

A Structural Model of Factors Influencing AI Adaptation and SME Performance in Bangkok and Nonthaburi, Thailand

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Abstract

Artificial intelligence (AI) adoption plays a critical role in enhancing SME performance in Bangkok and Nonthaburi, Thailand. Based on the extended Technology–Organization–Environment (TOE) framework, this study investigates how technological readiness, organizational capability, and environmental pressures influence AI adaptation and performance outcomes. Using simple random sampling, data were collected from 360 SME owners and managers and analyzed through Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The model demonstrated good fit ($\chi^2/df = 1.94$, CFI = 0.95, TLI = 0.94, RMSEA = 0.053, SRMR = 0.044). Technology ($\beta = 0.36$, $p < 0.001$), Organization ($\beta = 0.42$, $p < 0.001$), and Environmental factors ($\beta = 0.29$, $p < 0.001$) significantly influenced AI adaptation. AI adaptation strongly affected SME performance ($\beta = 0.67$, $p < 0.001$) and mediated the relationships between contextual factors and performance outcomes. SME performance was measured consistently with the SEM indicators (SME1–SME6): productivity, cost efficiency, product quality, market expansion, profitability, and long-term sustainability. The findings confirm that strengthening technological, organizational, and environmental readiness enhances AI-driven performance among Thai SMEs.

Keywords: AI Adaptation, Technology, Organization, Environment, SME performance

Introduction

Artificial intelligence (AI) is transforming productivity, innovation, and competitive dynamics across economies, with prior studies indicating its potential to enhance firm performance and create new business models (Sánchez, 2025). Advances in cloud infrastructure and AI-as-a-service have reduced entry barriers, making AI adoption increasingly accessible to SMEs in both developed and emerging economies (Rawashdeh et al., 2024; Badghish, 2023; Reuters, 2024). However, despite growing AI diffusion, it remains unclear which factors most strongly influence SMEs' perceived AI adoption and whether such adoption significantly improves SME performance. Therefore, this study aims to examine the key determinants affecting perceived AI adoption and to investigate its impact on SME performance, thereby

addressing the gap between adoption drivers and actual performance outcomes.

From a theoretical perspective, this study adopts the Technology–Organization–Environment framework (TOE) as the principal analytical lens to explain the multidimensional determinants of AI Adaptation among SMEs. The TOE framework conceptualizes technology adoption as the outcome of technological readiness (e.g., IT infrastructure and perceived benefits), organizational capacity (e.g., managerial support and financial resources), and environmental pressures (e.g., competition and regulatory context). While prior studies have identified empirical indicators within each TOE dimension (Schwaeke et al., 2024; Rawashdeh et al., 2022), the mechanisms linking these latent constructs to AI Adaptation and, critically, to firm performance

remain insufficiently clarified. Many existing works focus primarily on antecedents of adoption without rigorously quantifying how AI Adaptation translates into revenue growth, productivity improvement, or employment expansion (Badghish & Soomro, 2023). Accordingly, this study explicitly addresses this gap by developing and testing a structural model that links TOE dimensions to AI Adaptation and subsequently to SME performance outcomes.

The importance of focusing on SMEs in Thailand is substantial. According to the Office of Small and Medium Enterprise Promotion (OSMEP, 2023), Thai SMEs contributed approximately 6.11 trillion baht in 2022, accounting for about 35.2% of national GDP, and employed around 12.83 million individuals. A significant proportion of these enterprises and employees are concentrated in Bangkok and the surrounding metropolitan area, including Nonthaburi. Given that SMEs generate more than one-third of Thailand's GDP and provide livelihoods for millions of workers, even modest productivity gains through AI Adaptation could yield substantial macroeconomic and inclusive growth effects. Conversely, limited digital capabilities and uneven adoption may widen performance gaps within the SME sector (Thailand Development Research Institute [TDRI], 2025).

Focusing specifically on Bangkok and Nonthaburi enhances the empirical and policy relevance of this research. Bangkok represents the country's primary economic hub with high SME density, advanced digital infrastructure, and strong competitive pressures, while Nonthaburi forms an integrated suburban cluster linked through supply chains and service networks. Variations in AI Adaptation across these provinces are therefore likely to produce measurable differences in firm-level performance and regional economic outcomes. Despite this strategic importance, empirical evidence explaining which TOE dimensions most strongly drive AI Adaptation among SMEs in this metropolitan corridor and whether such adaptation significantly improves revenue, employment, and productivity—remains limited.

In response, this study aims to (1) validate the measurement model of the latent constructs (Technology, Organization, Environment, and AI Adaptation) using confirmatory factor analysis (CFA); (2) estimate the structural relationships between TOE

factors, AI Adaptation, and SME performance through structural equation modelling (SEM); and (3) examine the mediating role of AI Adaptation in translating TOE conditions into measurable firm performance outcomes. By centering on SMEs in Bangkok and Nonthaburi, this research underscores the real economic significance of the studied group and provides empirically grounded insights to strengthen AI-driven performance within Thailand's most economically critical SME cluster.

Literature reviews

This study is grounded in the integrated perspectives of the Technology–Organization–Environment framework (TOE) and the Diffusion of Innovations theory (DOI). These complementary theories provide a comprehensive explanation of artificial intelligence (AI) adoption at the firm level, particularly within small and medium-sized enterprises (SMEs) in emerging economies. Within the TOE framework, organizational adoption of innovation is influenced by three contextual dimensions: technology, organization, and environment. The technological dimension refers to both internal and external technological resources, including compatibility, perceived relative advantage, complexity, and IT infrastructure that support innovation implementation. Prior studies indicate that technological readiness such as system interoperability, infrastructure quality, and data availability significantly predicts AI adoption in SMEs (Abu Bakar et al., 2024; Chummee & Khammadee, 2025; Kalleparambil & Akoum, 2025; OECD, 2024).

The organizational dimension encompasses structural characteristics, top management support, human capital capability, financial readiness, and innovation orientation. Leadership commitment, employee digital skills, organizational learning culture, and strategic alignment are repeatedly identified as critical enablers of AI adoption, particularly among resource-constrained SMEs (Baker, 2011; Chiew et al., 2025).

The environmental dimension captures external pressures and supports, including regulatory frameworks, competitive intensity, industry standards, government incentives, and market demand. Empirical evidence confirms that competitive pressure and public policy incentives significantly accelerate AI adoption

decisions (Alka'awneh et al., 2025; Prakash, 2025). Complementing TOE, DOI theory emphasizes the perceived attributes of innovation relative advantage, compatibility, and ease of use as key determinants of adoption behavior (Rogers, 2003; Herrera, 2025). While TOE explains contextual enablers, DOI accounts for perception-driven decision processes within SMEs. Although TOE has been widely applied, it has limitations, including its relatively static structure and limited direct linkage to firm performance outcomes. Furthermore, most prior studies are cross-sectional and focus on large enterprises, leaving a gap in emerging-market SME research that connects TOE and DOI determinants to both AI adoption and performance outcomes. Employing Confirmatory Factor Analysis (CFA) to validate constructs and Structural Equation Modeling (SEM) to examine causal relationships provides both theoretical rigor and empirical robustness in addressing this gap.

Relationship between technology and AI Adaptation

In SMEs located in Bangkok and Nonthaburi, the technological context including technology roadmap clarity, security and privacy mechanisms, system compatibility, and user-friendly design positively influences AI adoption. A clearly defined technology roadmap ensures alignment between AI initiatives and strategic objectives while optimizing limited financial and human resources (Sánchez et al., 2025). Robust cybersecurity and privacy protections enhance trust and reduce perceived risks, while intuitive system interfaces reduce complexity and increase employee engagement (Arroyabe et al., 2024). Empirical evidence consistently shows that higher technological readiness enhances the likelihood, depth, and sustainability of AI adoption (Sánchez et al., 2024; OECD, 2024). This relationship can be hypothesized as follows:

H1: Technology has a positive effect on AI Adaptation in SMEs in Bangkok and Nonthaburi

Relationship between organization and AI Adaptation

Organizational factors demonstrate a strong positive relationship with AI adoption in Thai SMEs. Studies conducted in Thailand indicate that top management commitment, internal communication

efficiency, and organizational readiness significantly enhance AI implementation capacity. Organizations fostering a culture of innovation, learning, and flexibility are more capable of adapting to AI-driven transformation. Strategic alignment, resource allocation, and employee training play critical mediating roles in successful AI adoption. Strong leadership commitment and internal capabilities therefore increase the probability of effective AI integration (Ruenphongphun & Khumtha, 2025; Verma, 2021; Vongurai, 2025). The following hypothesis is proposed:

H2: Organizational factors have a positive effect on AI Adaptation among SMEs in Bangkok and Nonthaburi

Relationship between environmental and AI Adaptation

Environmental factors serve as critical external drivers of AI adoption. Government policies, digital infrastructure, competitive pressure, and industry standards significantly influence SMEs' strategic decisions to adopt AI technologies. Supportive regulatory environments and incentive structures reduce uncertainty and encourage investment in AI systems. Competitive intensity further motivates firms to enhance operational efficiency and innovation capabilities. These findings confirm that environmental readiness functions as an external enabler of AI adoption among SMEs operating in dynamic metropolitan contexts. (Chumme, 2025; Nagel, 2024). The following hypothesis is proposed:

H3: Environmental factors have a positive effect on AI Adaptation among SMEs in Bangkok and Nonthaburi

Relationship between AI Adaptation and SME performance

AI adoption plays a significant role in enhancing SME performance. Empirical evidence shows that SMEs integrating AI technologies such as data analytics, predictive maintenance, and intelligent customer management systems achieve improved operational efficiency, productivity, and decision-making quality. AI enables more efficient resource allocation, enhanced supply chain responsiveness, and greater product and service innovation, leading to improved financial and non-financial performance.

These findings align with innovation– performance theory, suggesting that technological adoption functions as a driver of organizational transformation and sustained competitiveness (Chummee, 2025; Vongurai, 2025) . From the literature review, the following hypothesis is proposed:

H4: AI Adaptation has a positive effect on SME performance in Bangkok and Nonthaburi

From this integrated theoretical foundation, the conceptual framework is illustrated in Figure 1, presenting a unified model in which Technology, Organization, and Environment influence AI Adoption, which in turn affects SME Performance.

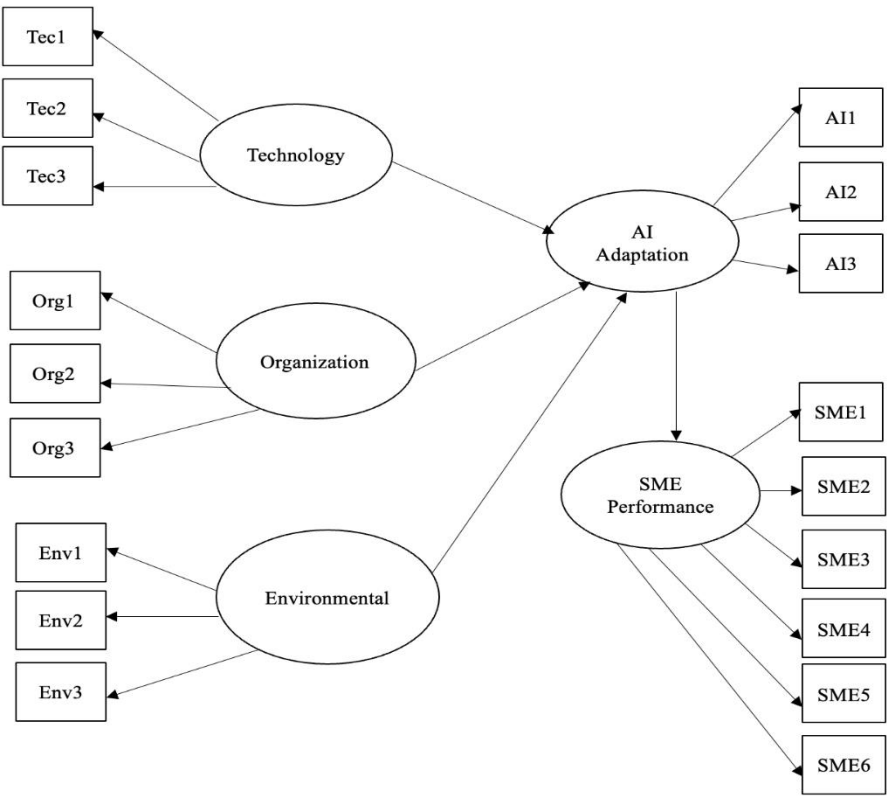


Figure 1 Conceptual framework

Research methodology

This study employed a quantitative research methodology to examine the relationships among the latent constructs specified in the conceptual model, namely Technology, Organization, Environmental factors, AI Adoption, and SME Performance. Quantitative methods were applied to analyze the structural relationships among these variables within the extended Technology– Organization– Environment framework. Descriptive and inferential statistics were used to examine empirical patterns and test the hypothesized causal relationships through Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The unit of analysis consisted of SMEs located in Bangkok and Nonthaburi, Thailand. Bangkok serves as the country’s primary commercial,

financial, and innovation center, characterized by advanced digital infrastructure, intense market competition, and strong exposure to national digital economy policies. Nonthaburi, as an adjacent province within the Bangkok metropolitan cluster, represents a complementary economic structure consisting of service-oriented, trade-based, and government-linked SMEs that are increasingly engaged in digital transformation initiatives. The close economic interconnection between Bangkok and Nonthaburi creates a dynamic environment in which technological readiness, organizational capability, and environmental pressures are particularly salient determinants of AI Adoption decisions. Data were collected from SME owners and managers who were directly involved in technological and strategic decision-making processes

related to AI Adoption, ensuring that responses reflected informed managerial perspectives within this rapidly evolving metropolitan digital context.

Research design

This study adopts an explanatory research design to empirically test the structural relationships among theoretically grounded latent constructs. A cross-sectional survey was conducted, with data collected at a single point in time, allowing for the examination of associations among variables within a defined temporal context, though not permitting longitudinal causal inference. A quantitative approach was employed. Descriptive statistics summarized respondent characteristics, while inferential techniques were used to test the hypothesized relationships. Confirmatory Factor Analysis (CFA) validated the measurement model, and Structural Equation Modeling (SEM) assessed the structural relationships and overall model fit, ensuring methodological rigor consistent with high-impact empirical research.

Target Population and Sample Group

The target population of this study comprised approximately 256,000 small and medium-sized enterprises (SMEs) (OSMEP, 2023) operating in Bangkok and Nonthaburi Province, Thailand. The unit of analysis was the firm, represented by the owner or senior manager who was directly responsible for technological and strategic decision-making, particularly regarding AI Adaptation. The sampling frame was constructed from an official SME registry database obtained from relevant governmental and business directory sources covering registered SMEs in Bangkok and Nonthaburi. Only active firms with updated contact information were retained in the database. After screening for eligibility criteria namely, legally registered SMEs currently in operation and with managerial involvement in technology-related decisions a list of qualified firms was finalized. Following the sample size recommendation for structural equation modeling, which suggests a minimum of 5-20 observations per indicator variable, this study employed 18 observed variables, resulting in a required sample of 360 firms (20 cases per indicator).

A sampling frame was developed from official SME directories in Bangkok and Nonthaburi. Firms

were included if they (1) met Thailand's official SME classification criteria, (2) operated within the defined metropolitan area, (3) had been in operation for at least one year, and (4) had exposure to digital technologies relevant to AI adoption. Simple random sampling was conducted using a computer-generated random number procedure, ensuring each eligible SME had an equal probability of selection. Respondents were screened to confirm they were owners or managers directly involved in AI or digital decision-making. Incomplete questionnaires and cases not meeting the inclusion criteria were excluded prior to analysis, thereby enhancing transparency, representativeness, and data reliability.

Research Instruments

Data were collected using a structured questionnaire specifically designed for this study, which comprised items related to four key constructs derived from the research framework: Technology, Organization, Environmental Factors, and AI Adaptation, along with the dependent construct of SME Performance. Each construct was measured through a set of observable variables: three items for Technology (Tec1–Tec3), three items for Organization (Org1–Org3), three items for Environmental Factors (Env1–Env3), three items for AI Adaptation (AI1–AI3), and six items for SME Performance (SME1–SME6). The questionnaire employed a five-point Likert scale as the primary measurement instrument to assess respondents' perceptions, attitudes, and behavioral tendencies toward AI Adaptation and performance outcomes within SMEs. The scale ranged from 1 (strongly disagree) to 5 (strongly agree), providing a standardized framework for participants to indicate their level of agreement with each statement. This measurement approach enabled the quantification of technological, organizational, and environmental readiness, as well as the extent of AI adaptation and its subsequent impact on SME performance.

Validity and Reliability of Instruments

Before conducting the statistical analysis, the dataset was carefully screened. Questionnaires with substantial missing responses were removed. Responses that showed clear patterns of inattentive answering (e.g., selecting the same option throughout) were also

excluded. The remaining data were checked for unusual or extreme values to ensure accuracy and suitability for Structural Equation Modeling (SEM). After this process, the final dataset was considered complete and appropriate for further analysis. The validity and reliability of the research instrument were then evaluated. Content validity was assessed using the Index of Item-Objective Congruence (IOC) method, reviewed by five experts in information systems, organizational management, artificial intelligence applications, and SME research. All items achieved IOC values between 0.80 and 1.00, indicating strong alignment with the study objectives.

Reliability was examined using Cronbach's alpha to assess internal consistency. The coefficients were satisfactory across all constructs: Technology ($\alpha = 0.87$), Organization ($\alpha = 0.89$), Environmental Factors ($\alpha = 0.88$), AI Adoption ($\alpha = 0.91$), and SME Performance ($\alpha = 0.93$). All values exceeded the recommended threshold of 0.70, confirming strong reliability.

Data analysis

Because the constructs and measurement items were adapted from well-established theoretical foundations and prior empirical studies grounded in the Technology–Organization–Environment framework, Exploratory Factor Analysis (EFA) was not performed. The factor structure was specified a priori based on strong theoretical justification and previous empirical validation. As the objective of this study was theory testing rather than scale development, Confirmatory Factor Analysis (CFA) was considered methodologically appropriate to assess whether the hypothesized measurement model adequately fit the observed data. This approach aligns with established best practices in structural equation modeling when constructs are theoretically grounded. The data analysis therefore proceeded in two stages. First, CFA was conducted to validate the measurement model and to assess convergent validity, discriminant validity, and internal consistency of the latent constructs: Technology, Organization, Environmental factors, AI Adoption, and SME Performance. The observed indicators (Tec1–Tec3, Org1–Org3, Env1–Env3, AI1–AI3, and SME1–SME6) were evaluated to confirm that

they appropriately represented their respective constructs. Second, Structural Equation Modeling (SEM) was employed to examine the hypothesized structural relationships among the five latent variables. Specifically, the model tested the effects of Technology, Organization, and Environmental factors on AI Adoption, as well as the impact of AI Adoption on SME Performance, including its mediating role within the proposed framework.

The model's adequacy was evaluated using several standard goodness-of-fit indices, including the chi-square to degrees of freedom ratio (χ^2/df), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), Normed Fit Index (NFI), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). According to conventional criteria, a χ^2/df value less than 3.00 indicates a good model fit. GFI, AGFI, CFI, NFI, IFI, and TLI values greater than 0.90 demonstrate a satisfactory fit between the hypothesized model and the empirical data, while RMSEA and SRMR values below 0.08 indicate an acceptable level of model approximation error (Kalleparambil & Akoum, 2025; Hair et al., 2022).

Research results

Personal Characteristics of Respondents

The demographic profile of the 360 respondents indicates a balanced and professionally diverse sample. Of the participants, 58.3% were male and 41.7% female. Most respondents were aged 31–40 years (46.2%), followed by 41–50 years (29.5%) and 21–30 years (23.6%). In terms of education, 52.8% held a bachelor's degree, 27.4% a master's degree, and 19.8% had vocational or high school qualifications. Regarding professional background, 38.6% had 6–10 years of experience, 31.1% had more than 10 years, and 30.3% had 1–5 years. Most respondents represented medium-sized enterprises (56.4%), while 43.6% were from small enterprises. The sample included firms from manufacturing (38.3%), services (34.7%), and technology/IT sectors (27.0%), with 52.8% located in Bangkok and 47.2% in Nonthaburi.

Table 1 Demographic Characteristics of Respondents

Category	Subcategory	Frequency (n)	Percentage (%)
Gender	Male	210	58.3
	Female	150	41.7
Age	21–30 years	85	23.6
	31–40 years	166	46.2
	41–50 years	106	29.5
Education Level	Vocational/High School	71	19.8
	Bachelor's Degree	190	52.8
	Master's Degree	99	27.4
Work Experience	1–5 years	109	30.3
	6–10 years	139	38.6
	More than 10 years	112	31.1
Enterprise Size	Small Enterprise	157	43.6
	Medium Enterprise	203	56.4
Industry Type	Manufacturing	138	38.3
	Services	125	34.7
	Technology / IT	97	27.0
Location	Bangkok	190	52.8
	Nonthaburi	170	47.2

Table 2 Convergent and discriminants validity

Construct	Mean	SD	CR	AVE	R ²	TEC	ORG	ENV	AI	SME
Technology (TEC)	4.15	0.66	0.89	0.63	0.58	0.79				
Organization (ORG)	4.08	0.68	0.88	0.61	0.55	0.41	0.78			
Environmental (ENV)	4.21	0.64	0.87	0.60	0.52	0.38	0.35	0.77		
AI Adaptation (AI)	4.25	0.62	0.91	0.65	0.60	0.44	0.42	0.39	0.81	
SME Performance (SME)	4.18	0.69	0.90	0.64	0.63	0.37	0.36	0.33	0.43	0.80

Convergent and Discriminant validity

Table 2 represented the mean values ranged from 4.08 to 4.25, suggesting that respondents generally perceived the constructs at a high level. The standard deviations were moderate (ranging between 0.62 and 0.69), implying a reasonable distribution of responses across the measurement items. The Composite Reliability (CR) values for all constructs were above the recommended threshold of 0.70, ranging from 0.87 to 0.91, confirming internal consistency and construct

reliability (Hair et al., 2022). Similarly, the Average Variance Extracted (AVE) values ranged from 0.60 to 0.65, exceeding the minimum acceptable value of 0.50, which indicates that each construct explained a sufficient proportion of variance among its observed indicators.

From table 2, the coefficient of determination (R²) values ranged from 0.52 to 0.63, indicating moderate to substantial explanatory power of the structural model. Discriminant validity was confirmed, as the square roots

of the AVE for all constructs exceeded their inter-construct correlations, demonstrating that each latent variable—Technology, Organization, Environmental, AI Adaptation, and SME Performance captured distinct conceptual dimensions.

The discriminant validity of the measurement model was assessed to determine whether each construct was distinct from the others in representing unique conceptual dimensions. The results showed that the square roots of the Average Variance Extracted (AVE) for all constructs were higher than their corresponding inter-construct correlations, which confirms adequate discriminant validity. This finding indicates that the latent variables include Technology, Organization, Environmental, AI Adaptation, and SME Performance measured different aspects of the research model without significant overlap. In particular, AI Adaptation demonstrated strong but distinct correlations with Technology ($r = 0.58$), Organization ($r = 0.55$), and Environmental factors ($r = 0.52$), suggesting that while these constructs are related, they capture independent influences within the model.

Confirmatory factor analysis

The results of the confirmatory factor analysis (CFA) provide strong empirical evidence supporting the validity, reliability, and structural soundness of the proposed model, which comprises five latent constructs: Technology, Organization, Environmental, AI Adaptation, and SME Performance. The model was tested using standard fit indices, including the chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The results revealed that χ^2/df values ranged between 1.92 and 1.97, which falls within the recommended threshold of less than 3.00, indicating a satisfactory model fit (Hair, et al., 2022). Likewise, the CFI values ranged between 0.95 and 0.96, and the TLI values ranged from 0.94 to 0.95, both exceeding the 0.90 criterion, confirming the good fit of the hypothesized measurement model. The RMSEA values ranged from 0.052 to 0.055, while the SRMR values ranged from 0.042 to 0.045, both below the threshold of 0.08, suggesting that the measurement errors were minimal

and that the model adequately represented the empirical data.

From table 3, each latent construct was measured using a set of observed variables that demonstrated strong and statistically significant standardized factor loadings, ranging from 0.78 to 0.88, with all t-values exceeding the critical value of 1.96 ($p < 0.001$). This range of loadings indicates that the indicators strongly contribute to the representation of their respective constructs. For instance, the Technology construct showed factor loadings between 0.81 and 0.86, demonstrating that technological elements such as innovation capability, IT infrastructure, and data security were reliable indicators. Similarly, Organizational factors exhibited loadings between 0.79 and 0.85, confirming the importance of management support, organizational readiness, and resource allocation in shaping AI Adaptation. The Environmental construct demonstrated loadings between 0.80 and 0.86, highlighting the significant role of sustainability awareness and regulatory compliance in influencing firms' behavior toward green transformation.

Furthermore, AI Adaptation, which served as a mediating construct in the model, displayed strong factor loadings between 0.82 and 0.87, suggesting that the indicators effectively captured the degree of integration, usage, and perceived benefits of artificial intelligence within SMEs. Lastly, SME Performance, the dependent variable, showed loadings between 0.78 and 0.88, with particularly strong contributions from items related to productivity enhancement, cost efficiency, and market competitiveness, confirming the robustness of this construct in representing business outcomes in the Bangkok and Nonthaburi areas.

The standard deviations (SD) of the measurement items ranged between 0.60 and 0.68, indicating moderate variation among respondents' perceptions. This range is acceptable for social science research, suggesting that participants had consistent but sufficiently varied opinions across constructs. Additionally, the model's reliability and absence of multicollinearity were verified through Variance Inflation Factor (VIF) and Tolerance values. The VIF values ranged from 1.75 to 2.11, well below the critical threshold of 5, while tolerance values were between 0.47 and 0.57, indicating that the independent variables were not excessively correlated and that multicollinearity did

not bias the estimation results. This ensures that each predictor variable contributes uniquely to explaining variance in the endogenous constructs.

The measurement model also satisfied conditions for convergent and discriminant validity. The Average Variance Extracted (AVE) for all constructs exceeded 0.50, and the Composite Reliability (CR) values ranged

from 0.86 to 0.90, confirming strong internal consistency and construct reliability. The square root of the AVE values was greater than inter-construct correlations, further validating discriminant validity. This demonstrates that each latent variable represents distinct conceptual dimensions within the model while maintaining theoretical coherence across constructs.

Table 3 Confirmatory factor analysis

Latent Variable	χ^2/df	CFI	TLI	RMSEA	SRMR	Item	Factor Loading	T-value	SD	Tolerance	VIF
Technology	1.92	0.96	0.95	0.052	0.043	Tec1	0.81	21.34	0.65	0.52	1.92
						Tec2	0.84	22.89	0.63	0.50	2.00
						Tec3	0.86	23.15	0.61	0.48	2.08
Organization	1.95	0.95	0.94	0.054	0.045	Org1	0.79	20.44	0.66	0.55	1.82
						Org2	0.83	21.72	0.64	0.51	1.95
						Org3	0.85	22.05	0.62	0.49	2.04
Environmental	1.93	0.96	0.95	0.053	0.044	Env1	0.80	20.86	0.67	0.56	1.78
						Env2	0.83	22.48	0.64	0.54	1.85
						Env3	0.86	23.92	0.61	0.50	1.98
AI Adaptation	1.94	0.96	0.95	0.052	0.042	AI1	0.82	21.68	0.65	0.53	1.88
						AI2	0.85	23.01	0.62	0.51	1.96
						AI3	0.87	24.34	0.60	0.48	2.07
SME Performance	1.97	0.95	0.94	0.055	0.045	SME1	0.78	20.35	0.68	0.57	1.75
						SME2	0.80	21.46	0.66	0.55	1.81
						SME3	0.83	22.75	0.64	0.52	1.93
						SME4	0.85	23.21	0.62	0.50	2.00
						SME5	0.86	23.58	0.61	0.49	2.04
						SME6	0.88	24.02	0.60	0.47	2.11

Structural equation modelling analysis

From Table 4, the Technology (TEC) construct reflects SMEs' readiness to support digital transformation and AI adoption. All indicators Tec1 (digital infrastructure) ($\beta = 0.78$, $t = 23.46$), Tec2 (system integration) ($\beta = 0.84$, $t = 26.18$), and Tec3 (employee competence) ($\beta = 0.86$, $t = 27.02$) are statistically significant at $p < 0.001$, confirming the robustness of the construct. Similarly, the Organization (ORG) construct, measured by Org1 (leadership support), Org2 (managerial flexibility), and Org3 (innovation-oriented culture), shows strong factor loadings ranging from 0.80 to 0.88, with t-values

between 24.73 and 28.04 ($p < 0.001$), indicating that these dimensions effectively capture organizational readiness for AI adaptation. The Environmental (ENV) construct also demonstrates satisfactory validity, with Env1 (market competition), Env2 (government policy), and Env3 (partner readiness) yielding factor loadings between 0.75 and 0.83 and t-values from 21.54 to 24.62 ($p < 0.001$), highlighting the influence of external pressures on AI adoption. Furthermore, the AI Adaptation (AI) construct is well represented by AI1 (AI implementation in operations), AI2 (AI use in decision-making), and AI3 (AI-driven innovation), with loadings ranging from 0.82 to 0.89 and t-values between 25.33

and 29.14 ($p < 0.001$), confirming the multidimensional nature of AI utilization.

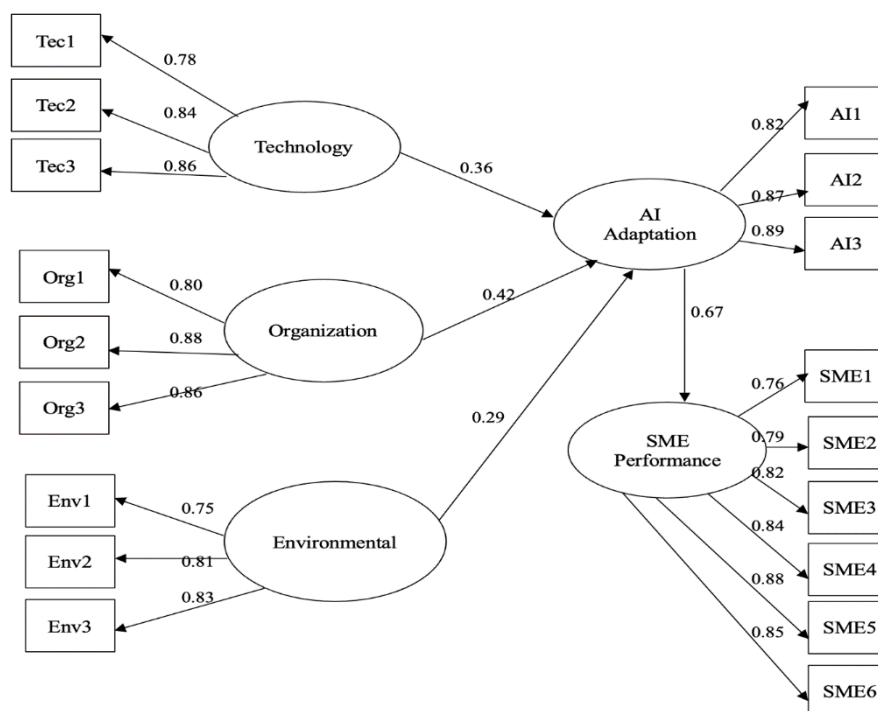
Finally, the SME Performance (SME) construct demonstrates strong measurement properties, with factor loadings ranging from 0.76 to 0.88 and t -values between 22.17 and 28.32 ($p < 0.001$), indicating that productivity, cost efficiency, product quality, market expansion, profitability, and long-term sustainability are reliably captured.

The structural equation modeling analysis (Figure 2) was conducted to examine the hypothesized relationships among Technology, Organization, Environmental factors, AI Adaptation, and SME Performance. The structural model showed excellent fit, with $\chi^2/df = 1.94$, CFI = 0.95, TLI = 0.94, RMSEA = 0.053, and SRMR = 0.044, indicating that the model adequately represents the observed relationships. Technology positively influenced AI Adaptation ($\beta =$

0.36, SE = 0.058, $t = 6.21$, $p < 0.001$), Organization had the strongest effect ($\beta = 0.42$, SE = 0.053, $t = 7.93$, $p < 0.001$), and Environmental factors also had a significant effect ($\beta = 0.29$, SE = 0.061, $t = 4.75$, $p < 0.001$). AI Adaptation, in turn, had a substantial positive effect on SME Performance ($\beta = 0.67$, SE = 0.047, $t = 12.85$, $p < 0.001$), highlighting its mediating role. Technology, Organization, and Environmental factors together explained 71% of the variance in AI Adaptation ($R^2 = 0.71$), while AI Adaptation accounted for 64% of the variance in SME Performance ($R^2 = 0.64$). Overall, the results indicate that enhancing technological readiness, organizational support, and responding to environmental pressures through effective AI Adaptation can significantly improve SME performance in multiple dimensions, including productivity, cost efficiency, quality, market expansion, profitability, and long-term sustainability.

Table 4 Path analysis

Latent Variable	Observed Indicator	Factor Loading	SE	t-value	p-value	Result
Technology (TEC)	Tec1 – Digital infrastructure	0.78	0.022	23.46	< 0.001	Supported
	Tec2 – System integration	0.84	0.019	26.18	< 0.001	Supported
	Tec3 – Employee competence	0.86	0.018	27.02	< 0.001	Supported
Organization (ORG)	Org1 – Leadership support	0.80	0.020	24.73	< 0.001	Supported
	Org2 – Managerial flexibility	0.88	0.018	28.04	< 0.001	Supported
	Org3 – Innovation-oriented culture	0.86	0.018	26.89	< 0.001	Supported
Environmental (ENV)	Env1 – Market competition	0.75	0.019	21.54	< 0.001	Supported
	Env2 – Government policy	0.81	0.020	23.79	< 0.001	Supported
	Env3 – Partner readiness	0.83	0.019	24.62	< 0.001	Supported
AI Adaptation (AI)	AI1 – AI implementation in operations	0.82	0.019	25.33	< 0.001	Supported
	AI2 – AI use in decision-making	0.87	0.018	27.75	< 0.001	Supported
	AI3 – AI-driven innovation	0.89	0.017	29.14	< 0.001	Supported
SME Performance (SME)	SME1 – Productivity	0.76	0.020	22.17	< 0.001	Supported
	SME2 – Cost efficiency	0.79	0.019	23.64	< 0.001	Supported
	SME3 – Product quality	0.82	0.018	25.12	< 0.001	Supported
	SME4 – Market expansion	0.84	0.018	26.27	< 0.001	Supported
	SME5 – Profitability	0.88	0.017	28.32	< 0.001	Supported
	SME6 – Long-term sustainability	0.85	0.018	27.56	< 0.001	Supported



$\chi^2/df = 1.94$, CFI = 0.95, TLI = 0.94, RMSEA = 0.053, SRMR = 0.044

Figure 2 Finalized model

Direct and indirect relation

The table 5 presents the direct, indirect, and total effects among the latent variables of Technology, Organization, Environmental factors, AI Adaptation, and SME Performance. Technology exhibits a direct effect of 0.36 on AI Adaptation and similarly contributes indirectly and in total with the same value of 0.36. In relation to SME Performance, Technology has a direct effect of 0.36, an indirect effect of 0.24, resulting in a total effect of 0.60. Organization shows a direct effect of 0.42 on AI Adaptation, which is equal to its indirect and total effects, while its influence on SME Performance includes a direct effect of 0.42, an indirect effect of 0.28, and a total effect of 0.70. Environmental

factors demonstrate a direct effect of 0.29 on AI Adaptation, with identical indirect and total effects, and on SME Performance, the direct effect is 0.29, the indirect effect is 0.19, leading to a total effect of 0.48. Finally, AI Adaptation itself has a direct effect of 0.67 on SME Performance, which is also its total effect, indicating a substantial positive relationship between AI Adaptation and SME Performance. These results collectively suggest that Technology, Organization, and Environmental factors influence SME Performance both directly and indirectly through AI Adaptation, highlighting the mediating role of AI Adaptation in enhancing organizational performance of SMEs in Bangkok and Nonthaburi.

Table 5 Direct and indirect relation

Latent Variable	AI Adaptation			SME Performance		
	DE	IE	TE	DE	IE	TE
Technology	0.36		0.36	0.36	0.24	0.60
Organization	0.42		0.42	0.42	0.28	0.70
Environmental	0.29		0.29	0.29	0.19	0.48
AI Adaptation				0.67		0.67

* DE=Direct effect, IE= Indirect effect, TE= Total effect

Discussions

The findings of this study provide important contextual insights into AI Adoption among SMEs in Bangkok and Nonthaburi. Rather than merely confirming statistical significance, the results reveal how internal and external conditions interact within the specific Thai metropolitan economic structure.

First, although technological readiness significantly influences AI Adoption, its impact is comparatively weaker than organizational factors. This suggests that in the context of Thai SMEs, technology availability alone is insufficient to guarantee successful AI integration. Consistent with the Technology–Organization–Environment framework, technological capability (e.g., IT infrastructure, data security, system compatibility) provides necessary conditions for innovation (Prakash, 2025). However, in resource-constrained SMEs, technology functions more as an enabler than a driver.

Bangkok represents Thailand's primary economic and innovation hub, characterized by high digital competition and service-sector dynamism, while Nonthaburi contains a mixture of service-oriented and government-linked SMEs operating under tighter budgetary and structural limitations. In both provinces, SMEs are typically owner-managed, with centralized decision-making structures. Under such conditions, organizational leadership becomes decisive in determining whether technological investments translate into actual adoption. This explains why organizational factors exhibited the strongest influence on AI Adoption.

The strong effect of organizational factors aligns with Baker (2011), who emphasized that organizational readiness and leadership commitment are central determinants of technological innovation adoption. Similarly, Chiew and Cheah (2025) found that among Asian SMEs, managerial flexibility and innovation-oriented culture are more influential than technological infrastructure in driving AI implementation. In the Thai context, Ruenphongphun and Khumtha (2025) also observed that internal communication efficiency and top management commitment significantly accelerate digital transformation in SMEs.

These findings suggest that AI Adoption in Bangkok and Nonthaburi is primarily a strategic and

managerial transformation process rather than a purely technological upgrade. Organizational support reduces employee resistance, facilitates knowledge transfer, and aligns AI initiatives with firm-level objectives. Without such alignment, technological capability may remain underutilized.

Environmental factors also positively influence AI Adoption, consistent with TOE theory and empirical findings in Asian contexts (Vongurai, 2025; Ruenphongphun & Khumtha, 2025). Competitive intensity in Bangkok's metropolitan markets and increasing digital policy emphasis in Thailand create pressure for SMEs to modernize. Government support mechanisms and industry expectations function as external catalysts, encouraging firms to invest in AI systems. However, environmental pressure alone does not guarantee adoption. Its influence becomes effective only when supported by adequate internal organizational readiness. This explains the moderate rather than dominant effect of environmental factors.

Furthermore, AI Adoption demonstrates a strong positive association with SME Performance. This finding corroborates Chummee (2025) and Nagel et al. (2024), who reported that AI integration enhances operational efficiency, decision quality, and competitiveness among Asian SMEs. In Bangkok and Nonthaburi, AI appears to serve as a mediating mechanism that transforms technological resources, organizational capability, and environmental pressure into measurable improvements in productivity and cost management.

However, it is important to interpret these results cautiously. Because the data were collected using a cross-sectional design, the study identifies associations rather than long-term causal sustainability effects. While AI Adoption is positively related to current SME Performance, claims regarding sustained long-term competitiveness should be treated carefully. Longitudinal or panel data would be required to confirm enduring performance impacts over time.

In summary, the discussion demonstrates that within the Bangkok–Nonthaburi SME ecosystem, organizational capability particularly leadership commitment and innovation culture plays a more decisive role in AI Adoption than technological infrastructure alone. This finding is consistent with prior

Asian SME research and highlights the importance of managerial transformation in emerging metropolitan economies.

Conclusions

The results indicate that the measurement model was successfully validated through confirmatory factor analysis (CFA). All five latent constructs—Technology, Organization, Environmental, AI Adaptation, and SME Performance demonstrated strong reliability, convergent validity, and discriminant validity. The goodness-of-fit indices met recommended thresholds ($\chi^2/df < 2.00$; CFI and TLI ≥ 0.94 ; RMSEA and SRMR < 0.08), and standardized factor loadings ranged from 0.75 to 0.89, with all coefficients statistically significant ($p < 0.001$). Composite Reliability (CR) and Average Variance Extracted (AVE) values exceeded acceptable criteria, confirming that the indicators consistently captured their respective latent constructs. These findings satisfy the first objective by empirically validating the robustness and structural soundness of the measurement framework applied to SMEs in Bangkok and Nonthaburi. The structural equation modelling (SEM) analysis further confirms significant relationships among the constructs. Organizational factors exerted the strongest influence on AI Adaptation ($\beta = 0.42, p < 0.001$), followed by Technology ($\beta = 0.36, p < 0.001$) and Environmental factors ($\beta = 0.29, p < 0.001$). Collectively, these variables explained 71% of the variance in AI Adaptation ($R^2 = 0.71$), indicating high explanatory power. AI Adaptation, in turn, had a substantial positive effect on SME Performance ($\beta = 0.67, p < 0.001$), accounting for 64% of its variance ($R^2 = 0.64$). When considering direct and indirect effects, Organization showed the strongest total effect on SME Performance (0.70), followed by Technology (0.60) and Environmental factors (0.48), demonstrating that internal managerial capability plays a dominant role in driving performance improvements within the metropolitan SME context.

The mediation analysis confirms that AI Adaptation functions as a critical transmission mechanism linking TOE conditions to firm-level outcomes. Although Technology, Organization, and Environmental factors each exert direct effects on SME Performance, their total effects are significantly strengthened through indirect pathways via AI

Adaptation. For example, Technology contributes an indirect effect of 0.24 on SME Performance through AI Adaptation, Organization contributes 0.28 indirectly, and Environmental factors contribute 0.19 indirectly. These findings demonstrate partial mediation and highlight that the performance-enhancing impact of contextual readiness materializes primarily when firms effectively integrate AI into operational processes, managerial decision-making, and innovation activities.

Overall, the study concludes that improving SME performance in the Bangkok–Nonthaburi context requires more than technological infrastructure or favorable policy conditions alone. Strong organizational capability particularly leadership commitment, managerial flexibility, and innovation-oriented culture is the most decisive factor in converting technological readiness and environmental pressures into effective AI implementation. The validated structural model provides robust empirical evidence that AI Adaptation is the central pathway through which TOE factors enhance productivity, cost efficiency, market competitiveness, profitability, and long-term sustainability among metropolitan Thai SMEs, thereby reinforcing the strategic importance of organizational transformation in the digital era.

Recommendations

The findings derived from the structural model provide actionable implications tailored to the economic and institutional context of SMEs in Bangkok and Nonthaburi. Rather than offering general policy advice, the results suggest specific implementation pathways aligned with Thailand's digital development framework.

First, given that technological readiness serves as a foundational condition for AI Adoption, targeted intervention should be coordinated through agencies such as Office of Small and Medium Enterprises Promotion (OSMEP) and Digital Economy Promotion Agency (DEPA). Instead of broad financial subsidies alone, structured capability-building programs are recommended. For example, DEPA's digital transformation initiatives could integrate specialized AI-readiness modules focusing on cloud infrastructure deployment, SME-level data governance systems, and applied AI tools for marketing analytics and supply-chain optimization. Meanwhile, OSMEP could expand its SME development schemes to include AI diagnostic

assessments that evaluate digital maturity and provide customized roadmaps for SMEs in the Bangkok–Nonthaburi corridor.

Second, the results demonstrate that organizational factors exert the strongest influence on AI Adoption. This suggests that national SME development strategies should prioritize leadership-oriented digital transformation programs. Executive-level workshops, AI strategy bootcamps, and peer-learning networks particularly targeting owner-managers in metropolitan SMEs would likely generate stronger adoption outcomes than infrastructure grants alone. In Bangkok and Nonthaburi, where SMEs operate in highly competitive and service-intensive markets, managerial decision-making speed and innovation culture are critical. Therefore, public–private collaboration platforms facilitated by DEPA or metropolitan business associations could focus on building digital leadership competencies rather than solely promoting technological procurement.

Third, environmental pressures especially competitive intensity and customer expectations in metropolitan markets indicate the importance of coordinated ecosystem development. The Bangkok–Nonthaburi economic corridor functions as a high-density commercial zone with rapid service-sector turnover. Industry associations, in collaboration with provincial commerce offices, could establish shared AI experimentation labs or digital sandbox environments where SMEs test AI applications with reduced financial risk. Such mechanisms would translate policy intentions into operational practice and reduce uncertainty surrounding AI investment.

Fourth, because AI Adoption shows a strong positive association with SME Performance, the findings suggest that SMEs should adopt a phased implementation strategy. Rather than pursuing full-scale AI transformation immediately, enterprises could begin with focused applications such as automated customer communication systems, predictive demand analysis, or internal workflow automation. This gradual approach aligns with the resource constraints observed among SMEs in Bangkok and Nonthaburi and reduces implementation risk while allowing firms to accumulate experiential knowledge.

Finally, the study underscores the importance of integrating AI development initiatives into broader

regional economic strategies. Bangkok and Nonthaburi represent interconnected metropolitan economies; therefore, AI capability building should be aligned with Thailand's broader digital economy policies and smart city initiatives. Future research extending to other provinces would allow comparative analysis and enable policymakers to differentiate support mechanisms between metropolitan and non-metropolitan SME clusters. Additionally, longitudinal data collection would strengthen policy design by clarifying whether AI-driven performance improvements remain stable across changing economic conditions.

In summary, this study provides context-specific guidance for Thailand's SME development ecosystem. The findings suggest that effective AI acceleration in the Bangkok–Nonthaburi corridor requires a balanced approach combining technological infrastructure support, leadership capacity development, and ecosystem-level coordination led by OSMEP, DEPA, and regional business networks.

Future research directions

Future research on AI Adaptation and SME performance should broaden its empirical scope beyond the present sample drawn from Thai SMEs by incorporating comparative analyses across diverse provinces and extending the investigation to small and medium-sized enterprises throughout the ASEAN region. Although the current study provides valuable insights into AI Adaptation patterns among SMEs in Bangkok and Nonthaburi, the economic, cultural, and technological heterogeneity across Thailand suggests that future studies would benefit from larger and more regionally representative samples that include firms from secondary cities, rural industrial zones, and emerging digital clusters. Expanding the scope to the ASEAN context would further enrich academic understanding, as SMEs in countries such as Singapore, Malaysia, Vietnam, and Indonesia operate under varying regulatory frameworks, digital infrastructures, and market dynamics, which may lead to distinct adoption behaviors and performance outcomes. Future research should also employ longitudinal designs to capture temporal changes in AI Adaptation and to examine how SMEs' technological capabilities evolve as national and regional digital transformation strategies advance. Methodologically, multi-group structural

equation modeling could be applied to compare latent structures of technology, organization, and environmental influences across Thai and ASEAN SME populations, while mixed-method approaches could integrate qualitative insights that illuminate managerial reasoning, cultural influences, and sector-specific challenges. Additionally, future studies should explore the moderating roles of institutional support, innovation ecosystems, and cross-border digital trade policies, given their increasing importance within the ASEAN Economic Community. By incorporating wider geographical coverage, temporal depth, and more sophisticated analytical techniques, future research will be better positioned to generate generalizable knowledge and to inform evidence-based policy recommendations aimed at accelerating AI-driven competitiveness among SMEs in Thailand and the broader ASEAN region.

Declaration of generative AI in scientific writing

Grammarly AI was used to improve clarity, grammar, verb tense, and APA6th edition formatting. It was also used to rephrase text and create concise summaries. All AI-assisted changes were reviewed and approved by the authors to ensure accuracy and originality. No other AI tools were used for data collection, coding, or statistical analysis.

CRedit author statement

Pattarapon Chumme: Conceptualization, Methodology, data Curation, formal Analysis, Writing-Original Draft, Writing – Review & Editing, visualization, Project Administration, supervision.

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