“Cloud computing adoption in education-oriented SMES: From technological conditions to readiness”

AUTHORS	Chinh Thu Vu Huong Thi Lan Le Hai Ninh Nguyen

ARTICLE INFO	Chinh Thu Vu, Huong Thi Lan Le and Hai Ninh Nguyen (2026). Cloud computing adoption in education-oriented SMES: From technological conditions to readiness. *Problems and Perspectives in Management*, *24*(2), 619–631. doi:10.21511/ppm.24(2).2026.42
DOI	http://dx.doi.org/10.21511/ppm.24(2).2026.42
RELEASED ON	Thursday, 25 June 2026
RECEIVED ON	Friday, 30 January 2026
ACCEPTED ON	Friday, 12 June 2026

JOURNAL	"Problems and Perspectives in Management"
ISSN PRINT	1727-7051
ISSN ONLINE	1810-5467
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
28	**2**	**6**

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Chinh Thu Vu (Vietnam), **Huong Thi Lan Le** (Vietnam), **Hai Ninh Nguyen** (Vietnam)

CLOUD COMPUTING ADOPTION IN EDUCATION-ORIENTED SMEs: FROM TECHNOLOGICAL CONDITIONS TO READINESS

Abstract

Cloud computing has become an important infrastructure for digital transformation, yet its adoption remains uneven among education-oriented small and medium-sized enterprises (SMEs), particularly in developing countries. This study examines how technological factors influence cloud computing adoption among education-oriented SMEs, with particular emphasis on the mediating role of organizational technology readiness. A structured online questionnaire survey was conducted with 117 legally registered education-oriented SMEs in Vietnam, including private training centers, EdTech firms, private schools, corporate training providers, and other private education service providers. These firms were selected because they directly provide educational or training services and represent key private-sector users or prospective users of cloud-based solutions. Data were collected from August to October 2025 from one designated key informant in each firm and analyzed using partial least squares structural equation modeling (PLS-SEM). The model explains 59.2% of the variance in organizational technology readiness and 57.5% of the variance in cloud computing adoption. Experience with technology positively affects readiness ($\beta = 0.300$, $t = 4.236$, $p < 0.001$) and adoption ($\beta = 0.366$, $t = 5.040$, $p < 0.001$), whereas perceived privacy and security risk negatively affect readiness ($\beta = -0.407$, $t = 7.342$, $p < 0.001$) and adoption ($\beta = -0.318$, $t = 4.999$, $p < 0.001$). Technology compatibility and technology knowledge influence adoption indirectly through organizational technology readiness. The findings indicate that readiness is a key organizational mechanism through which technological conditions are translated into cloud adoption decisions in education-oriented SMEs.

Keywords cloud computing, adoption, readiness, SMEs, education, Vietnam

JEL Classification L26, O33, M15

Type of the article: Research Article

Received on: 30th of January, 2026
Accepted on: 12th of June, 2026
Published on: 25th of June, 2026

Chinh Thu Vu, Ph.D. Student, Admissions Department, FPT International University Institute, FPT University, Vietnam.

Huong Thi Lan Le, Dr., Associate Professor, Business School, National Economics University, Vietnam.

Hai Ninh Nguyen, Dr., Associate Professor, Department of Marketing and Communications, School of International Business and Economics, Foreign Trade University, Vietnam. (Corresponding author)

Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

In the digital era, rapid advancements in information technology have fundamentally reshaped organizational operations across industries, with education emerging as one of the sectors most strongly affected by digital transformation. Cloud computing (CC) has been increasingly recognized as a core technological infrastructure supporting this process. According to Gartner (2022), global spending on cloud services reached nearly 500 billion USD in 2022 and is expected to continue growing substantially, underscoring the strategic role of CC in contemporary business environments. Prior studies indicate that CC enables SMEs to optimize operational processes, reduce infrastructure costs, and enhance organizational flexibility, while cloud-based solutions have evolved into strategic resources that strengthen firms' adaptability and long-term competitiveness (Lin & Chen, 2012; Jain, 2024).

In the education sector, recent years have witnessed a rapid shift from traditional teaching models toward online and blended learning formats, largely driven by developments in cloud computing technologies. Marston et al. (2011) argue that CC has become a foundational platform enabling education and training organizations to streamline operations, reduce costs, and expand access to learners beyond geographical boundaries. A key advantage of CC is that it provides access to advanced technological services without substantial upfront investment in physical infrastructure (Armbrust et al., 2010). Empirical evidence further suggests that cloud adoption enhances teaching effectiveness and supports adaptive training strategies (Sayginer & Ercan, 2020; Alimboyong & Bucjan, 2021).

Despite these benefits, cloud computing adoption among education-oriented SMEs, particularly in developing countries such as Vietnam, remains uneven and requires closer empirical examination. Although the pay-as-you-go model reduces operational costs, initial deployment, training, and system integration still require significant investment (Ali, 2021; Al-Sharafi et al., 2023). Data security and privacy concerns further constrain adoption in the education sector, where learner data and instructional information require careful protection (Amo-Filva et al., 2024). In Vietnam, national policy has emphasized digital transformation in government, enterprises, and education, including specific initiatives for digital transformation in education and cloud computing platforms (Prime Minister of Vietnam, 2020, 2022, 2025). At the same time, personal data protection requirements have become more explicit under Decree No. 13/2023/ND-CP, making learner-data governance an important issue for cloud adoption (Government of Vietnam, 2023).

Therefore, the existence of technological advantages does not necessarily lead education-oriented SMEs to adopt cloud computing in practice. In many cases, firms may recognize the potential benefits of CC but still face difficulties in converting those conditions into actual adoption decisions. This issue appears particularly important in Vietnam, where education-oriented SMEs are under increasing pressure to digitalize their activities while still facing limitations in resources, technological capability, and organizational preparedness. Thus, the central problem is to explain why technological conditions do not lead uniformly to cloud computing adoption among education-oriented SMEs and under what organizational conditions these factors are translated into actual adoption decisions.

1. LITERATURE REVIEW AND HYPOTHESES

Technology adoption at the organizational level refers to a formal strategic commitment in which a firm integrates a new technology into its core managerial and operational processes, rather than using it experimentally (Rogers, 2003; Ali et al., 2018). Unlike individual-level perspectives that focus on user attitudes, organizational adoption reflects collective decision-making shaped by strategic objectives, governance structures, and internal capabilities. It involves evaluating expected benefits, risks, and organizational fit before implementation (Gangwar et al., 2015). For small and medium-sized enterprises (SMEs), adoption is often driven by competitive and digital transformation pressures but constrained by limited resources (Khayer et al., 2020).

In the education sector, cloud computing (CC) adoption has distinctive features due to the knowledge-intensive nature of services and reliance on digital platforms for instructional delivery and learner data management. In education-oriented SMEs, it is frequently viewed as foundational infrastructure affecting scalability, continuity, and service quality rather than as a peripheral support tool (Jain, 2024; Ekawaty et al., 2025). Adoption decisions are therefore highly sensitive to reliability, performance stability, and data privacy concerns (Nyamwesa, 2024). Given common limitations in IT expertise and budgets, firms often prefer SaaS-based solutions and adopt CC incrementally, from basic instructional functions to more advanced applications (Dincă et al., 2019; Soleman, 2025). These sectoral conditions indicate that technological evaluation, preparedness, and risk perception jointly shape adoption.

The Diffusion of Innovation (DOI) theory explains adoption as a multi-stage process: knowledge, persuasion, decision, implementation, and confirma-

http://dx.doi.org/10.21511/ppm.24(2).2026.42

tion, emphasizing that value emerges through sustained integration (Rogers, 2003). Central to DOI are perceived innovation attributes such as compatibility and complexity, which influence feasibility assessments. In SMEs, where resource constraints heighten sensitivity to disruption, compatibility with existing systems and manageable implementation requirements are especially critical (Gangwar et al., 2015; Dincă et al., 2019; Khayer et al., 2020). The Technology-Organization-Environment (TOE) framework complements DOI by situating adoption within technological, organizational, and environmental contexts (Tornatzky & Fleischer, 1990). While technological attributes may trigger evaluation, organizational conditions determine whether adoption proceeds (Dincă et al., 2019; Ali et al., 2018). Because TOE primarily categorizes determinants rather than clarifying mechanisms, scholars often introduce mediating constructs to explain how technological conditions translate into organizational action (Gangwar et al., 2015; Khayer et al., 2020). In this study, organizational technology readiness is positioned as that mediating capability.

Building on DOI and TOE, the study proposes that CC adoption is shaped by four key technological factors: technology compatibility, technology knowledge, experience with technology, and perceived privacy and security risk, while organizational technology readiness functions as a mediating capability. From a DOI perspective, compatibility reduces perceived disruption by aligning CC with existing infrastructure and routines, thereby lowering adjustment costs and uncertainty (Rogers, 2003). Empirical evidence shows that higher compatibility facilitates integration and strengthens organizational preparation for implementation (Gangwar et al., 2015; Dincă et al., 2019; Khayer et al., 2020). Thus, compatibility is expected to enhance technology readiness.

Technology knowledge enhances a firm's capacity to evaluate CC accurately, anticipate implementation requirements, and allocate resources effectively. By reducing ambiguity and supporting planning and training activities, knowledge strengthens organizational readiness (Erosa, 2013; Kinkel et al., 2022). Firms with greater understanding of cloud technologies are more proactive in preparing infrastructure and competencies (Jain, 2024), whereas limited knowledge may explain reluctance despite perceived benefits (Dincă et al., 2019). Accordingly, technology knowledge is expected to strengthen readiness.

Experience with technology reflects accumulated organizational learning. Prior IT initiatives build routines, skills, and managerial confidence, reducing perceived complexity when approaching CC (Rogers, 2003). Empirical studies show that experienced firms prepare more effectively and demonstrate higher readiness levels (Gangwar et al., 2015; Khayer et al., 2020; Ruslaini et al., 2025). Experience may also directly encourage adoption by shaping favorable expectations (Dincă et al., 2019; Khayer et al., 2020). Therefore, experience is expected to enhance readiness and potentially exert a direct positive effect on adoption.

Perceived privacy and security risk represent a critical inhibitor, particularly in education-oriented SMEs handling sensitive learner data. Concerns regarding breaches and regulatory exposure may discourage preparation and delay adoption (Nyamwesa, 2024). High perceived risk reduces willingness to allocate resources to implementation activities (Ali et al., 2018; Dincă et al., 2019) and may directly suppress adoption (Ali et al., 2018; Nyamwesa, 2024). However, stronger readiness can mitigate risk perceptions through improved governance and safeguards (Ruslaini et al., 2025). Thus, perceived risk is expected to negatively influence readiness and adoption.

Organizational technology readiness reflects the extent to which a firm possesses sufficient infrastructure, human resources, and managerial capabilities to implement CC effectively. Within TOE, readiness is pivotal: even when technological benefits are recognized, adoption is unlikely without adequate implementation capacity. Empirical research consistently identifies readiness as a strong predictor of CC adoption and long-term institutionalization (Gangwar et al., 2015; Khayer et al., 2020). In education-oriented SMEs, readiness ensures instructional continuity, system integration, and data protection compliance (Jain, 2024; Ekawaty et al., 2025). Accordingly, readiness is expected to positively influence CC adoption and mediate the effects of technological antecedents. Previous studies confirm that cloud computing adoption is influenced by technological condi-

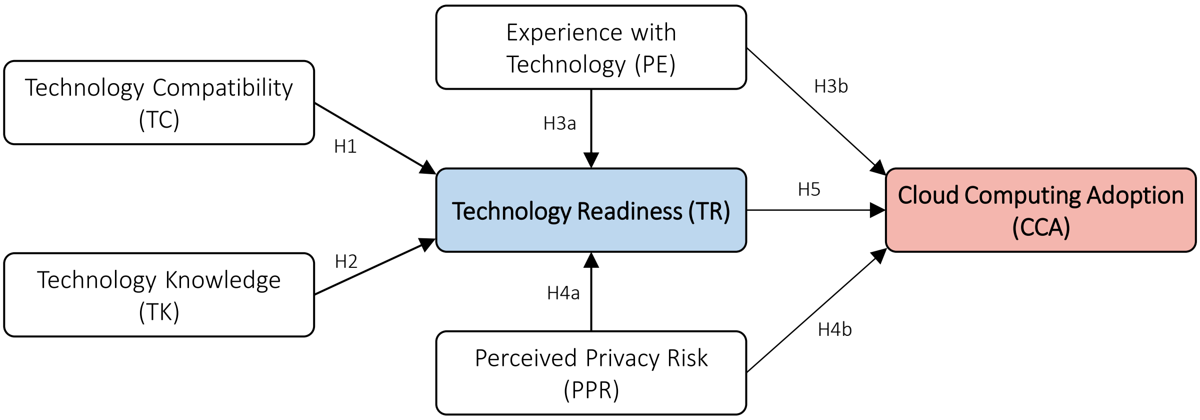

Figure 1. Proposed research model

tions and organizational factors (Gangwar et al., 2015; Khayer et al., 2020; Ali et al., 2018). However, most existing research focuses on general SME populations or large firms, while education-oriented SMEs remain less examined despite their distinctive operational logic and sensitivity to learner-related data (Jain, 2024; Nyamwesa, 2024; Ekawaty et al., 2025). Prior findings on technological factors are also not fully consistent, especially regarding whether such factors influence adoption directly or through internal organizational conditions (Dincă et al., 2019; Khayer et al., 2020; Ruslaini et al., 2025). This suggests the need to clarify how organizational technology readiness translates technological conditions into cloud adoption decisions.

This study aims to examine how technological factors affect cloud computing adoption in education-oriented SMEs and to clarify the mediating role of organizational technology readiness in this process. Figure 1 shows the conceptual model of the study.

Study hypotheses are as follows:

H1: *Technology compatibility positively affects organizational technology readiness.*

H2: *Technology knowledge positively affects organizational technology readiness.*

H3a: *Experience with technology positively affects organizational technology readiness.*

H3b: *Experience with technology positively affects cloud computing adoption.*

H4a: *Perceived privacy and security risk negatively affects organizational technology readiness.*

H4b: *Perceived privacy and security risk negatively affects cloud computing adoption.*

H5: *Organizational technology readiness positively affects cloud computing adoption.*

H6a: *Organizational technology readiness mediates the relationship between technology compatibility and cloud computing adoption.*

H6b: *Organizational technology readiness mediates the relationship between technology knowledge and cloud computing adoption.*

H6c: *Organizational technology readiness mediates the relationship between experience with technology and cloud computing adoption.*

H6d: *Organizational technology readiness mediates the relationship between perceived privacy and security risk and cloud computing adoption.*

2. METHODOLOGY

This study employs a quantitative research design to examine the technological factors influencing cloud computing (CC) adoption among small and medium-sized enterprises (SMEs) operating in the education sector in Vietnam. A deductive approach is adopted, whereby the research model and hypotheses are derived from established theoretical foundations, namely the Diffusion of

http://dx.doi.org/10.21511/ppm.24(2).2026.42

Innovation (DOI) theory and the Technology-Organization-Environment (TOE) framework, as well as prior empirical studies on organizational technology adoption. Given the predictive nature of the model, the inclusion of multiple latent constructs, and the presence of mediation effects, partial least squares structural equation modeling (PLS-SEM) is selected as the primary analytical technique. PLS-SEM is appropriate for this study because it supports prediction-oriented models, handles complex relationships involving mediation, and is suitable for studies with relatively moderate sample sizes.

2.1. Scales development

Data were collected using a structured questionnaire targeting key informants directly involved in technology-related decisions, including owners, managers, senior administrators, and IT/technical staff. This ensured that responses reflected organizational positions rather than individual opinions.

All constructs were operationalized as reflective latent variables using multi-item scales adapted from established studies to ensure theoretical consistency. Items were contextually refined to reflect education-oriented SMEs while preserving original meanings. Technology compatibility was measured with four items adapted from Dincă et al. (2019), Gangwar et al. (2015), Khayer et al. (2020), and Ruslaini et al. (2025). Technology knowledge was measured using items adapted from Gangwar et al. (2015), Jain (2024), Khayer et al. (2020), and Ruslaini et al. (2025). Experience with technology was derived from Dincă et al. (2019), Gangwar et al. (2015), Khayer et al. (2020), and Ruslaini et al. (2025). Perceived privacy and security risk was adapted from Ali et al. (2018), Nyamwesa (2024), Dincă et al. (2019), and Ruslaini et al. (2025). Organizational technology readiness was adapted from Gangwar et al. (2015), Khayer et al. (2020), Ruslaini et al. (2025), and Jain (2024). Cloud computing adoption was operationalized as an organizational-level commitment to using, expanding, or investing in cloud-based solutions for management and training activities. Its items capture regular operational use, planned replacement or extension of existing systems, and resource commitment for implementation, and were adapted from Rogers (2003), Ali et al. (2018), Khayer et al. (2020), Gangwar et al. (2015), and Ruslaini et al. (2025). All items were measured using a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). The questionnaire was reviewed by domain experts and pilot-tested with 20 firms, resulting in minor revisions.

2.2. Sampling and sample characteristics

The unit of analysis in this study is the firm. The target population comprises education-oriented small and medium-sized enterprises (SMEs) operating in Vietnam. In this research, education-oriented SMEs are defined as legally registered independent SMEs whose primary business activities involve educational, training, digital learning, or corporate learning services. This category includes private training centers, EdTech firms, private schools, corporate training providers, and other private education service providers. These firms were included only if they met the Vietnamese government's official SME classification criteria in terms of number of employees and/or annual revenue, operated in the education or training sector, and had adopted or were considering the adoption of cloud computing solutions. Public educational institutions, large educational corporations, and organizations whose education-related activities were only peripheral were excluded from the sample.

Data were collected from August to October 2025 using direct email invitations sent to eligible firms together with a Google Forms survey link. Because a comprehensive sampling frame for education-oriented SMEs in Vietnam was unavailable, a non-probability sampling approach combining purposive and convenience sampling was employed. Potential respondents were identified through publicly available business information, professional networks, and referrals from education and technology-related contacts. Each participating SME provided a single response from a designated key informant who was directly involved in technology-related decision-making or cloud-related operations. Only one questionnaire was collected per firm to ensure that each observation represented an independent organizational unit. A total of 120 questionnaires were distributed, and 117 valid responses were retained after data screening. The majority of respondents were managers or leaders (58.1%) and IT/technical staff (41.9%), ensuring informed organizational perspectives.

Table 1 presents the profile of the participating firms and respondents. The sample covers different types of education-oriented SMEs and includes firms from Northern, Central, and Southern Vietnam. Most firms were relatively small and young, which is consistent with the SME context. However, because the study relies on non-probability sampling, the sample should be interpreted as analytically relevant rather than statistically representative of all education-oriented SMEs in Vietnam.

Table 1. Sample and respondent profile

Characteristics	Category	n	%
Firm type	Private training centers	30	25.6
	EdTech firms	16	13.7
	Private schools	24	20.5
	Corporate training providers	22	18.8
	Other private education service providers	25	21.4
Firm age	Less than 3 years	35	29.9
	3–5 years	39	33.3
	6–10 years	33	28.2
	More than 10 years	10	8.5
Region	Northern Vietnam	43	36.8
	Southern Vietnam	56	47.9
	Central Vietnam	18	15.4
Firm size	Fewer than 10 employees	49	41.9
	10–29 employees	33	28.2
	30–49 employees	24	20.5
	50–99 employees	11	9.4
Respondent position	Managers/leaders	68	58.1
	IT/technical staff	49	41.9

The final sample size was considered adequate for the selected PLS-SEM approach. First, the maximum number of structural paths directed at an endogenous construct is four, meaning that the sample exceeds the minimum requirement suggested by the commonly used 10-times rule. Second, a power calculation based on a medium effect size (f2 = 0.15), $\alpha = 0.05$, statistical power = 0.80, and four predictors indicates a required sample size below 117 observations (Cohen, 1988). Therefore, the sample is sufficient for estimating the proposed predictive PLS-SEM model, although purposive and convenience sampling limits the statistical generalizability of the findings.

2.3. Data analysis and bias assessment

Data analysis was conducted using SmartPLS 4 following a two-stage procedure. First, the measurement model was evaluated by examining internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted – AVE), and discriminant validity (HTMT ratio). Second, the structural model was assessed to test the hypothesized relationships by estimating path coefficients, coefficient of determination (R^2), predictive relevance (Q^2), and effect sizes (f^2). Statistical significance was evaluated using a bootstrapping procedure with 5,000 resamples. The mediating role of organizational technology readiness was examined through bootstrapped indirect effects, including t-values, p-values, and 95% confidence intervals, allowing for a robust assessment of both direct and indirect relationships in the proposed model.

To address potential common method bias (CMB), several procedural and statistical remedies were applied. Procedurally, the questionnaire ensured respondent anonymity and reduced evaluation apprehension to minimize social desirability bias. In addition, measurement items were carefully adapted from validated prior studies and arranged to reduce ambiguity and item patterning. Statistically, Harman's single-factor test was conducted to assess whether a single factor accounted for the majority of variance. The results indicated that the first unrotated factor explained less than 50% of the total variance, suggesting that common method bias was unlikely to be a serious concern. Furthermore, full collinearity variance inflation factors (VIFs) were examined following the approach recommended for PLS-SEM. All full collinearity VIF values were below the conservative threshold of 3.3, indicating that common method bias did not significantly threaten the validity of the findings.

2.4. Ethical considerations

This study was conducted in accordance with national and international research ethics guidelines. Participation in the survey was entirely voluntary. Prior to completing the questionnaire, respondents were informed about the purpose of the

http://dx.doi.org/10.21511/ppm.24(2).2026.42

study, the academic nature of the research, and their right to withdraw at any time without consequences. Informed consent was obtained from all participants. To ensure confidentiality and impartiality, no personally identifiable information was collected. The questionnaire was designed to capture organizational-level perceptions rather than individual evaluations, thereby reducing sensitivity. All responses were anonymized and stored securely. The collected data were used exclusively for academic research purposes and were not shared with any third party.

3. RESULTS AND DISCUSSION

3.1. Measurement model assessment

Prior to testing the causal relationships in the structural model, the measurement model was evaluated to ensure that the constructs were measured reliably and validly. Following the recommendations of Hair et al. (2019) for reflective measurement models in PLS-SEM, the assessment focused on indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, as visualized in Figure 2.

The results of the outer loading analysis (Table 2) indicate that all measurement items exhibit loadings greater than 0.80, well above the recommended threshold of 0.708. This suggests that all indicators strongly represent their corresponding latent constructs and that no item removal was necessary. High and stable loadings further imply that the measurement items were clearly understood by respondents and appropriately captured the technological and organizational characteristics of education-oriented SMEs adopting cloud computing.

At the construct level, Cronbach's alpha and composite reliability (rho_a and rho_c) values for all constructs exceed the recommended threshold of 0.70, with most values above 0.85 (Table 2). These results confirm strong internal consistency reliability across all measurement scales. Constructs directly related to technological aspects (technology knowledge, technology compatibility, and organizational technology readiness) demonstrate particularly high reliability, indicating that they

Table 2. Outer loadings, construct reliability, and convergent validity

Constructs	Items	Measurement statements	Loadings	CA	CR	AVE
Cloud Computing Adoption (CCA)	CCA1	CC is regularly used in management, training delivery, or learner-related activities	0.841	0.842	0.848	0.760
	CCA2	We plan to extend or replace existing systems with cloud-based solutions	0.878			
	CCA3	We will allocate resources to implement and expand CC solutions	0.895			
Experience with Technology (PE)	PE1	Our firm has successfully implemented IT systems	0.848	0.899	0.902	0.768
	PE2	We have experience integrating new technologies	0.899			
	PE3	Prior experience increases confidence in adopting CC	0.884			
	PE4	We are accustomed to adjusting processes for technologies	0.874			
Perceived Privacy and Security Risk (PPR)	PPR1	We fear unauthorized access to data on CC	0.811	0.853	0.862	0.694
	PPR2	CC increases dependence on service providers	0.841			
	PPR3	Ensuring data privacy on CC involves risks	0.871			
	PPR4	CC may threaten learner and training data security	0.808			
Technology Compatibility (TC)	TC1	CC solutions fit our existing IT systems	0.876	0.875	0.889	0.727
	TC2	CC solutions integrate easily with current work processes	0.834			
	TC3	CC solutions fit our management and operational model	0.839			
	TC4	CC solutions effectively support core operations	0.860			
Technology Knowledge (TK)	TK1	We understand key functions of relevant CC solutions	0.833	0.890	0.893	0.751
	TK2	We understand CC benefits for training and management	0.860			
	TK3	Management understands how to implement CC solutions	0.882			
	TK4	Staff possess sufficient knowledge to operate CC	0.891			
Technology Readiness (TR)	TR1	Our IT infrastructure supports CC implementation	0.846	0.853	0.858	0.694
	TR2	We have capable personnel to operate CC	0.812			
	TR3	We have clear processes for managing CC	0.864			
	TR4	We are ready to invest resources in CC	0.809			

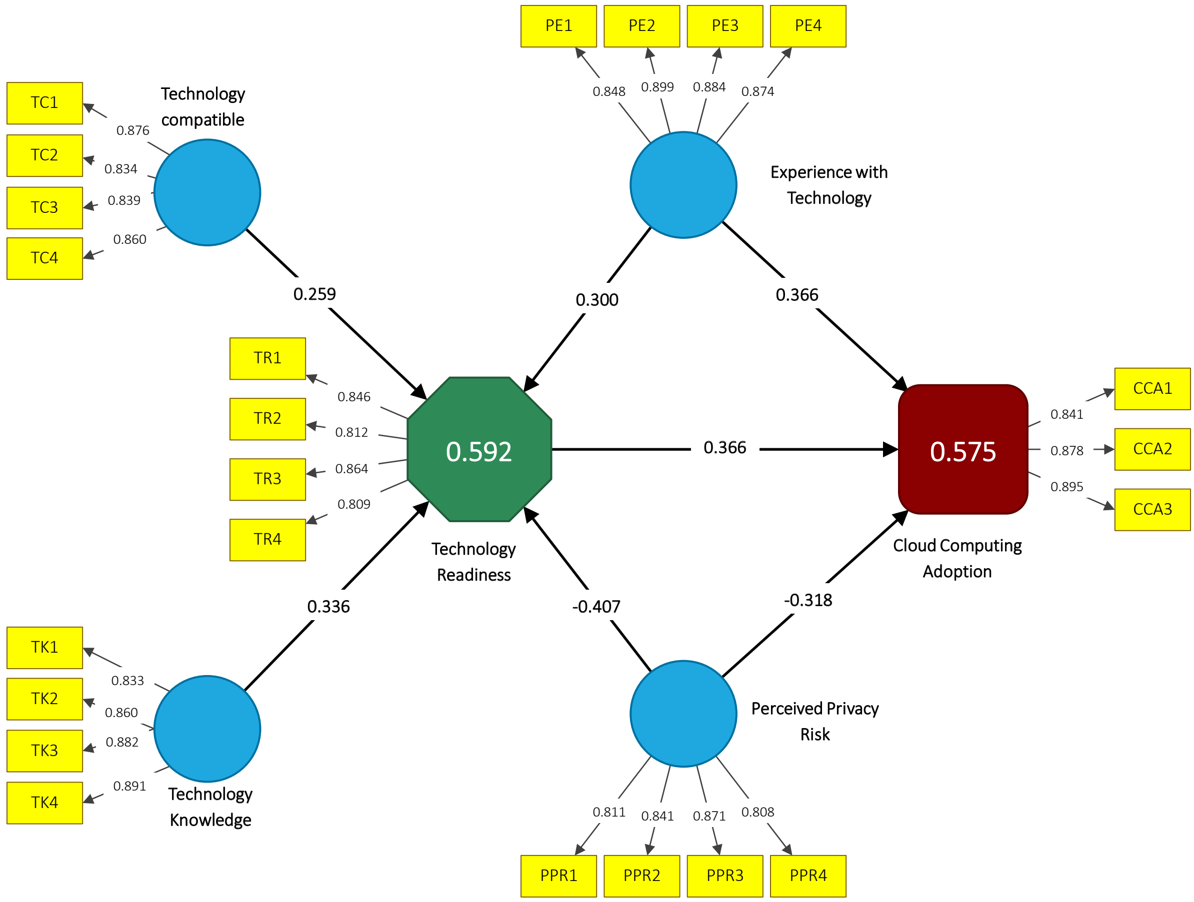

Figure 2. Measurement model assessment

are consistently perceived among education-oriented SMEs in Vietnam. Convergent validity was assessed using average variance extracted (AVE), and all constructs achieved AVE values greater than 0.50, with several exceeding 0.70. This indicates that the latent constructs explain a substantial proportion of variance in their indicators.

Discriminant validity was examined using the HTMT criterion. As reported in Table 3, all HTMT values are below the conservative threshold of 0.85, confirming that the constructs are empirically distinct despite their conceptual relatedness. In addition, the variance inflation factor (VIF) values reported in Table 4 range from 1.012 to 1.807, all well below the conservative threshold of 3.3. This indicates that multicollinearity among the predictor constructs is not a concern and that the estimated path coefficients are stable and reliable.

3.2. Structural model assessment

After confirming the adequacy of the measurement model (Figure 2), the structural model was

Table 3. Discriminant validity (HTMT criterion)

Variable	CCA	PE	PPR	TC	TK	TR
CCA						
PE	0.603					
PPR	0.497	0.109				
TC	0.453	0.438	0.054			
TK	0.374	0.486	0.047	0.181		
TR	0.788	0.582	0.444	0.486	0.588	

Note: PE = Experience with Technology; PPR = Perceived Privacy and Security Risk; TC = Technology Compatibility; TK = Technology Knowledge; TR = Technology Readiness; CCA = Cloud Computing Adoption.

http://dx.doi.org/10.21511/ppm.24(2).2026.42

Table 4. VIF, R2, Q2, and SRMR

Constructs	VIF (CCA)	VIF (TR)	R^2	Q^2	SRMR
Experience with Technology (PE)	1.554	1.437			
Perceived Privacy and Security Risk (PPR)	1.345	1.012			
Technology Compatibility (TC)		1.183			
Technology Knowledge (TK)		1.238			
Technology Readiness (TR)	1.807		0.592	0.394	0.050
Cloud Computing Adoption (CCA)			0.575	0.424	

Note: PE = Experience with Technology; PPR = Perceived Privacy and Security Risk; TC = Technology Compatibility; TK = Technology Knowledge; TR = Technology Readiness; CCA = Cloud Computing Adoption.

evaluated to test the hypothesized relationships. Following Hair et al. (2019), the assessment focused on explanatory power (R^2), predictive relevance (Q^2), overall model fit, and the significance of structural paths.

The results indicate satisfactory explanatory power. The R^2 value for organizational technology readiness (TR) is 0.592, suggesting that approximately 59.2% of the variance in readiness is explained by the technological antecedents in the model. Similarly, cloud computing adoption (CCA) exhibits an R^2 value of 0.575, indicating that 57.5% of the variance in adoption decisions is accounted for by the proposed predictors. These values exceed the commonly accepted threshold of 0.50, demonstrating strong explanatory capability for organizational-level technology adoption research.

Predictive relevance was assessed using the blindfolding procedure. The Q^2 values for TR (0.394) and CCA (0.424) are both positive and substantial, confirming that the model possesses meaningful predictive power beyond the estimation sample. In addition to explanatory and predictive performance, overall model fit was evaluated using the standardized root mean square residual (SRMR). The SRMR value of 0.050 is well below the recommended threshold of 0.08, indicating a good fit between the proposed model and the observed data. Taken together, the R^2, Q^2, and SRMR results suggest that the proposed model provides a robust and well-fitting representation of cloud computing adoption behavior among education-oriented SMEs.

3.3. Hypotheses testing results

Hypotheses were tested using a bootstrapping procedure with 5,000 resamples. The results of the structural model analysis are presented in Table 5.

Experience with technology has a positive effect on organizational technology readiness (β = 0.300, t = 4.236, 95% CI [0.154, 0.435], $p < 0.001$) and cloud computing adoption (β = 0.366, t = 5.040, 95% CI [0.224, 0.505], $p < 0.001$). Perceived privacy and security risk negatively affects both technology readiness (β = –0.407, t = 7.342, 95% CI [–0.513, –0.295], $p < 0.001$) and CC adoption (β = –0.318, t = 4.999, 95% CI [–0.445, –0.195], $p < 0.001$). Technology compatibility (β = 0.259, t = 4.158, 95% CI [0.135, 0.380], $p < 0.001$) and technology knowledge (β = 0.336, t = 5.648, 95% CI [0.219, 0.450], $p < 0.001$) positively influence organizational technology readiness. Organizational

Table 5. Path coefficients, effect sizes, and hypotheses testing

Path	β	t-value	95% CI	f^2	p-value
PE → CCA	0.366	5.040	[0.224, 0.505]	0.203	<0.001
PE → TR	0.300	4.236	[0.154, 0.435]	0.154	<0.001
PPR → CCA	–0.318	4.999	[–0.445, –0.195]	0.177	<0.001
PPR → TR	–0.407	7.342	[–0.513, –0.295]	0.402	<0.001
TC → TR	0.259	4.158	[0.135, 0.380]	0.139	<0.001
TK → TR	0.336	5.648	[0.219, 0.450]	0.223	<0.001
TR → CCA	0.366	4.902	[0.214, 0.506]	0.174	<0.001

Note: PE = Experience with Technology; PPR = Perceived Privacy and Security Risk; TC = Technology Compatibility; TK = Technology Knowledge; TR = Technology Readiness; CCA = Cloud Computing Adoption.

Table 6. Mediation effects of technology readiness

Indirect path	β	t-value	95% CI	p-value
PE → TR → CCA	0.110	3.300	[0.050, 0.179]	0.001
PPR → TR → CCA	−0.149	4.064	[−0.226, −0.081]	< 0.001
TC → TR → CCA	0.095	3.065	[0.040, 0.159]	0.002
TK → TR → CCA	0.123	3.485	[0.060, 0.196]	< 0.001

Note: PE = Experience with Technology; PPR = Perceived Privacy and Security Risk; TC = Technology Compatibility; TK = Technology Knowledge; TR = Technology Readiness; CCA = Cloud Computing Adoption.

technology readiness positively affects CC adoption (β = 0.366, t = 4.902, 95% CI [0.214, 0.506], p < 0.001). All proposed direct hypotheses are supported.

The mediation analysis (Table 6) reveals that organizational technology readiness significantly mediates the effects of experience, technology compatibility, technology knowledge, and perceived privacy and security risk on CC adoption. The bootstrapped indirect effects are significant for PE → TR → CCA (β = 0.110, t = 3.300, 95% CI [0.050, 0.179], p = 0.001), PPR → TR → CCA (β = −0.149, t = 4.064, 95% CI [−0.226, −0.081], p < 0.001), TC → TR → CCA (β = 0.095, t = 3.065, 95% CI [0.040, 0.159], p = 0.002), and TK → TR → CCA (β = 0.123, t = 3.485, 95% CI [0.060, 0.196], p < 0.001). These results support *H6a–H6d* and demonstrate that readiness functions as a key mechanism through which technological conditions are translated into adoption decisions.

The findings provide a more nuanced understanding of organizational cloud computing adoption by situating technological conditions within a capability-based perspective. The positive effect of experience with technology is broadly consistent with prior SME research emphasizing experiential learning as a means of reducing uncertainty and perceived complexity (Gangwar et al., 2015; Khayer et al., 2020). The present results further show that prior experience affects adoption both directly and indirectly through organizational technology readiness. This indicates that, in education-oriented SMEs, accumulated technological experience becomes more consequential when it is institutionalized into infrastructure, processes, and managerial preparedness before strategic commitment occurs.

The negative impact of perceived privacy and security risk corroborates earlier findings identifying risk as a critical inhibitor of cloud adoption (Ali et al., 2018; Nyamwesa, 2024). This effect is particularly salient in the education context, where learner data and instructional content are sensitive and where small firms may lack specialized governance capacity. The finding suggests that sectoral characteristics and institutional capacity constraints intensify the role of perceived vulnerability in shaping cloud adoption behavior.

Consistent with DOI-based arguments, technology compatibility and technology knowledge strengthen organizational technology readiness. However, the model did not specify direct paths from compatibility and knowledge to adoption; therefore, the findings should be interpreted as evidence of indirect pathways through readiness rather than evidence that direct effects are absent. This clarification is important because it shows that favorable technological perceptions may support adoption mainly when they improve internal preparedness for implementation.

From a theoretical perspective, this study contributes to the literature on organizational cloud computing adoption by integrating the Diffusion of Innovation (DOI) theory with the Technology-Organization-Environment (TOE) framework. Rather than treating technological factors as having direct and uniform effects, the findings show that their influence is partly conditional on organizational technology readiness. This advances a more process-oriented explanation of adoption at the organizational level and extends prior research that has often treated readiness as a background organizational attribute rather than as a core explanatory mechanism.

The study also refines existing empirical evidence by clarifying the distinct roles of technological antecedents. Experience and perceived privacy and security risk influence adoption both directly and

http://dx.doi.org/10.21511/ppm.24(2).2026.42

indirectly, whereas compatibility and knowledge operate through readiness within the proposed model. This helps explain why similar technological conditions may lead to different adoption outcomes across organizations, particularly in education-oriented SMEs in a developing-country context.

From a practical perspective, the findings offer important implications for managers of education-oriented SMEs and policymakers responsible for digital transformation in the education sector. For SME managers, cloud computing adoption should be treated as a staged organizational transformation rather than a purely technical procurement decision. The strong role of organizational technology readiness indicates that firms need to invest proactively in internal capabilities, including IT infrastructure, staff skills, and clear implementation processes, before expecting successful cloud adoption outcomes. Managers should also leverage prior technology experience as an organizational learning resource and improve technology knowledge among both managers and operational staff. The negative influence of perceived privacy and security risk highlights the need to strengthen data governance practices, clarify data ownership and access control with providers, and communicate safeguards internally to reduce resistance to adoption.

From a policy perspective, the findings underscore the importance of institutional support in promoting cloud adoption among SMEs. Policymakers can facilitate adoption by developing clearer guidance on educational data protection, cloud security standards, and training programs to strengthen organizational technology readiness. Such initiatives can help reduce perceived risks and support SMEs in translating technological opportunities into sustainable digital transformation.

CONCLUSION

This study aimed to examine how technological factors influence cloud computing adoption in education-oriented SMEs, with particular emphasis on the mediating role of organizational technology readiness. The results show that experience with technology positively affects both readiness and adoption, while perceived privacy and security risk negatively affect these outcomes. Technology compatibility and technology knowledge influence adoption indirectly through organizational technology readiness, and the mediation analysis confirms readiness as a significant mechanism linking technological conditions to adoption. These findings indicate that cloud computing adoption in education-oriented SMEs depends not only on technological characteristics but also on the firm's internal capability to translate these conditions into implementation readiness.

Several limitations should be acknowledged. First, the cross-sectional design does not capture changes in readiness and adoption over time. Second, although the sample size is adequate for PLS-SEM, the use of non-probability sampling and the focus on education-oriented SMEs in Vietnam limit the generalizability of the findings. Third, the use of self-reported data from one key informant per firm may introduce perceptual bias, although procedural and statistical remedies were applied. Future research may adopt longitudinal designs, compare different SME sectors or countries, and incorporate additional organizational and environmental factors such as leadership support, competitive pressure, or regulatory conditions.

AUTHOR CONTRIBUTIONS

Conceptualization: Huong Thi Lan Le, Hai Ninh Nguyen.
Data curation: Chinh Thu Vu.
Formal analysis: Chinh Thu Vu, Huong Thi Lan Le.
Methodology: Huong Thi Lan Le, Hai Ninh Nguyen.
Project administration: Huong Thi Lan Le, Hai Ninh Nguyen.

Resources: Chinh Thu Vu.
Software: Chinh Thu Vu.
Supervision: Huong Thi Lan Le, Hai Ninh Nguyen.
Validation: Chinh Thu Vu, Hai Ninh Nguyen.
Visualization: Chinh Thu Vu.
Writing – original draft: Chinh Thu Vu, Huong Thi Lan Le, Hai Ninh Nguyen.
Writing – review & editing: Chinh Thu Vu, Huong Thi Lan Le, Hai Ninh Nguyen.

DECLARATION ON THE USE OF AI STATEMENT

In preparing this manuscript, the authors used ChatGPT (OpenAI) solely to improve grammar, clarity, and overall readability. The research design, theoretical framework, data collection, statistical analysis, and interpretation of results were conducted independently by the authors. The authors take full responsibility for the content of the publication.

REFERENCES

1. Amo-Filva, D., Fonseca, D., García-Peñalvo, F. J., Forment, M. A., Guerrero, M. J. C., & Godoy, G. (2024). Exploring the landscape of learning analytics privacy in fog and edge computing: A systematic literature review. *Computers in human behavior*, *158*, 108303. https://doi.org/10.1016/j.chb.2024.108303
2. Al-Sharafi, M. A., Iranmanesh, M., Al-Emran, M., Alzahrani, A. I., Herzallah, F., & Jamil, N. (2023). Determinants of cloud computing integration and its impact on sustainable performance in SMEs: An empirical investigation using the SEM-ANN approach. *Heliyon*, *9*(5), e16299. https://doi.org/10.1016/j.heliyon.2023.e16299
3. Ali, M. B. (2021). Multi-Perspectives of Cloud Computing Service adoption quality and Risks in Higher Education. *In Handbook of Research on Modern Educational Technologies, Applications, and Management* (pp.1-19). IGI Global https://doi.org/10.4018/978-1-7998-3476-2.ch001
4. Ali, M. B., Wood-Harper, T., & Mohamad, M. (2018). Benefits and Challenges of Cloud Computing Adoption and Usage in Higher Education: A Systematic Literature Review. *International Journal of Enterprise Information Systems*, *14*(4), 14. https://doi.org/10.4018/ijeis.2018100105
5. Alimboyong, C. R., & Bucjan, M. E. (2021). Cloud computing adoption among state universities and colleges in the Philippines: Issues and challenges. *International Journal of Evaluation and Research in Education (IJERE), 10*(4), 1455. https://doi.org/10.11591/ijere.v10i4.21526
6. Armbrust, M., Fox, A., Griffith, R., Joseph, A. D., Katz, R., Konwinski, A., Lee, G., Patterson, D., Rabkin, A., Stoica, I., & Zaharia, M. (2010). A view of cloud computing. *Communications of the ACM, 53*(4), 50-58. https://doi.org/10.1145/1721654.1721672
7. Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
8. Dincă, V. M., Dima, A. M., & Rozsa, Z. (2019). Determinants of cloud computing adoption by Romanian SMEs in the digital economy. *Journal of Business Economics and Management (JBEM)*, *20*(3), 798-820. https://doi.org/10.3846/jbem.2019.9856
9. Ekawaty, A., Rizky, A., Ramadan, A., & Ndlovu, Z. (2025). Digital transformation strategies for effective business management in SMEs: A SmartPLS approach. *Aptisi Transactions on Management (ATM), 9*(1), 60-71. https://doi.org/10.33050/atm.v9i1.2410
10. Erosa, V. E. (2013). Technology policy implementation road: Exploring firms' technology readiness in a mandatory vertical diffusion environment. *Journal of Service Science and Management, 6*(5), 20-31. Retrieved from https://scispace.com/papers/technology-policy-implementation-road-exploring-firms-2l3ghqc3w7
11. Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management, 28*(1), 107-130. https://doi.org/10.1108/jeim-08-2013-0065
12. Gartner. (2022, October 31). *Gartner forecasts worldwide public cloud End-User spending to reach nearly $600 billion in 2023* (Press Release). Retrieved from https://www.gartner.com/en/newsroom/press-releases/2022-10-31-gartner-forecasts-worldwide-public-cloud-end-user-spending-to-reach-nearly-600-billion-in-2023
13. Government of Vietnam. (2023). *Decree No. 13/2023/ND-CP on personal data protection.* (In Vietnamese). Retrieved from https://vanban.chinhphu.vn/?docid=207408&pageid=27160
14. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

http://dx.doi.org/10.21511/ppm.24(2).2026.42

15. Jain, P. (2024). Cloud adoption strategies for small and medium enterprises (SMEs): A comprehensive guide to overcoming challenges and maximizing benefits. *Scholars Journal of Engineering and Technology, 12*(01), 28-30. https://doi.org/10.36347/sjet.2024.v12i01.003

16. Khayer, A., Talukder, M. S., Bao, Y., & Hossain, M. N. (2020). Cloud computing adoption and its impact on SMEs' performance for cloud supported operations: A dual-stage analytical approach. *Technology in Society, 60,* Article 101225. https://doi.org/10.1016/j.techsoc.2019.101225

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

18. Lin, A., & Chen, N. (2012). Cloud computing as an innovation: Percepetion, attitude, and adoption. *International Journal of Information Management, 32*(6), 533-540. https://doi.org/10.1016/j.ijinfomgt.2012.04.001

19. Marston, S., Li, Z., Bandyopadhyay, S., Zhang, J., & Ghalsasi, A. (2011). Cloud computing – The business perspective. *Decision Support Systems, 51*(1), 176-189. https://doi.org/10.1016/j.dss.2010.12.006

20. Nyamwesa, A. (2024). Cloud computing technology adoption: Challenges for SMEs, a case of selected SMEs in Tanzania. *International Journal of Advanced Business Studies, 3*(2), 1-12. https://doi.org/10.59857/ijabs.3118

21. Prime Minister of Vietnam. (2020). *Decision No. 749/QD-TTg approving the national digital transformation program to 2025, with orientation to 2030.* (In Vietnamese). Retrieved from https://vanban.chinhphu.vn/default.aspx?docid=200163&pageid=27160

22. Prime Minister of Vietnam. (2022). *Decision No. 131/QD-TTg approving the scheme on strengthening information technology application and digital transformation in education and training during 2022–2025, with orientation to 2030.* Retrieved from https://vanban.chinhphu.vn/default.aspx?docid=205236&pageid=27160

23. Prime Minister of Vietnam. (2025). *Decision No. 1121/QD-TTg approving the national action program for development and transition to cloud computing platforms during 2025-2030.* (In Vietnamese). Retrieved from https://vanban.chinhphu.vn/?docid=213903&pageid=27160

24. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

25. Ruslaini, R., Supratikno, H., & Hariandja, E. S. (2025). Current challenges of organizational learning and cloud adoption technology toward SMEs' performance. *International Journal of Innovative Research and Scientific Studies, 8*(3), 1486-1496. https://doi.org/10.53894/ijirss.v8i3.6825

26. Sayginer, C., & Ercan, A. (2020). Multi-perspective decision-making cloud computing adoption model for small and medium enterprises (SMEs). *Emerging Science Journal, 4*(si), 141-143. https://doi.org/10.28991/esj-2021-SP1-010

27. Soleman, S. (2025). A comparative analysis of cloud-based information systems adoption in small and medium enterprise. *RIGGS Journal of Artificial Intelligence and Digital Business, 4*(2), 3513-3518. https://doi.org/10.31004/riggs.v4i2.1050

28. Tornatzky, L. G., & Fleischer, M. (1990). *Processes of technological innovation*. Lexington Books.