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Artificial Intelligence Adoption in the Management of Vietnamese Small and Medium-Sized Enterprises: An Analysis of Technological, Organizational and Environmental Factors

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ABSTRACT: This study examines the current level of artificial intelligence (AI) adoption in the management of Vietnamese small and medium-sized enterprises (SMEs) and investigates the relationships between technological, organizational and environmental conditions and AI adoption through the technology–organization–environment (TOE) framework. The study uses 138 valid questionnaire responses collected from SMEs in Hanoi, Hung Yen and Bac Ninh. The analysis comprises descriptive statistics, Cronbach's alpha reliability testing, exploratory factor analysis (EFA) and multiple linear regression. Leadership awareness and commitment ($\beta = 0.292$), technological capability ($\beta = 0.248$), digital human-resource capability ($\beta = 0.187$) and the external environment ($\beta = 0.143$) are positively associated with AI adoption and statistically significant at the 5% level. Financial resources have a positive coefficient ($\beta = 0.087$), but the relationship is not statistically significant at the 5% level ($p = 0.091$). Descriptively, 51.4% of the sampled enterprises are exploring or experimenting with AI. Marketing/content creation and customer service are the most frequently reported application areas. The findings highlight the importance of managerial direction, technology and data readiness, and employees' digital capabilities. The results should be interpreted within the limits of the convenience sample and cross-sectional design.

KEYWORDS: artificial intelligence, AI adoption, small and medium-sized enterprises, TOE framework, technological, organizational and environmental factors.

1. INTRODUCTION

Rapid advances in digital technologies, particularly artificial intelligence (AI), are reshaping the ways in which enterprises operate and manage their activities. Unlike conventional automation technologies, AI can process large volumes of data, identify patterns, support forecasting and improve information-based decision-making. Russell and Norvig [1] describe AI as a field concerned with developing systems capable of performing tasks that typically require human intelligence, including learning, reasoning and problem-solving. Kaplan and Haenlein [2] similarly characterize AI as a system's ability to interpret external data, learn from it and use the resulting knowledge to pursue specific objectives through adaptive behaviour. For small and medium-sized enterprises (SMEs), AI creates opportunities to use resources more efficiently, improve customer engagement and strengthen competitiveness. Nevertheless, SMEs often face constraints in finance, technological infrastructure, management data and digital talent. The central challenge is therefore not simply gaining access to AI tools, but selecting, implementing and using solutions that fit an enterprise's operational context. The technology–organization–environment (TOE) framework proposed by Tornatzky and Fleischer [3] explains organizational technology adoption through technological, organizational and external environmental contexts. The technology acceptance model (TAM), in contrast, emphasizes perceived usefulness and perceived ease of use in individual technology acceptance [4].

In Vietnam, the digital transformation of SMEs has increased the need to adopt and exploit emerging technologies, including AI. Digital transformation involves changes in value creation and organizational processes in response to digital technologies [5]; AI adoption is one specific form of technology deployment and should not be equated with the entirety of digital transformation. Hoang [6] applied the TOE framework to examine digital transformation adoption among SMEs in Da Nang. Nguyen Van Phuoc [7] investigated factors associated with AI application adoption in Vietnam using TOE and structural equation modelling. Tran Duc Tung [8] examined technological, organizational and environmental factors in relation to stages of AI adoption among SMEs in Ho Chi Minh City. Although these studies provide useful evidence, digital transformation in general and AI adoption in business management are not identical phenomena. AI deployment has specific requirements relating to data quality, technological infrastructure, employee capabilities and managerial readiness. Moreover, adoption should be considered not only in terms of whether an enterprise has accessed AI, but also in terms of whether AI has been incorporated into concrete management activities.

Against this background, this study addresses two research questions: (1) What is the current state of AI adoption in the management of the SMEs included in the Vietnamese survey? and (2) How are technological, organizational and environmental factors associated with the level of AI adoption? Using the TOE framework, the study examines five factors: technological capability, leadership awareness and commitment, digital human-resource capability, financial resources and the external environment. Its contribution lies in providing additional empirical evidence

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from 138 surveyed enterprises and identifying differences in the strength and statistical significance of the relationships, particularly the prominent association of leadership and the non-significant result for financial resources.

2. RESEARCH CONTENT

2.1. Literature review and theoretical foundation

AI applications in business have attracted increasing scholarly attention because of their potential to improve operational efficiency, information analysis and decision-making. Davenport and Ronanki [9] group business AI applications into process automation, cognitive insight and cognitive engagement. This classification indicates that AI value depends not only on technical characteristics but also on the extent to which the technology is integrated into organizational activities.

From an organizational adoption perspective, Jöhnk et al. [10] emphasize the conditions required for AI readiness, including strategic orientation, resources and the ability to organize implementation. For SMEs, shortages of specialist personnel, finance and structured data can make the transition from awareness to practical use more difficult. Badghish and Soomro [11] apply the TOE framework to AI adoption and sustainable business performance among SMEs in Saudi Arabia. Arroyabe et al. [12] highlight the role of digital and innovation capabilities in AI adoption among European SMEs, while reporting a more limited role for external business support. Ul Haq and Suki [13], studying 500 middle- and senior-level managers in manufacturing SMEs in Pakistan, find positive relationships between technological readiness, organizational preparedness, leadership and AI adoption and innovation outcomes.

In Vietnam, the studies by Nguyen Van Phuoc [7], Hoang [6] and Tran Duc Tung [8] provide relevant evidence, although they differ in research setting, technology scope, geographical coverage and analytical approach. Further examination of how technological, organizational and environmental conditions relate to AI adoption in SME management in Hanoi, Hung Yen and Bac Ninh therefore offers additional empirical value. In particular, leadership commitment, digital human-resource capability and financial resources warrant examination in a context where AI tools are becoming increasingly accessible.

The TOE framework, developed by Tornatzky and Fleischer [3], explains organizational innovation adoption through three contexts. The technological context concerns the technologies available to the enterprise and its ability to implement them. For AI, this includes digital infrastructure, data collection and management, information-system readiness and the integration of AI solutions into existing processes. The organizational context includes internal characteristics that enable or constrain adoption. In this study, it is represented by leadership awareness and commitment, digital human-resource capability and financial resources. The environmental context covers external conditions such as competitive pressure, customer requirements, policy support and the technology ecosystem.

TOE is selected as the principal framework because its three contexts align with the five factors measured in this study. Leadership awareness and commitment are treated as an organizational condition; they are not equated with TAM's perceived usefulness or perceived ease of use. Similarly, dynamic capabilities are not directly tested because the study does not include separate measures of sensing, seizing and resource reconfiguration.

2.2. Research model and hypotheses

The proposed model specifies AI adoption in enterprise management as the dependent variable and five explanatory factors: technological capability (TECH), leadership awareness and commitment (LEAD), digital human-resource capability (HUMAN), financial resources (FIN) and the external environment (ENV). Each factor is hypothesized to be positively associated with AI adoption.

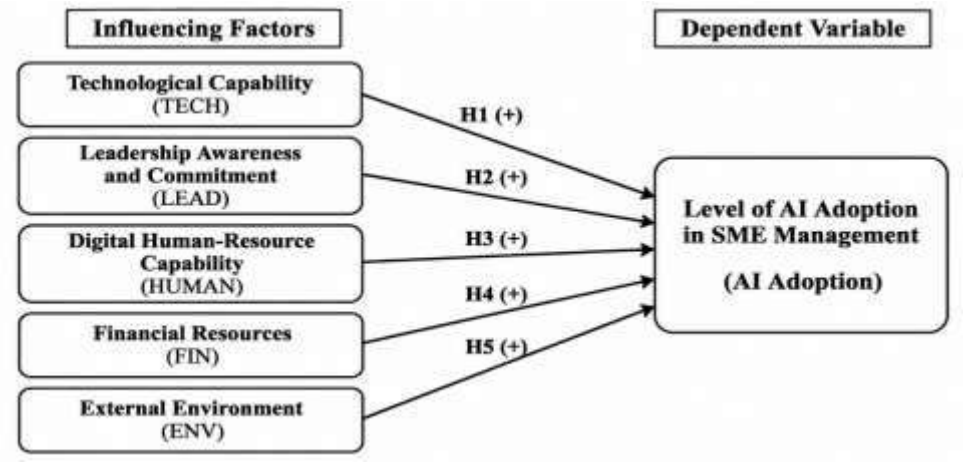

Figure 1. Proposed Research Model
Source: Proposed by the authors.

H1: Technological capability is positively associated with the level of AI adoption in SMEs.
H2: Leadership awareness and commitment are positively associated with the level of AI adoption in SMEs.
H3: Digital human-resource capability is positively associated with the level of AI adoption in SMEs.
H4: Financial resources are positively associated with the level of AI adoption in SMEs.
H5: External environmental conditions are positively associated with the level of AI adoption in SMEs.

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Technological infrastructure, data-management capability and system integration may reduce technical barriers to AI implementation. Leadership can shape technology selection, resource allocation and process change. Employees' digital skills can support the use, evaluation and integration of AI outputs. Financial resources may enable investment in infrastructure, services and training, while competition, customer requirements and external support may encourage adoption. These arguments underpin the five directional hypotheses.

2.3. Research methodology

2.3.1. Research design and data collection

The study adopts a quantitative design supported by a review of the relevant literature to develop the theoretical foundation, research model and measurement scales. Primary data were collected through a questionnaire administered to enterprise owners, managers and personnel directly involved in information technology or digital transformation. A convenience sampling approach was used. SMEs were identified with reference to applicable criteria concerning business sector, average annual number of employees participating in social insurance, revenue or total capital.

The survey was conducted from August to September 2026 in Hanoi, Hung Yen and Bac Ninh, using a combination of in-person and online distribution. A total of 162 questionnaires were distributed or invited online; 146 responses were received. After eight responses were excluded because of incomplete information or inadequate response quality, 138 valid responses were retained for analysis.

2.3.2. Measurement scales

The questionnaire operationalized five independent constructs and one dependent construct. TECH, LEAD, HUMAN and ENV were each measured by three observed items; FIN was measured by two items; and AI Adoption was measured by four items. The items captured infrastructure adequacy, data organization, system integration, managerial awareness and commitment, employee digital skills, financial capacity, competitive and customer pressures, external support, and the use and integration of AI in management activities.

Construct	Code	Measurement item
TECH	TECH1	The enterprise has digital infrastructure adequate for AI adoption.
TECH	TECH2	Management data are appropriately organized and stored.
TECH	TECH3	Existing technology systems can integrate AI solutions.
LEAD	LEAD1	Management recognizes the value of AI in business management.
LEAD	LEAD2	Management supports AI experimentation and adoption.
LEAD	LEAD3	Management provides direction and commitment to promote AI adoption.
HUMAN	HUMAN1	Employees possess the necessary digital skills.
HUMAN	HUMAN2	Employees can use AI tools in their work.
HUMAN	HUMAN3	Employees can learn and adapt to AI technologies.
FIN	FIN1	The enterprise can allocate funds for AI adoption.
FIN	FIN2	The enterprise can sustain the operating costs of AI.
ENV	ENV1	Competitive pressure encourages the enterprise to consider AI.
ENV	ENV2	Customer requirements motivate AI adoption.
ENV	ENV3	Policies and the technology ecosystem support AI adoption.
AI Adoption	AI1	AI is used in management activities.
AI Adoption	AI2	AI is integrated into some work processes.
AI Adoption	AI3	AI is used to process or analyse information.
AI Adoption	AI4	The scope of AI use in the enterprise is expanding.

2.3.3. Data analysis

Data were analysed in four stages. First, questionnaire quality was checked, invalid responses were removed and sample characteristics were summarized using descriptive statistics. Second, internal consistency was assessed using Cronbach's alpha. Third, exploratory factor analysis (EFA) was conducted to examine the structure of the observed items and the suitability of the measurement scales. Fourth, multiple linear regression was used to estimate the relationships between the five independent factors and AI adoption.

The regression model is specified as follows: $AI\ Adoption_i = \beta_0 + \beta_1 TECH_i + \beta_2 LEAD_i + \beta_3 HUMAN_i + \beta_4 FIN_i + \beta_5 ENV_i + \varepsilon_i$, where β_0 is the intercept, β_1–β_5 are regression coefficients and ε_i is the random error term. Statistical significance was assessed at the 5% level. The coefficients are interpreted as statistical associations within the specified model and do not, by themselves, establish causality.

2.4. Results and discussion

2.4.1. Sample characteristics

The study surveyed small and medium-sized enterprises (SMEs) in Vietnam to assess the current state of AI adoption in management activities and identify the factors influencing the level of AI adoption. After reviewing the responses and excluding incomplete questionnaires, 138 valid

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responses were retained for subsequent quantitative analyses. The characteristics of the research sample are presented in terms of business sector, workforce size, and years of business operation.

To establish the profile of the enterprises represented in the dataset, the sample is described across three dimensions: business sector, workforce size and years of operation. These characteristics provide context for interpreting the subsequent findings on AI adoption, since firms operating in different sectors and at different stages of development may face different management needs and levels of digital readiness. The distribution of the 138 valid responses is summarized in Table 1.

Table 1. Characteristics of the Research Sample

Characteristic	Category	Frequency	%
Business sector	Manufacturing	39	28.3
	Trade	38	27.5
	Services	48	34.8
	Other	13	9.4
Number of employees	Fewer than 10	43	31.2
	10–50	62	44.9
	51–200	33	23.9
Years of operation	Fewer than 5 years	35	25.4
	5–10 years	47	34.1
	More than 10 years	56	40.5

Source: Author's 2026 survey.

The sample covers several business sectors. Service enterprises account for the largest share (34.8%), followed by manufacturing (28.3%) and trade (27.5%). Enterprises with 10–50 employees represent 44.9% of the sample. In terms of operating history, 40.5% have been operating for more than ten years. This composition provides perspectives from enterprises with different operating profiles; however, the convenience sampling design limits the extent to which the sample can be treated as representative of all Vietnamese SMEs.

2.4.2. Current state of AI adoption

Having established the sample profile, the analysis next examines how far the surveyed SMEs have progressed in adopting AI. The adoption categories distinguish enterprises that have not yet begun using AI from those exploring, experimenting with, or applying it in selected or regular management activities. This distinction helps separate initial awareness and trial use from more established organizational adoption. The distribution across these stages is reported in Table 2.

Table 2. Level of AI Adoption among SMEs

AI adoption status	Frequency	%
Not using AI	30	21.7
Exploring AI	40	29.0
Experimenting with AI	31	22.5
Using AI in selected activities	30	21.7
Using AI regularly	7	5.1

Source: Author's 2026 survey.

The descriptive results indicate that AI has attracted the attention of SMEs, although regular use remains limited. The largest group is exploring AI (29.0%), followed by enterprises experimenting with it (22.5%). Only 5.1% report regular use. Taken together, 51.4% (71 of 138 enterprises) are exploring or experimenting with AI; the percentage is consistent with the 51.4% reported in the source abstract. This distribution illustrates a gap between awareness of AI's potential and its stable integration into business operations.

The most frequently reported application areas are marketing and content creation (55 enterprises; 39.9%), customer service (37; 26.8%), data analysis (21; 15.2%), business forecasting (15; 10.9%) and human-resource management (12; 8.7%). Respondents could select more than one application area; percentages are calculated using the 138 surveyed enterprises as the denominator. The pattern suggests that AI is currently more common in support tasks that are relatively accessible, while applications requiring more structured data and analytical capability are less prevalent.

2.4.3. Reliability and exploratory factor analysis

Before examining the relationships between the explanatory factors and AI adoption, the internal consistency of the measurement scales was assessed using Cronbach's alpha. This test evaluates whether the observed items within each construct show an acceptable degree of consistency and provides an initial assessment of scale reliability. The number of items and the corresponding alpha coefficient for each construct are presented in Table 3.

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Table 3. Cronbach's alpha reliability test results

Construct	Number of items	Cronbach's alpha
TECH	3	0.781
LEAD	3	0.824
HUMAN	3	0.795
FIN	2	0.746
ENV	3	0.772
AI Adoption	4	0.817

Source: Authors' analysis of the 2026 survey data.

Cronbach's alpha values range from 0.746 to 0.824, exceeding the commonly used 0.70 reference value. LEAD has the highest alpha (0.824), followed by AI Adoption (0.817), while FIN has the lowest value (0.746) and contains two items. These results indicate acceptable internal consistency at the scale level. A fuller assessment would also consider corrected item–total correlations and additional evidence of convergent and discriminant validity.

Following the reliability assessment, exploratory factor analysis (EFA) was used to examine whether the observed variables were suitable for factor extraction and whether the independent-variable items could be organized into the intended underlying factors. The Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's test assess the adequacy of the correlation matrix for factor analysis, while the number of extracted factors and total variance explained summarize the resulting factor solution. The principal EFA indicators reported in the study are presented in Table 4.

Table 4. Exploratory factor analysis (EFA) results

EFA indicator	Reported value
Sample size	138
Observed variables entered into EFA	14
Kaiser–Meyer–Olkin (KMO)	0.782
Bartlett's test	$p < 0.001$
Number of extracted factors	5
Total variance explained	67.35%
Minimum eigenvalue	1.24
Extraction method	Principal Axis Factoring
Rotation method	Promax

Source: Authors' analysis of the 2026 survey data.

The KMO value of 0.782 and significant Bartlett's test ($p < 0.001$) indicate that the data meet basic conditions for factor analysis. The reported five-factor solution explains 67.35% of the total variance, and the minimum eigenvalue is 1.24. The reported pattern matrix shows the 14 observed items loading on the five independent constructs: TECH, LEAD, HUMAN, FIN and ENV. Importantly, the four AI Adoption items are not included in the 14-item EFA matrix presented in the source manuscript. Therefore, the factor structure of the dependent-variable scale requires a separate verification using the original dataset; the reported EFA results should not be interpreted as having validated all six scales together.

To provide a more detailed view of the EFA solution, the pattern coefficients for the observed items are reported by construct. The loading pattern indicates the extent to which each item is associated with its corresponding factor and allows the intended grouping of the five explanatory constructs—TECH, LEAD, HUMAN, FIN and ENV—to be examined. Table 5 presents the reported factor loadings; the four AI Adoption items are not included in this 14-item matrix and therefore require separate verification.

Table 5. Factor loading matrix

Item	TECH	LEAD	HUMAN	FIN	ENV
TECH1	0.812	–	–	–	–
TECH2	0.784	–	–	–	–
TECH3	0.756	–	–	–	–
LEAD1	–	0.845	–	–	–
LEAD2	–	0.813	–	–	–
LEAD3	–	0.779	–	–	–
HUMAN1	–	–	0.806	–	–

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Item	TECH	LEAD	HUMAN	FIN	ENV
HUMAN2	–	–	0.772	–	–
HUMAN3	–	–	0.741	–	–
FIN1	–	–	–	0.831	–
FIN2	–	–	–	0.798	–
ENV1	–	–	–	–	0.792
ENV2	–	–	–	–	0.765
ENV3	–	–	–	–	0.738

Source: Authors' analysis of the 2026 survey data.

2.4.4. Multiple regression results

After assessing the measurement scales, multiple linear regression was used to estimate the direction, relative magnitude and statistical significance of the relationships between the five TOE-related factors and AI adoption. Standardized coefficients facilitate comparison of the relative associations across factors, while the reported p-values indicate whether each association is statistically significant at the 5% level. The coefficient estimates and significance assessments are summarized in Table 6.

Table 6. Multiple linear regression analysis results

Factor	Standardized β	Reported p-value	Significance at 5%
LEAD	0.292	0.001	Significant
TECH	0.248	0.004	Significant
HUMAN	0.187	0.018	Significant
ENV	0.143	0.046	Significant
FIN	0.087	0.091	Not significant

Source: Authors' analysis of the 2026 survey data.

Four factors have positive standardized coefficients and are statistically significant at the 5% level. LEAD has the largest coefficient (β = 0.292), followed by TECH (β = 0.248), HUMAN (β = 0.187) and ENV (β = 0.143). FIN also has a positive coefficient (β = 0.087), but its reported p-value (0.091) does not meet the 5% significance threshold. Accordingly, the results do not provide sufficient evidence to support H4 in this model.

In addition to the individual coefficients, the explanatory and diagnostic statistics are considered to evaluate the overall performance of the regression model. R-squared and adjusted R-squared indicate the proportion of variation in AI adoption accounted for by the predictors, the F-test evaluates the joint statistical significance of the model, and the maximum variance inflation factor (VIF) provides an indicator of potential multicollinearity. The model-fit statistics reported in the manuscript are shown in Table 7.

Table 8. Assessment of regression model fit

Model-fit indicator	Reported value
Number of observations (N)	138
Number of independent variables (k)	5
Residual degrees of freedom	132
R-squared (R^2)	0.720
Adjusted R-squared	0.709
F-statistic (5, 132)	67.886
Significance of F-test	$p < 0.001$
Maximum VIF	3.55

Source: Authors' analysis of the 2026 survey data.

The model reports $R^2 = 0.720$ and adjusted $R^2 = 0.709$. The overall F-statistic is 67.886 ($p < 0.001$), indicating that the set of explanatory variables is statistically significant as a group in the reported model. The maximum VIF is 3.55. These summary indicators should be interpreted alongside the underlying regression output and the measurement-scale verification noted above.

2.4.5. Discussion

The largest standardized coefficient belongs to leadership awareness and commitment (β = 0.292; p = 0.001). This result suggests that managerial direction is particularly relevant to AI adoption among the sampled SMEs. Leaders in SMEs often participate directly in technology

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selection, resource allocation and organizational change. Awareness of AI's potential and commitment to experimentation may help enterprises move from initial exploration to practical implementation. This interpretation is consistent with the organizational-readiness perspective discussed by Jöhnk et al. [10] and with the emphasis on leadership and organizational preparedness reported by Ul Haq and Suki [13]. The present study, however, does not test the mediating mechanisms through which leadership commitment may be associated with AI adoption.

Technological capability is the second strongest factor (β = 0.248; p = 0.004). This finding is consistent with the TOE proposition that the technological context matters for organizational innovation adoption. Adequate digital infrastructure, organized management data and the ability to integrate AI with existing systems may reduce implementation barriers. The result is also broadly consistent with the importance of digital capabilities discussed by Arroyabe et al. [12]. From a managerial perspective, SMEs should assess data quality, system compatibility and infrastructure readiness before expanding AI use. The study does not, however, estimate the separate contribution of each component of technological capability.

Digital human-resource capability is positively associated with AI adoption (β = 0.187; p = 0.018). AI implementation requires employees who can select appropriate tools, formulate tasks, assess outputs and incorporate them into work processes. The result indicates that technology readiness alone may be insufficient if employees lack the skills needed to use and evaluate AI outputs. SMEs may therefore benefit from job-specific training and practical learning opportunities.

The external environment has a positive coefficient (β = 0.143; p = 0.046). Although statistically significant at the 5% level, the p-value is close to the threshold and should be interpreted cautiously. Competitive pressure, customer requirements and the availability of policy or ecosystem support may encourage enterprises to consider AI. Since these elements are measured as a combined construct, the present analysis cannot identify which specific external condition has the strongest association.

Financial resources have a positive but statistically non-significant coefficient (β = 0.087; p = 0.091). This result does not establish that finance is unimportant; rather, the model does not provide sufficient evidence of a statistically significant association at the 5% level. One possible explanation is that some AI services are available through subscription or low-entry-cost models, potentially changing the role of upfront investment in early adoption. This explanation remains speculative because the study does not separately measure AI expenditure, technology budgets or investment models.

Overall, the results suggest that AI adoption in the management of the sampled SMEs should be considered through the combined technological, organizational and environmental contexts of the TOE framework. Leadership commitment, technological capability and employee digital skills emerge as notable correlates. The findings are specific to the sample, locations and cross-sectional design and should not be generalized as causal effects or as nationally representative estimates.

3. CONCLUSIONS AND RECOMMENDATIONS

3.1. Conclusions

This study applied the TOE framework to examine factors associated with AI adoption in the management of Vietnamese SMEs. Based on 138 valid responses from enterprises in Hanoi, Hung Yen and Bac Ninh, the analysis used descriptive statistics, Cronbach's alpha, EFA and multiple linear regression to examine technological capability, leadership awareness and commitment, digital human-resource capability, financial resources and the external environment.

The reported regression results show positive and statistically significant associations at the 5% level for leadership awareness and commitment (β = 0.292), technological capability (β = 0.248), digital human-resource capability (β = 0.187) and the external environment (β = 0.143). Financial resources have a positive coefficient (β = 0.087), but the relationship is not statistically significant at the 5% level (p = 0.091); therefore, H4 is not supported by the reported results. Descriptive findings show that many sampled enterprises remain at the exploration or experimentation stages, while regular AI use is limited.

The findings provide additional empirical insight into the technological, organizational and environmental conditions associated with AI adoption among the surveyed SMEs. They also suggest that managerial commitment, data and infrastructure readiness, and employee digital capability deserve attention when enterprises develop AI adoption plans. Given the convenience sample, cross-sectional design and the need to verify the EFA structure of the AI Adoption scale, the findings should be interpreted within the scope of the data and should not be taken as evidence of causality or as representative of all Vietnamese SMEs.

3.2. Recommendations

Strengthen leadership awareness and commitment. As LEAD has the largest standardized coefficient in the reported model, SME leaders should identify management problems that AI could address, select priority use cases and establish a phased implementation plan. Initial pilots should focus on tasks with clear processes, adequate input data and measurable outputs. Enterprises should assess processing time, output quality, implementation costs and service performance before deciding whether to adjust, maintain or expand a pilot.

Improve technological capability and data governance. SMEs should digitize and standardize management data and establish consistent procedures for data collection, storage, updating and use. They should review existing infrastructure, assess integration with current information systems and select AI solutions that fit operational requirements. Access controls, customer-data protection, input-data quality and cybersecurity risks should be addressed from the outset. Technology investment should be phased and linked to defined management needs.

Develop employees' digital capabilities. Training should be tailored to job roles and cover the use of AI tools, task formulation, output verification, information security and human–AI collaboration. Marketing, customer service, accounting, administration and management teams can practise with tasks drawn from their routine work. Training effectiveness should be assessed by employees' ability to apply skills on the job rather than by participation numbers alone.

Make effective use of external support. SMEs should explore digital-transformation support programmes and collaborate with technology providers, universities and advisory organizations to identify suitable solutions. Public agencies and business-support organizations

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can contribute through accessible guidance, expert connections and practical AI training, particularly for enterprises with clear adoption needs but limited technological or human-resource capacity.

Manage AI investment in line with financial capacity. Although the financial-resource coefficient is not statistically significant at the 5% level, cost and investment-risk management remain practical necessities. SMEs should consider phased deployment, beginning with small-scale pilots. Total cost assessments should include software, operation, employee training, data governance, security and system maintenance. Expected benefits should be tracked through indicators such as time saved, processing costs and service quality.

These recommendations combine managerial direction with preparation in technology, data, human resources and external collaboration. AI adoption should be aligned with each enterprise's size, sector, management objectives and level of readiness. The recommendations are practical implications suggested by the reported statistical associations; they should not be interpreted as interventions whose causal effectiveness has been established.

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