumental technology and has become a strategic capability in its own right. Innovation intermediaries are key to developing such capabilities within SME ecosystems, as they facilitate knowledge transfer and enable capabilities that no single firm can achieve [17]. A strategic approach to AI adoption shifts the focus from viewing AI merely as a technology to recognizing it as a strategic need that requires additional capabilities to harness its full transformative power.

2.3 Leadership and policy environment dynamics

Leadership is viewed as one of the most important determinants of agility and successful digital transformations, and transformational types of leadership have shown significant influence in this area. According to empirical studies, digital transformational leadership is shown to have a significant influence on agility in organizations, acting as a mediating factor between transformational leadership and success associated with digital transformation [18]. The role of leaders' vision-building capabilities to overcome inertia linked to digital transformation initiatives takes special importance in this regard. Transformational and adaptive types of leaders have shown differential influence on development associated with dynamic capabilities, having better capabilities to assemble resources for exploration than adaptive leaders in exploitation situations [19].

Digital Leadership involves skills different from those required for management, such as technology literacy skills, data-driven decision-making skills, and cross-functional collaboration skills for environments mediated by technology. The association between Digital Leadership and performance at the organizational level is complex and assumes the role of big data analysis capabilities and Green Innovation as mediating factors, while AI Change Readiness acts as a moderator for this association [20]. Transformational leaders create agility at the organizational level by putting trust in knowledge sharing and openness to innovation for environments where information is freely exchanged or collaborative problem-solving takes place [21]. This is especially significant for SMEs, as all decision-making authority is vested in higher management levels.

The SME's strategic formulations are highly impacted by the policy environments surrounding them through regulations or lack of regulation measures and uncertainty associated with policies [22]. Green orientation for sustainable environments and corporate social responsibility activities induced or promoted by policies have been shown

to influence environmental performance via green capability development as mediating factors [22]. The uncertainty surrounding environmental policies affects strategic formulation by imposing limitations on investments and innovations associated with unknown policy formulations and requirements for SMEs to comply with. However, AI technology provides strategic means to mitigate environmental policy risks associated with SME strategic formulations through advanced monitoring capabilities for policies and strategic planning for adaptations and requirements to comply with environmental policies for SME success. Green innovations induced by policies have been shown to offer sustainable business performance outcomes and strategies through combined capabilities between green innovations and technology advancements for SME success within energy-intensive industries [23].

2.4 Theoretical framework and research hypotheses

Based on dynamic capability theory, whereby sustained competitive advantage is established by firms' efforts to integrate and rebuild and reconstruct capabilities both inside and outside their organizations to respond to environmental change [24], this study adopts an integrative approach to analyze the role of AI in promoting agility within organizations. Digital transformation reshapes organizational value chains, enabling the creation of new business models by integrating technology into business strategy [25]. The approach integrates insights into the relationship among agility, digital strategy, and management, as effective digital transformation requires balancing technological capabilities and managerial qualities [26].

As shown in Figure 1, the theoretical framework posits that AI strategic capabilities have direct positive effects on agility (H1), mediated by digital dynamic capabilities (H2) and learning (H3). Leadership impacts both directly (H4) and moderates the relationship between AI capabilities and agility (H5). Technology-management alignment impacts AI capabilities' effectiveness (H6), while uncertainty of policy environments limits agility (H7). Notably, AI strategic capabilities mitigate the effects of policy uncertainty (H8) and thus convert threats into controllable risks. This theoretical framework advances theory development by clarifying the processes through which AI capabilities move beyond simple technology to emerge as strategic capabilities, yet are moderated by organizational dimensions that either enable or constrain their transformative power.

3. Methodology

3.1 Research Design and Sample

This paper adopts a mixed-method approach to research, where quantitative surveys are combined with case studies to gain a rounded perception of AI adoption and agility within SMEs. While the dominant approach to the study is quantitative surveys, case studies are conducted to gain insight into implementation processes from different perspectives. Using this approach to validate discoveries is expected to enhance validity, as different techniques are applied to different datasets to uncover new insights. The research proposes an explanatory sequential approach in which explanations are developed after data analysis using quantitative techniques. Integration of the results will occur at the interpretation stage, where case results are combined with hypothesis testing.

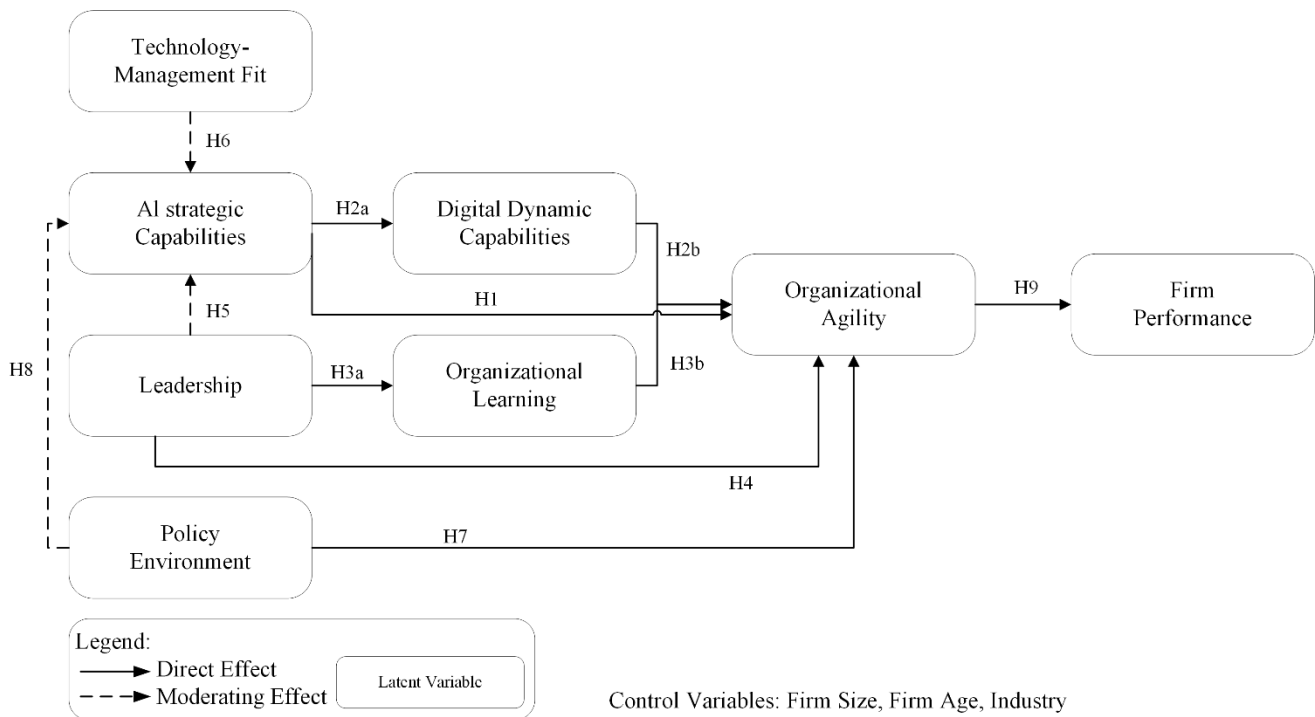


Figure 1. Theoretical framework and research hypotheses

The sampling frame involves SMEs from three strategic sectors: manufacturing (42%), service industries (38%), and technology companies (20%). This sectoral distribution is consistent with global data for small & medium sized enterprises (SMEs) recorded by OECD (2023), where the value-added percentage for manufacturing sectors is 40-45%, services sectors amount to 35-40%, while technology-intensive sectors amount to 15-22% for innovative SMEs [27], thus roughly representing the industrial structure of China. The criteria for SMEs' definition are determined by the standards set by the Ministry of Industry & Information Technology (MIIT) of China (Gong Xin Bu Lian Qi Ye [2011] No. 300) that classify SMEs on the basis of certain industry-specific criteria. The criteria include the number of employees, as well as the total operational revenue. The study's sample consists of small enterprises that employ 20-99 persons, as well as medium enterprises that employ 100-299 persons, belonging to the chosen sectors. Through a stratified random sampling method, sufficient representatives were chosen for the selected sectors as well as the geographical locations. The sampling procedure targeted those organizations for participation that belong to different sectors. These were approached through different chambers of commerce, as well as some entrepreneurial ventures that were aided & assisted by their respective governments. The geographical boundaries cover all SMEs that operate within China. This is due to the fact that China has different economic locations. These locations include the Yangtze River Delta region, the Pearl River Delta region, Beijing, Tianjin, & Hebei Greater Beijing Region. Pre-analysis using ANOVA showed that there were no significant differences between the values of the variables for the different locations (all $p > 0.10$). A combination of strategies was taken for the distribution of the questionnaires: use of online survey sites for online organizations, use of physical

mail for traditional firms, or administering through partner firms for others. The invitations to take the surveys were to executive or equivalent managers responsible for overseeing digital transformation projects to guarantee expert knowledge of AI capabilities and strategic thinking among respondents. Of 520 distributed questionnaires, 327 were retrieved to establish a preliminary response rate of 62.9%. Upon exclusion for incomplete or unattended questions, 300 valid questionnaires were obtained for an effective response rate of 57.7%. Firms sampled were diverse: median age 12.6 years (SD=8.3) and median number of employees 87 (SD=54) for various levels of AI use intensity. Such a technique of respondent selection could potentially result in response bias at the level of the executive. To address such a worry, the qualitative part of the research was conducted by conducting middle manager interviews on three research cases. The acknowledgment of the possibility of single informant bias follows a test of common method bias. Non-response bias was checked by comparing the characteristics of initial respondents (first quartile, $n = 75$) to the late respondents (last quartile, $n = 75$) according to Armstrong and Overton (1977) [28]. Both independent samples t-tests revealed no statistically significant difference in the characteristics of firm size, AI strategic capabilities, and organizational agility ($p > 0.10$).

For the purpose of the qualitative enrichment study, five case companies were selected through theoretical sampling: companies should have shown implementation of AI, have differentiated performance achievements, have offered to participate, and have to be accessible for further analysis. The cases include diverse industries and types of organizations to offer settings for comparison to highlight findings from quantitative analysis through cross-case analysis. The study consists of five cases, which follow the guidelines provided in Eisenhardt (1989) [29], who proposes that theory-building

studies require between four and ten cases. The pool of cases consists of two literal replications and three theoretical replications. Theoretical saturation was assessed cumulatively, and there were no new categories in the final two cases.

3.2 Variable measurement

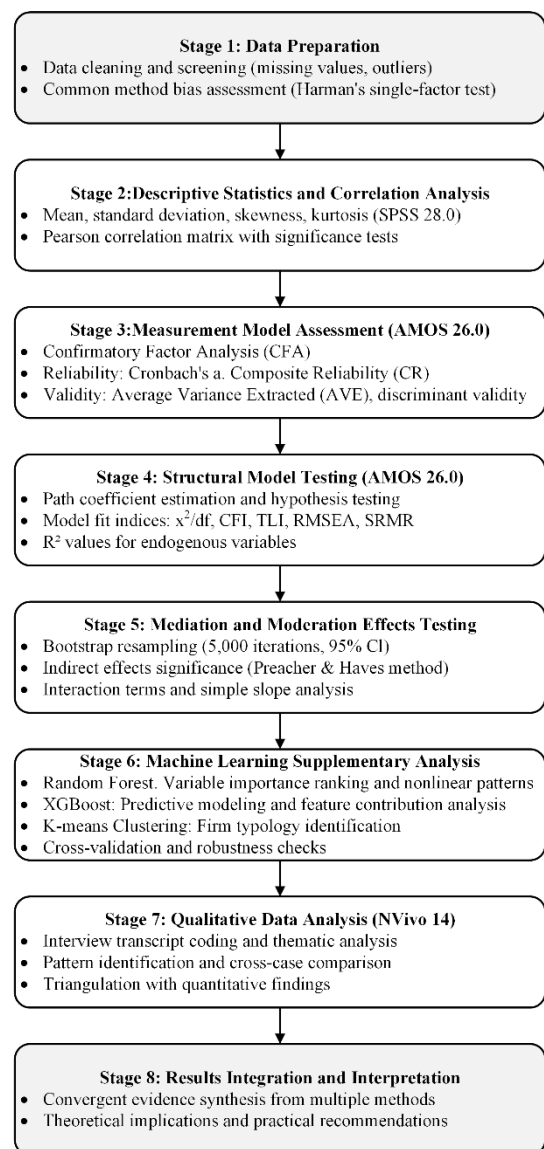
Each of these constructs was operationalized through established multi-item scales derived from previous studies to establish content validity and reliability. Because the original scales were created in the English language, translation and back-translation were performed to ensure that the items are suitable for China. The bilingual researchers chose to translate the items from English to Chinese. The translation process was followed by back-translation from Chinese to English. Also, for all perceptual measures, survey questions were administered through seven-point Likert scales (1 = strongly disagree to 7 = strongly agree) to create variance while being able to discriminate between respondents. Specifically, the strategic capabilities of AI were drawn from Mikalef & Gupta (2021) [30]. Digital dynamic capabilities were generated from both Warner & Wäger (2019) [6] and Teece (2007) [24]. Questions were modified to retain the same meaning as the original questions and modified to fit the context of small and medium-sized enterprises. The seven-point scale has higher discriminatory validity than the five-point scale and has lower cognitive demands when compared to other scales that are up to ten points.

The strategic capabilities of AI were measured using five items that capture the use of AI technology to create value for organizations. Leadership was measured using six items that reflect transformational processes, such as articulation of vision and individualized consideration in digital transformation contexts. The policy environment was assessed across four dimensions to evaluate how it influences digital initiatives. The mediating role of digital dynamic capabilities was measured using nine items and three theoretical dimensions: sensing capabilities (environmental scanning and opportunity seeking), seizing capabilities (resource mobilization and opportunity exploitation), and transforming capabilities (organizational rearrangement and restructuring). Organizational learning was measured through the use of five items for knowledge acquisition, information distribution, interpretation, and organizational memory in technology adoption settings.

The key outcome measure was business agility, operationalized as six indicators: sensing agility (environmental awareness), decision-making agility (response speed), and acting agility (implementation speed). Firm performance was measured using four indicators: financial performance, market performance, and measures of innovative performance relative to competitors. The moderating effect of technology management fit was measured using four indicators assessing the alignment between technology capabilities and management processes. Control variables include firm size (log of the number of employees), firm age (years since establishment), and industry dummies for manufacturers, service providers, and technology firms. Table 1 presents the complete framework used to measure all constructs and explains the variables measured. Validation was conducted on 45 SME managers and yielded acceptable reliability. Items with correlations below 0.40 were excluded. There were problems associated with the wording. Results had Cronbach's alpha values ranging from 0.82 to 0.91.

3.3 Data analysis methods

The data analysis followed a planned eight-step procedure, using various software packages and analytical techniques, as shown in Figure 2. The initial analysis was conducted in SPSS 28.0, including descriptive statistics, correlation analyses, and a Harman single-factor test to assess common method bias. The procedure followed within the structural equation modeling framework used AMOS 26.0 to analyze both the measurement model and the structural model, in accordance with best-practice guidelines for evaluating construct validity and hypothesis testing [31]. The analysis of the measurement model involved evaluating construct reliability using Cronbach's alpha and overall composite reliability, while using average variance extracted for convergent validity and Fornell-Larcker criterion tests for discriminant validity.



Analysis proceeded sequentially with iterative refinement based on diagnostic Quality thresholds applied at each stage to ensure methodological rigor.

Figure 2. Data analysis procedure

Table 1. Variable measurement and scale sources

Construct	Dimensions	Items	Representative Item Example	Scale Source	Scale Type
AI Strategic Capabilities	-	5	"Our firm actively uses AI technologies to improve strategic decision-making"	Adapted from Mikalef & Gupta (2021)	7-point Likert
Transformational Leadership	Vision/Stimulation /Consideration	6	"Leaders articulate a compelling vision for digital transformation"	Adapted from Bass & Riggio (2006)	7-point Likert
Policy Environment	Support/Incentives/Infrastructure	4	"Government policies provide strong support for SME digitalization"	Adapted from OECD (2025)	7-point Likert
Digital Dynamic Capabilities	Sensing/Seizing/Transforming	9	"Our firm quickly identifies emerging digital opportunities"	Adapted from Warner & Wäger (2019)	7-point Likert
Organizational Learning	Acquisition/Distribution/Memory	5	"Our organization effectively shares knowledge about new technologies"	Adapted from Sinkula et al. (1997)	7-point Likert
Organizational Agility	Sensing/Decision/Acting	6	"Our firm can quickly respond to market changes"	Adapted from Tallon & Pinsonneault (2011)	7-point Likert
Firm Performance	Financial/Market/Innovation	4	"Our financial performance exceeds competitors"	Adapted from Delaney & Huselid (1996)	7-point Likert
Technology-Management Fit	Alignment	4	"Technology investments align well with management practices"	Adapted from Henderson & Venkatraman (1993)	7-point Likert
Control Variables	-	3	Measured objectively from records	Organizational data	Mixed types
• Firm Size	-	1	Number of employees (log-transformed)	Company records	Continuous
• Firm Age	-	1	Years since establishment	Company records	Continuous
• Industry	Manufacturing/Services/Technology	1	Industry sector classification	Company classification	Categorical dummy

Testing the structural model involved the use of maximum likelihood procedures in the estimation of the path coefficients, and a detailed assessment of the overall fit of the model was conducted using a battery of fit indices. In the testing of mediation and moderation effects, bias-corrected bootstrapping analyses with 5,000 resampling values were employed in the construction of 95% confidence intervals for mediated effects following existing best practices [32]. The interaction variables were mean-centered in the testing, and the use of simple slope analyses was employed in the testing of moderators at the condition levels.

Machine learning techniques complement SEM by detecting nonlinear effects. Random forest provides variable importance rankings, XGBoost reveals nonlinear relationships, and K-means identifies firm typologies, enhancing confidence through convergent evidence. Variable importance rankings were ascertained by random forest algorithms, while XGBoost analysis estimated predictive closeness to actual observations, and K-Means clustering helped to discern unique firm categories for AI adoption behaviors. The analysis of themes on interview data allowed for NVivo 14 software-driven coding to conduct rigorous explorations to determine meaningful associations between discoveries from statistical analysis. Random forest employed 500 trees. XGBoost used 10-fold cross-validation.

Data were split 70/30 for training/testing. K-means evaluated 2-8 cluster solutions using silhouette coefficients.

3.4 Reliability and Validity Criteria

This analysis utilized established thresholds for judging the goodness of measurements and overall model fit. Establishing construct reliability was approached by ensuring Cronbach's alphas were higher than 0.70 for all constructs and values for composite reliability exceeded 0.80 for all constructs, signifying satisfactory levels of internal consistency for the entire proposed model. Convergent validity was established by ensuring average variance extracted values higher than 0.50 for all constructs, while also ensuring values for factor loadings higher than 0.60 for all single items, signifying satisfactory item-to-construct fit for all single items within each respective construct category. Establishing overall adequacy for the proposed structural model was done using various overall goodness of fit measures: ratios of chi-squared to degrees of freedom values below 3.0 for χ^2/df ratios (signifying acceptable overall model fit to measures for all proposed constructs).

4. Results

4.1 Descriptive Statistics and Correlations

The final dataset consisted of 300 SMEs with heterogeneous firm attributes. Company size varied from 12 to 248 workers (M=87.3, SD=54.2), and business age ranged

from 3 to 32 years ($M=12.6$, $SD=8.3$). The industries were also grouped according to the sampling approach: 126 manufacturers (42%), 114 service providers (38%), and 60 tech firms (20%). As for AI adoption intensity, participants were divided into three groups according to self-reports of respective implementation levels: high adopters (102 or 34%) showed widespread AI adoption for many corporate functions at once, moderate adopters (123 or 41%) adopted AI selectively for particular operational tasks, while low adopters (75 or 25%) showed elementary or testing AI adoption activities.

Data analysis of particular AI applications showed a significant disparity in implementation processes. The most widely adopted application area was customer analytics, where 201 companies (67%) utilized AI-powered customer segmentation software, customer preference prediction software, or customer behavior analysis software. The second most widely adopted application area was demand forecasting software for use in inventory optimization and production planning by 156 companies (52%). Other implemented applications include automated reporting software for 144 companies (48%), while others, such as chatbots for 38% of companies, preventive maintenance software for 31% of companies, and quality control software for 27% of companies, showed slower adoption rates.

Table 2 reports descriptive statistics and correlation coefficients for all variables under study. Mean scores showed moderate to high levels for all constructs, with transformational leadership ($M=4.78$, $SD=1.12$) and organizational learning ($M=4.64$, $SD=1.09$) registering higher scores than others because of perceptions of policy environments ($M=3.95$, $SD=1.28$) being rated rather low because of concerns for uncertainty associated with regulation policies. Correlation analysis confirmed expected inter-relations for all variables: strategic capabilities for AI relating positively to organizational agility ($r=0.48$, $p<0.01$), dynamic capabilities for digital technology ($r=0.54$, $p<0.01$), as well as total firm performance ($r=0.43$, $p<0.01$). The correlation between all diagonal elements and their respective squared roots of average variance.

Harman's single-factor test was used for common method bias analysis, and the findings showed that 38.7% of total variance was explained by the first unrotated factor, which was below 50%. In addition to this, comparison between the single-factor model and the proposed measurement model through confirmatory factor analysis showed poor fit to the single-factor model ($\Delta\chi^2 = 2847.3$, $\Delta df = 28$, $p < 0.001$). While Harman's test has limitations, these results suggest common method bias does not substantially inflate observed relationships.

4.2 Measurement model assessment

The confirmatory factor analysis was used to assess the psychometric attributes of the proposed measurement model before testing the structural model. Based on Table 3, all constructs portrayed good reliability values. Their Cronbach's alpha values lay between 0.82 and 0.91, while their respective Composite Reliability values lay between 0.85 and 0.93, exceeding 0.70 and 0.80 values prescribed for acceptance. Convergent validity was confirmed by Average Variance Extracted values between 0.63 and 0.78, all exceeding the 0.50 validity criterion values. Their respective factor loadings stood between 0.72 and 0.89 values, most exceeding 0.75 values, signifying good indicators to portray respective latent constructs.

Multiple criteria have been used to demonstrate the assessment of discriminant validity. First, the Fornell and Larcker criterion is violated because, for all constructs, the square roots of the average variance extracted exceed the correlations reported in Table 2. Furthermore, for all pairs of constructs, heterotrait-monotrait ratios of correlations were found to range between 0.52 and 0.84, all of which are below 0.85, confirming discriminant validity below the 0.85 threshold. The overall fit of the measurement model was evaluated using several fit statistics. The ratio of chi-square to degrees of freedom is 2.34 ($\chi^2=687.4$, $df=294$). This is satisfactory for overall fit. The comparative fit index was 0.94, and the Tucker-Lewis coefficient was 0.93, both of which exceeded 0.90. Root mean squared error of approximation is 0.067 (90% CI [0.061, 0.073]). This is below the 0.08 threshold to become satisfactory. Standardized root mean squared residual is 0.058. Taken together, these values indicate a good overall fit of the measurement model to the observed covariance matrix and establish the validity of further structural equation analysis.

4.3 Hypothesis testing

Structural equation modeling was employed to analyze the proposed relationships between variables, and the outcomes are presented in Table 4. The resultant values for goodness of fit for the structural model indicate acceptable fit measures ($\chi^2/df=2.48$, $CFI=0.93$, $TLI=0.92$, $RMSEA=0.071$), justifying the use of the path coefficients. The direct hypothesis was largely supported by empirical evidence. AI strategic capabilities were positively associated with organizational agility ($\beta=0.42$, $t=6.87$, $p<0.001$), thus confirming hypothesis H1. A similar positive association between transformational leaders and organizational agility ($\beta=0.28$, $t=4.63$, $p<0.001$) was also established for hypothesis H2. A direct negative association between uncertainty surrounding policy environments and organizational agility was confirmed ($\beta=-0.18$, $t=-3.21$, $p<0.01$) for hypothesis H3, which implies that ambiguity associated with regulating policies hampers agile organization performance.

Hypotheses for mediation analysis were examined employing bias-corrected bootstrapping techniques to assess indirect effects for 5,000 iterations. Digital dynamic capabilities mediated between AI strategic capabilities and organizational agility for an indirect effect of 0.31 (95% CI [0.21, 0.42], $p < 0.001$), confirming H4. A specific mediating mechanism is positively related to AI capabilities' advancements in sensing, seizing, and transforming capabilities ($\beta=0.54$, $p < 0.001$), thereby enhancing overall organizational agility components. Another mediating factor is organizational learning for the transformational leadership-organizational agility association (indirect effect=0.19, 95% CI [0.12, 0.27], $p < 0.001$), thus verifying H5. This is because leaders' efforts influence knowledge development and sharing ($\beta=0.47$, $p < 0.001$), further advancing adaptive capabilities. Total direct and indirect values for both mediations demonstrate partial mediation and point toward dual processes being at work to shape antecedents for organizational agility outcomes. Moderation analysis revealed nuanced boundary conditions for the focal relationships. Technology-management fit significantly moderated the AI-agility relationship ($\beta=0.21$, $t=3.18$, $p<0.01$), supporting H6.

Table 2. Descriptive statistics and correlation matrix

Variable	M	SD	1	2	3	4	5	6	7	8
1. AI Strategic Capabilities	4.52	1.18	(0.81)							
2. Transformational Leadership	4.78	1.12	.45**	(0.83)						
3. Policy Environment	3.95	1.28	.32**	.29**	(0.79)					
4. Digital Dynamic Capabilities	4.31	1.15	.54**	.47**	.28**	(0.82)				
5. Organizational Learning	4.64	1.09	.49**	.51**	.24**	.56**	(0.84)			
6. Organizational Agility	4.43	1.21	.48**	.42**	.28**	.52**	.47**	(0.80)		
7. Firm Performance	4.28	1.14	.43**	.38**	.31**	.46**	.41**	.55**	(0.81)	
8. Technology-Management Fit	4.17	1.24	.46**	.39**	.26**	.49**	.44**	.51**	.40**	(0.79)
9. Firm Size (log)	1.89	0.24	.18**	.15*	.22**	.19**	.16**	.14*	.21**	.12*
10. Firm Age	12.6	8.3	.09	.11	.17**	.13*	.08	.06	.14*	.10

Note: N=300. M=Mean; SD=Standard Deviation. Diagonal values in parentheses represent the square roots of AVE. **p<0.01, *p<0.05 (two-tailed). Firm size is log-transformed. Industry dummies included but not shown.

Table 3. Measurement model: reliability and validity assessment

Construct	Items	Factor Loadings Range	Cronbach's α	CR	AVE	Model Fit
AI Strategic Capabilities	5	0.78 - 0.87	0.88	0.89	0.65	$\chi^2/df = 2.34$
Transformational Leadership	6	0.76 - 0.85	0.89	0.91	0.68	CFI = 0.94
Policy Environment	4	0.74 - 0.84	0.82	0.85	0.63	TLI = 0.93
Digital Dynamic Capabilities	9	0.75 - 0.89	0.91	0.93	0.67	RMSEA = 0.067
Organizational Learning	5	0.79 - 0.88	0.87	0.90	0.71	[0.061, 0.073]
Organizational Agility	6	0.72 - 0.86	0.86	0.88	0.65	SRMR = 0.058
Firm Performance	4	0.77 - 0.85	0.84	0.87	0.66	
Technology-Management Fit	4	0.73 - 0.83	0.83	0.86	0.63	

Note: N=300. All factor loadings are significant at p<0.001. CR=Composite Reliability; AVE=Average Variance Extracted. Model fit indices represent the overall measurement model. HTMT ratios for all construct pairs < 0.85 (range: 0.52-0.84).

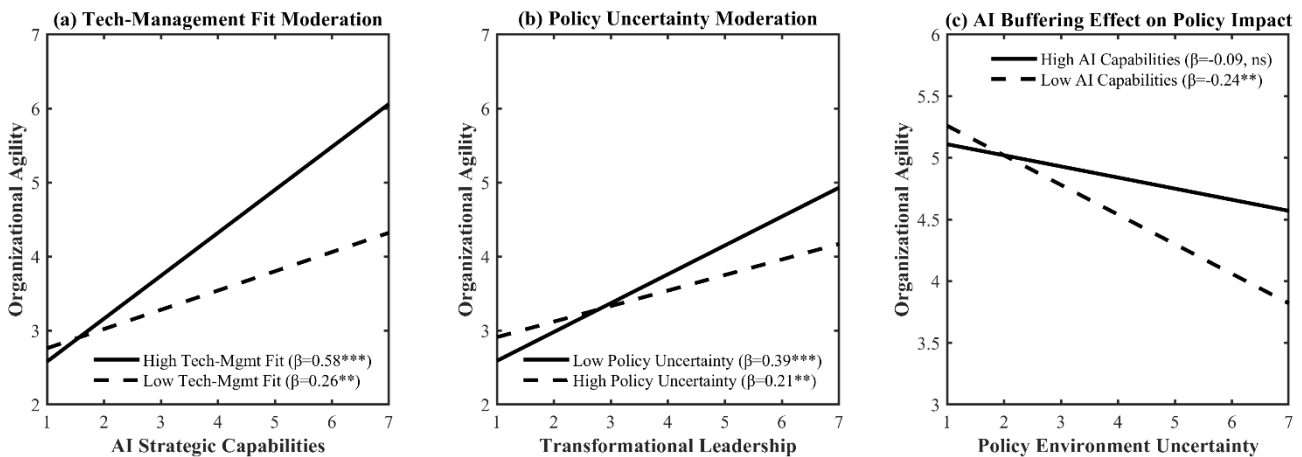


Figure 3. Moderation effects

Table 4. Structural model results: hypothesis testing

Hypothesis	Path	β	SE	t-value	p-value	95% CI	Result
Direct Effects							
H1	AI Capabilities → Agility	0.42	0.061	6.87	<0.001	[0.30, 0.54]	Supported
H2	Leadership → Agility	0.28	0.060	4.63	<0.001	[0.16, 0.40]	Supported
H3	Agility → Performance	0.35	0.059	5.94	<0.001	[0.23, 0.47]	Supported
	Policy Uncertainty → Agility	-0.18	0.056	-3.21	0.001	[-0.29, -0.07]	-
Mediation Effects (Indirect)							
H4	AI → Dynamic Capabilities → Agility	0.31	0.054	-	<0.001	[0.21, 0.42]	Supported
H5	Leadership → Learning → Agility	0.19	0.038	-	<0.001	[0.12, 0.27]	Supported
Moderation Effects (Interaction)							
H6	AI × Tech-Mgmt Fit → Agility	0.21	0.066	3.18	0.002	[0.08, 0.34]	Supported
H7	Leadership × Policy Uncertainty	-0.16	0.055	-2.89	0.004	[-0.27, -0.05]	Supported
H8	AI × Policy × Agility (3-way)	0.12	0.059	2.03	0.042	[0.00, 0.24]	Partial support

Simple slope analysis, illustrated in Figure 3(a), demonstrated that AI strategic capabilities more strongly predicted organizational agility when technology-management fit was high ($\beta=0.58$, $t=7.42$, $p<0.001$) compared to low fit conditions ($\beta=0.26$, $t=3.14$, $p<0.01$). This interaction accounted for an additional 4.2% of variance in organizational agility. Policy environment uncertainty moderated the relationship between transformational leadership and organizational agility ($\beta=-0.16$, $t=-2.89$, $p<0.01$), confirming H7. As depicted in Figure 3(b), leadership effectiveness diminished under high policy uncertainty ($\beta=0.21$, $t=2.87$, $p<0.01$) relative to low uncertainty contexts ($\beta=0.39$, $t=5.24$, $p<0.001$).

The three-way interaction hypothesis (H8) received partial support. The coefficient for the interaction among AI capabilities, policy uncertainty, and organizational agility was marginally significant ($\beta=0.12$, $t=2.03$, $p<0.05$). This buffering hypothesis is depicted in Figure 3(c), where AI capabilities moderated the negative impact of policy uncertainty to some extent but to a limited extent. At high levels of AI capabilities, the negative influence of policy uncertainty became weaker (simple slope=-0.09, ns) than at low levels of AI capabilities (simple slope=-0.24, $p<0.01$). The overall explanatory power of the structural model was strong, as it explained 64% and 52% of the variance for endogenous constructs of organizational agility and firm performance, respectively. The marginal significance may be ascribed to the boundary conditions; the SME capabilities in AI may not have attained the level of sophistication adequate for effective monitoring of policies; the buffering mechanism may require a level of maturity in AI that most companies (only 34% are high adopters) have not achieved.

4.4 Supplementary analyses

Machine learning models added further verification and insights to those already derived from structural equation modeling. Variable importances from random forest analysis

yielded rankings for predictors of organizational agility, which ranked AI strategic capabilities as most important (importance=0.34) and strongly followed by digital dynamic capabilities (0.22), transformational leadership (0.18), and policy environment (0.13). XGBoost gradient boosting also reached $R^2=0.58$ for predictive validity for out-of-sample testing, validating the explanatory utility of the structural equation modeling approach. It is also interesting to note from partial dependence plots for AI capabilities and organizational agility that while its marginal effect shows diminishing marginal returns past positions beyond the 75th percentile (around 5.8 out of seven points for AI capabilities' influence on agility), no further proportional agility improvements are achieved at high levels of AI strategic capabilities investments.

K-means clustering analysis with silhouette coefficient optimization identified four distinct firm typologies based on AI adoption patterns and performance outcomes. The four-cluster solution exhibited the highest silhouette width among the alternatives tested. AI Leaders (54 firms, 18%) had high-intensity AI adoption and superior performance, marked by comprehensive digital infrastructure and committed leadership. Pragmatic Adopters were the 105 firms, accounting for 35%, who adopted AI in a medium manner, prioritizing some valuable use cases. These companies performed better than the average group because they adopted AI in an organized manner. The Skeptics, who comprised 87 firms, standing at 29%, retained less-than-adequate AI adoption even when they had sufficient means. Therefore, they continued to perform at an average level. Laggards (54 firms, 18%) were resource-poor and could not even consider the use of AI, and, hence, their performance was below average on all dimensions. The chi-square test on the distribution across the clusters, by industry sectors, was significant ($\chi^2=28.4$, $p<0.001$), and technology companies were overrepresented in the AI Leaders.

Qualitative analysis of semi-structured interviews conducted among five case organizations provided rich contextual insights. Regarding the sentiment of the CEO on AI adoption, strong proponents constituted 64% who strongly advocated for digital transformation, while passive critics were 22% observing from a distance and hence being cautious, and resistant critics comprised 14% showing apprehension regarding the cost of implementation and challenges related to the workforce. Case analysis provided an overview of three approaches to implementation: fast implementors, entering into external partnerships to acquire capabilities; step-wise implementors, planning for step-wise implementation; and exploratory implementors, who intend to implement pilot initiatives with the intention of larger-scale deployment at a later stage. Cross-case insights into key factors for success with regard to the company-level change management process have been obtained beyond the CEO's vision or idea. Case organizations mapped onto K-means clusters, with qualitative evidence reinforcing H6: high-performing cases emphasized concurrent capability investments.

5. Discussion

This study investigates how AI strategic capabilities, along with leadership and policy environments, influence the organizational agility of SMEs through dynamic capabilities. Empirical results indicate interesting trends. The effect of AI strategic capabilities was the strongest predictor of organizational agility, with $\beta = 0.42$, $p < 0.001$, far above transformational leadership with $\beta = 0.28$, and even stronger than earlier conceptualizations of AI as organizational capability [31]. This means that 67% of the effect was mediated by digital dynamic capabilities, showing that, in fact, dynamic capabilities play a mediating role in this relationship. Technology-management fit was significant in moderating the effectiveness of AI, where conditions increased coefficients from 0.26 to 0.58. Similarly, transformational leadership was associated with organizational agility through a dual role: as a direct effect and as a moderator of AI effectiveness. Surprisingly, AI capabilities buffered the negative effect of uncertainty in the policy environment on organizational agility.

The above findings have many benefits since they enhance the building of theory in several areas. The proposed research contributes to dynamic capability theory by conceptualizing digital dynamic capabilities as distinct organizational capabilities that mediate between technological investments and strategic outcomes [24]. In contrast, traditional dynamic capabilities primarily rest on managers' cognition. Digital dynamic capabilities, however, entail algorithmic sensing, algorithmic seizing through machine learning, and AI-driven transforming through intelligent allocations [1]. This research contributes to strategic management theory by positing AI not as an operational technology, but as strategic potential, which intentionally redefines decision architecture and competition by dramatically modifying strategic outcomes. As opposed to conventional information technology investments, where the primary result is the augmentation of efficiency in operations through automation, strategic-level effects arise from algorithmic sensing and seizing mechanisms associated with AI. This is what differentiates dynamic capabilities involving AI from conventional information technology capabilities. The collaborative AI and human relationship model proposed in this research indicates that value-creation synergies between algorithmic accuracy and human decision-making

skills correspond to recommendations regarding multiple viewpoints on digital transformation practices and events [3]. Within leadership theory, it has been argued that new forms of algorithmic and data-related skills and competencies in leadership and strategy are added to traditional transformational leadership skills in AI and its application. This research redefines environments by demonstrating that AI's potential transforms regulatory unpredictability from an uncontrollable threat into a predictable, manageable variable through monitoring and simulation.

Implications are diverse, ranging over various stakeholder groups. Managers of SMEs must focus on stepwise AI adoption, aligning with overall organizational readiness, achieving technology and management fit by making concurrent investments in capabilities and infrastructure, and building digital leadership skills. The nonlinear relationship observed implies decreasing marginal returns once adoption thresholds are met, suggesting selective use for high-priority tasks. Technology developers must produce technology catering specifically to SMEs, with friendly interfaces, flexible designs, and clear logic, and offer sustained support services. The government must formulate financial schemes, make investments in infrastructure, set up regulatory environments, and prepare competency-building programs focusing jointly on technology and management skills.

There are some limitations to these findings. The observational nature of this research does not allow one to make conclusions regarding causal hypotheses, although such hypotheses can be constructed and controlled for in research design. The findings are restricted in application by the choice of one national context, as there may be differing regulatory and cultural conditions in various institutions. The research may be biased by its measures, although these biases can be controlled for by statistical adjustments. Findings apply only to current conditions and may need to be revised regarding advances in AI capabilities. Boundary conditions suggest that the association between AI agility and firm size may vary, while digital maturity within industry groups may affect the effectiveness of AI adoption. Cross-sectional studies can effectively identify variations in the maturity stages of AI adoption across firms. Moreover, issues associated with the responsible adoption of AI in SMEs, such as algorithmic bias, data privacy, and displacement, warrant further research.

The next generation of research should consider longitudinal approaches, focusing on dynamic capability development paths and performance outcomes. Cross-national research designs that analyze the role of context can enhance external validity. Industry-oriented studies on contingencies related to AI application may provide insights into conditions obscured by aggregate analyses. Studies on issues related to AI adoption, such as job displacement, bias, and overreliance on the technology, could raise interesting questions. The relationship between AI's effects on delineations and ecosystem networks could prove beneficial, given the evolving collaboration frameworks enabled by intelligent technologies.

6. Conclusion

The present work systematically examines the role of AI strategic capabilities, together with transformational leadership and policy context, in determining the agility of small and medium-sized enterprises through the lens of digital dynamic capability. Through dynamic capability theory, the work interprets and demonstrates the complex causal relationship through which AI affects the agility of an

organization in a mixed-methodological investigation conducted on 300 SMEs. The empirical findings unveiled that AI strategic capability has been the primary determinant in the process of defining agility, with a regression coefficient, $\beta = 0.42$, and a statistical significance, $p < 0.001$, with 67% mediated by digital dynamic capability. Technology alignment fit was thereby uncovered as a critical boundary condition, where the high-tech alignment conditions strengthened the performance impact of AI by 123% ($\beta = 0.58$ compared with $\beta = 0.26$). Transformational leadership confirmed the role of the positive direct effects on agility ($\beta = 0.28$) and the moderating roles in the relationships among AI and agility performance ($\beta = 0.21$). Furthermore, it is enlightening to highlight the role of the AI capabilities, acting as buffers in the uncertainties in the policy environment, and turning limitations into viable strategic variables ($\beta = 0.12$). The model explained the variance at high levels for variables related to organizational agility and overall company performance ($R^2 = 0.52$ and $R^2 = 0.64$, respectively). The contribution of the present work to theory lies in applying dynamic capability theory in a digital setting, conceptualizing AI strategic capability, and clarifying the dimensions of digital leadership. The findings and results of the work are presented as management guidance on the adoption and implementation of AI in SMEs, technology solutions in SMEs, and suggestions for developing enabling environments, respectively, for management and development. The integration of AI technology, management theory, and methodology enhances understanding of developments in digital strategy theory. In light of the contributions, several factors warrant further attention. Longitudinal studies of the adoption of AI systems would provide insights into the development of dynamic capabilities and their performance. Comparative studies across different national settings would offer greater generalizability. The emergence of generative AI technologies presents a novel area of inquiry into their differential effects on strategic management. The role of AI decision-making systems with respect to bias, transparency, and human oversight arrangements is also a fruitful area, given the extent to which firms rely on AI systems in strategic decision-making.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere. All survey participants provided informed consent prior to participation, and the anonymity and confidentiality of all respondents were strictly maintained throughout the research process.

Data availability statement

The manuscript contains all the data. However, additional data will be provided by the corresponding author upon reasonable request.

Conflict of interest

The authors declare no potential conflict of interest.

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