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PAPER

Understanding Student Engagement with Mobile Learning: A Structural Model for Interactive Education in Vietnam

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ABSTRACT

The factors that impact the willingness of Vietnamese secondary school students to embrace mobile learning are examined in this study using the framework of the technology acceptance model (TAM). The study utilized a quantitative research approach, and data were gathered accordingly from 611 students via structured questionnaires. The research focused on critical variables, including perceived usefulness (PU), perceived ease of use (PEU), perceived mobility (PM), social influence (SI), self-efficacy (SE), learning autonomy (LA), and perceived enjoyment (PE). Covariance-based structural equation modeling (CB-SEM) was utilized to analyze the relationships among these variables. The findings revealed that PU, PEU, and PE significantly affect students' behavioral intention (BI) to adopt mobile learning. At the same time, external factors such as PM, SI, SE, and LA indirectly shape PU and PEU. These results deepen the understanding of mobile learning adoption within the Vietnamese educational context and underscore the need for targeted policy development to foster student engagement with mobile technologies. This study contributes to the broader educational technology literature, offering valuable insights for educators and policymakers aiming to optimize learning experiences through mobile platforms.

KEYWORDS

technology acceptance model (TAM), structural equation modeling (SEM), mobile learning, mobile devices, acceptance

1 INTRODUCTION

1.1 Evolution of technology in education

Education in the early 21st century has witnessed digital technology's deep and broad integration. It offers new options for presenting learning information and

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engaging students [1], encouraging lifelong learning to prepare for a rapidly changing world of global connectivity and collaboration [2]. In particular, the integration of ICT in developing countries improves learning outcomes when technology is appropriately tailored to specific educational constraints and needs [3]. Many generations of technology have been deployed in education, from primitive, non-digital tools like the abacus to electronic devices [4]. Mobile technology has become increasingly prevalent among teachers and students, facilitating learning that can occur anytime and anywhere. This growing integration of mobile devices has fully realized the concept of mobile learning (m-learning), a trend that UNESCO has highlighted since 2013 [5]. Smartphones are integral to modern education, with high penetration rates among school-age populations, especially teenagers [6], [7]. The COVID-19 pandemic has accelerated this trend and highlighted the need for flexible learning [8], [9]. As a result, mobile technology offers ease of use and accessibility, allowing learning to occur anytime and anywhere [10], [11], [12], and [13].

1.2 Mobile devices as versatile educational tools

The widespread availability of broadband technology, coupled with increasingly affordable prices and diverse features, has led to the pervasive presence of mobile technology in educational settings [14]. Mobile technology has positively impacted students by fostering constructivist learning and enhancing student behavior. It has also transformed learning spaces and promoted collaborative, informal, and self-directed learning [15]. Mobile applications, in particular, have simplified learning for students in various subjects, such as science, mathematics, language, art, and social [6], [13]. For instance, Duolingo has revolutionized language learning by providing interactive lessons and personalized student feedback, making the process engaging and effective [16]. In another case, the mobile app Ubiquitous-Fraction creates opportunities to learn fractions in a daily context [17]. An augmented reality app developed for STEM education recently allows students to analyze environmental data, such as harmful algal blooms, thereby integrating mathematical analysis with real-world problems [18]. This approach helps students delve into complex concepts of the subject and helps connect academic concepts with their practical applications.

Mobile devices offer several advantages over traditional educational tools, making them increasingly integral to modern learning environments [13], [19]. One of the primary advantages is their flexibility and accessibility. With the "anytime and anywhere" characteristics of mobile technology [20], [21], [22], students can access educational resources and conduct learning activities outside of regular school locations and times [23]. The second advantage is the ability to personalize learning through mobile apps. These apps allow learning according to individual needs, style, and pace, thereby creating a more effective learning experience. They also create a collaborative workspace [21] where students can connect, share, and discuss without being limited by geographical scope [14]. These learning conditions encourage and motivate learning [24], [25], [26].

Although incorporating mobile technology into education offers numerous benefits, it has disadvantages and limitations. First, students may be uncomfortable with technical constraints such as limited hardware, connectivity issues, and slow download speeds [27]. Second, mobile devices, with their diverse functionalities and access to social media, games, and other entertainment, can quickly become sources of distraction for students [21], [27]. This can decrease focus on academic tasks and hinder learning outcomes if not managed effectively. The potential for misuse, such as cheating during assessments or accessing inappropriate content, is also a significant concern [28]. Third, misuse of mobile devices can lead to health or psychological problems, such as eye strain, sleep disorders, addiction, and anxiety.

The successful implementation of mobile learning in educational contexts critically depends on its widespread acceptance [29]. However, achieving this acceptance for mobile learning presents significant challenges [22], [30]. The numerous obstacles to mobile learning require examining various factors influencing its acceptance. Many empirical studies have substantiated the original variables of the technology acceptance model (TAM)—namely, perceived usefulness (PU), perceived ease of use (PEU), and attitude [22], [31]. Additionally, some external variables that affect these original variables have been mentioned in the literature, although with comparatively weaker influence, such as self-efficacy (SE), subjective norm, enjoyment, system quality, and information quality [10], [22]. The trend of scholarly inquiry into the determinants of mobile learning acceptance continues to grow, as evidenced by the increasing number of publications each year [10], [31], and [32]. Primarily, these studies adopt a quantitative approach and are mainly situated within Asian contexts [22]. However, [22] further advocates diversifying this study to include learners from various cultural regions and educational levels. Their meta-analysis indicates that the relationships between external and original variables of TAM and the interrelationships among these original variables are notably more pronounced within Asian geographical contexts. Despite existing investigations into mobile learning acceptance [22], [28], [32], there remains a pressing need for further research, considering the distinct educational environments across different cultures.

1.3 Relevance to the Vietnamese education system

Smartphones have become integral to everyday life in Vietnam, reflecting the country's rapid social advancement. In 2022, Vietnam's ICT infrastructure ranks 70th out of 132 countries surveyed by the World Intellectual Property Organization [33]. In 2020, the percentage of households with Internet connectivity is 74.8%, 1.4 times higher than the global average of 57.4% [34]. Vietnam is the second-largest exporter of mobile phones in the world [34]. Additionally, the number of smartphone users in Vietnam ranks 10th globally, comprising 63.1% of the population [35]. According to a report by UNICEF [36], children under 18 comprise 27% of Vietnam's population. In this report, a survey conducted on 994 children aged 12–17 revealed that the internet penetration rate among this age group was 89% in 2020, increasing as children age. Notably, 98% of these children access the Internet via mobile devices, and 74% use the Internet at school. Additionally, 87% of children aged 12–17 go online at least once a day, with 72% engaging in school-related activities online at least once a week.

In line with the country's digital transformation trend, the Vietnamese Ministry of Education and Training has invested heavily in facilities and training staff and teachers to bring technology into schools more effectively. The new general education program, implemented in 2018, sets requirements for students' computer literacy and the use of digital tools and automated systems, emphasizing the importance of technological competence [37].

In Vietnam, the educational context significantly influences the factors affecting acceptance. Historically, Vietnam's education system has been heavily influenced by Confucian ideals and remains exam-oriented, as seen in the national high school graduation exam determining university admissions [38]. Additionally, the weak self-learning ability of students in Vietnam poses a challenge to the feasibility of mobile learning. [39] indicates that while most Vietnamese students own a mobile phone, approximately 12.6% need access to the Internet to find suitable educational resources, which hampers their ability to self-study effectively. Furthermore, existing research on the adoption of mobile learning in secondary schools needs to be enhanced [6], [27]. Studies of this field in Vietnam have primarily focused on university students [40], [41], [42], [43] or on EFL learners in secondary education [7], [44]. The investigation of secondary school students' acceptance of smartphones in Vietnam is crucial for improving the effective integration of technology in education and addressing existing gaps.

In the given context, this study's research question is, "What factors influence Vietnamese high school students' acceptance of mobile learning?"

2 THEORETICAL FRAMEWORK

The TAM [45] provides a theoretical framework to determine the factors influencing technology acceptance. It is applicable across various technologies and user groups while remaining concise and theoretically sound. The model focuses on two primary beliefs: PU, which is the user's belief that using technology will enhance their job performance, and PEU, defined as the expectation that the technology will be effortless to use. TAM posits that actual technology usage is determined by behavioral intention (BI), influenced by the user's attitude toward using the technology and its PU. TAM further suggests that PEU directly affects both PU and attitude and then impacts behavioral intention.

Subsequent studies have proposed numerous external variables that impact the fundamental constructs in [45]. In this study, we examine several external variables that have been utilized in [46] (refer to Table 1) and propose a lens for our research based on these extensions to the TAM (see Figure 1).

Table 1. Definitions of external variables

Variable	Definition
Perceived Mobility (PM)	Perceived mobility refers to the extent to which high school students believe they can engage in learning activities using mobile technology anytime and anywhere, enabled by internet connectivity.
Social Influence (SI)	Social influence encompasses the impact of peers, teachers, and parents on high school students' decisions to use mobile technology for learning.
Self-Efficacy (SE)	Self-efficacy pertains to students' confidence in their ability to effectively utilize mobile technology for learning tasks, such as engaging with educational content and collaborating using social technologies.
Learning Autonomy (LA)	Learning autonomy refers to high school student's ability to set learning objectives and manage their progress using mobile technology.
Perceived Enjoyment (PE)	Perceived enjoyment is the degree to which high school students find learning activities using mobile technology to be enjoyable, reflecting their intrinsic motivation.

These external variables are selected based on their significant influence on mobile learning adoption among Vietnamese secondary school students. Perceived mobility (PM) is essential because it highlights the flexibility and accessibility of mobile environments, enabling students to engage with educational content anytime and anywhere. SI plays a vital role in influencing students' attitudes and behaviors, especially in collectivist cultures such as Vietnam, where encouragement from peers and teachers greatly affects technology adoption. SE affects students' confidence in using mobile learning tools effectively, directly influencing their engagement and persistence. LA is increasingly relevant as mobile learning supports self-directed education, empowering students to take ownership of their learning process. PE boosts motivation, as teenagers who find mobile learning enjoyable are more likely to adopt and integrate it into their learning routines.

Based on the research model in Figure 1, eighteen hypotheses (H1 to H18) will be examined. Each hypothesis relates a significant positive direct effect between two variables. This study will also look at the impacts of two moderator factors, "gender" and "mobile learning experience," on these outcomes.

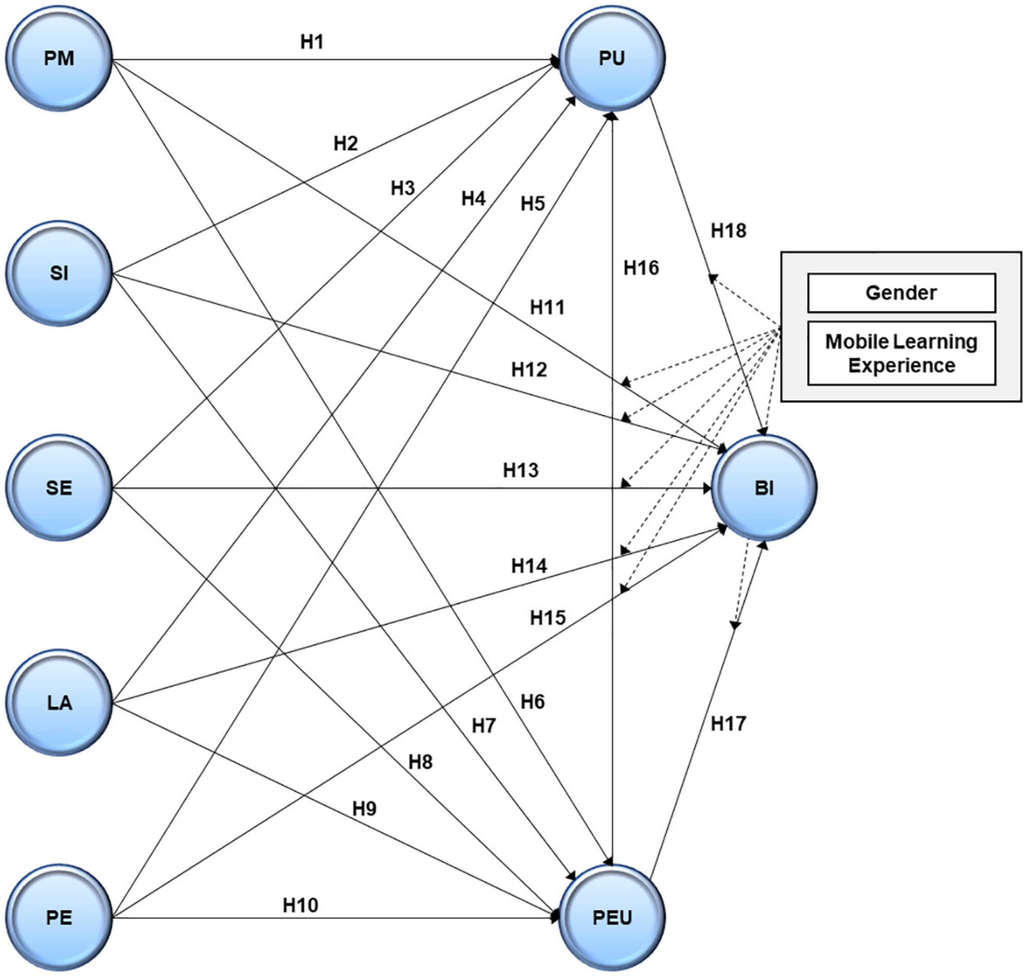

Fig. 1. Conceptual research model

3 METHOD

3.1 Participant and data collection

The study adopted a quantitative approach. Data were collected using questionnaires distributed to 945 Vietnamese high school students from July to October 2021.

After removing statistically insignificant responses, the remaining 611 observation samples were analyzed. The study adhered to ethical standards commonly upheld in educational research, ensuring informed consent from all participants. Although no significant ethical concerns were identified, the study acknowledges the importance of safeguarding student data privacy, particularly given the sensitive nature of self-reported responses. To this end, all data were anonymized prior to analysis to prevent the identification of individual participants. Regarding gender, females accounted for 61.4%, while males accounted for 38.6%. Regarding technology usage experience, 43.0% of students frequently used technology for learning, while 57.0% had limited experience. Specifically, 87.9% of students used smartphones for learning, 60.6% used laptops, and 17.3% used tablets.

This study's primary data collection instrument was a structured questionnaire administered to participants via a Google Forms link. This method ensured a systematic approach to gathering self-reported data. The questionnaire was designed to capture various aspects of students' experiences and perceptions of mobile learning. The study adhered to ethical guidelines commonly established in educational research, prioritizing participant rights and confidentiality. Informed consent was obtained from all participants before their involvement, ensuring they were fully aware of the study's purpose and their rights as participants. No significant ethical concerns arose during the data collection process. Nevertheless, given the sensitive nature of self-reported data, special care was taken to maintain participants' privacy. All responses were anonymized before analysis, safeguarding individual identities by best ethical practices [47].

3.2 Instrument

The questionnaire consisted of two main sections. Section a collected demographic information, including grade level, gender, school location, mobile device types, how long these devices were accessed, and the average daily usage time. Section B consisted of eight groups of items aligned with the eight variables shown in Figure 1. Each group consisted of four questions rated on a 5-point Likert scale (1 – Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree). The questions were adapted from a validated mobile learning questionnaire for Indonesian students created by [46]. They were translated into Vietnamese and carefully modified to suit Vietnam's educational context and cultural nuances. This adaptation process involved a review by a bilingual expert in the science of education and a pilot test with a small group of Vietnamese high school students to ensure clarity, relevance, and appropriateness. This approach aimed to maintain the validity of the original questionnaire while customizing it for the target audience population.

3.3 Data analysis

Data analysis was conducted using SPSS version 24 and AMOS version 25. Covariance-based structural equation modelling (CB-SEM) was employed to examine both the measurement and structural models. The analysis followed three major steps [48]:

Step 1. Assessment of the measurement model. The measurement model was first assessed to understand the relationships among the observed variables. This involved examining internal consistency reliability, convergent validity, and discriminant validity [49]. Cronbach's alpha (CRA) and composite reliability (CR) were used to assess internal consistency. CRA measures the degree of correlation among items within a scale [50].

Step 2. Assessment of the structural model. Next, the structural model was evaluated to examine the relationships between the latent variables. This involved assessing the overall model fit, the path coefficients (β) within the structural model, and the coefficient of determination (R^2) for the dependent variables.

Step 3. Multi-group analysis. Following hypothesis testing, multi-group analysis was conducted to explore differences between specific student subgroups, particularly across gender and mobile learning experience groups. This analysis sought to identify any statistically significant differences in path coefficients and other parameter estimates between the predefined groups.

4 RESULTS

4.1 Description of sample

Table 2. Descriptive statistics of model variables

Indicator	Mean	Median	Standard Deviation	Skewness	Kurtosis
PM1	3.611	4.000	0.959	–0.619	–0.043
PM2	3.583	4.000	0.987	–0.616	–0.171
PM3	3.941	4.000	0.896	–1.214	1.997
PM4	3.894	4.000	0.847	–0.979	1.790
SI1	3.224	3.000	0.794	–0.087	0.378
SI2	3.234	3.000	0.841	–0.149	0.160
SI3	3.072	3.000	0.920	–0.232	–0.036
SI4	3.519	4.000	0.775	–0.413	1.081
SE1	3.732	4.000	0.795	–0.736	1.128
SE2	3.288	3.000	0.942	–0.178	–0.361
SE3	3.429	3.000	0.960	–0.288	–0.345
SE4	3.485	4.000	0.878	–0.513	0.132
LA1	3.475	4.000	0.820	–0.500	0.294
LA2	3.339	3.000	0.854	–0.346	–0.083
LA3	3.393	4.000	0.857	–0.472	–0.099
LA4	3.396	3.000	0.796	–0.323	0.142
PE1	3.015	3.000	0.954	–0.086	–0.292
PE2	3.177	3.000	0.931	–0.334	0.130
PE3	3.110	3.000	0.910	–0.166	0.122
PE4	3.087	3.000	0.932	–0.246	0.088
PU1	3.403	3.000	0.892	–0.491	0.205

(Continued)

Table 2. Descriptive statistics of model variables *(Continued)*

Indicator	Mean	Median	Standard Deviation	Skewness	Kurtosis
PU2	3.363	3.000	0.908	–0.491	0.069
PU3	3.061	3.000	0.959	–0.155	–0.228
PU4	3.116	3.000	0.982	–0.130	–0.143
PEU1	3.246	3.000	0.849	–0.265	0.063
PEU2	3.471	4.000	0.760	–0.465	0.650
PEU3	3.445	3.000	0.773	–0.445	0.479
PEU4	3.416	3.000	0.804	–0.455	0.454
BI1	3.219	3.000	0.974	–0.269	–0.306
BI2	3.229	3.000	0.914	–0.185	–0.052
BI3	3.232	3.000	0.928	–0.391	–0.122
BI4	3.160	3.000	0.974	–0.262	–0.144

The sample utilized in this study demonstrated a normal distribution [51], as evidenced by the near equivalence of the mean and median, with absolute skewness and kurtosis values falling below 2 (refer to Table 2).

4.2 Exploratory factor analysis

Before conducting the confirmatory measurement model using CB-SEM, an exploratory factor analysis (EFA) was carried out to condense or eliminate inappropriate observed variables in the scale [48]. As the model identified independent variables (PM, SI, SE, LA, PE), mediating variables (PEU, PU), and dependent variables (BI), we performed separate EFAs for each type of variable using principal component analysis (PCA) with Varimax orthogonal rotation. The calculation of CRA, and EFA for the formal research model yielded results as shown in Table 3.

Table 3. Reliability and validity results for the measurement scale

Independent Variable							
Factor	Indicator	CRA	Factor Loading				
			1	2	3	4	5
PM	PM1	0.839					0.654
	PM2						0.714
	PM3						0.786
	PM4						0.777
SI	SI1	0.856				0.804	
	SI2					0.807	
	SI3					0.605	
	SI4					0.695	

(Continued)

Table 3. Reliability and validity results for the measurement scale *(Continued)*

Independent Variable							
Factor	**Indicator**	**CRA**	**Factor Loading**				
			1	**2**	**3**	**4**	**5**
SE	SE1	0.904		0.695			
	SE2			0.867			
	SE3			0.841			
	SE4			0.775			
LA	LA1	0.899			0.750		
	LA2				0.867		
	LA3				0.803		
	LA4				0.803		
PE	PE1	0.947	0.796				
	PE2		0.836				
	PE3		0.879				
	PE4		0.862				
KMO = 0.913; $Sig_{Bartlett's\ Test}$ = 0.000; Eigenvalue = 1.107; TVE = 72.713%							
Mediating Variable							
Factor	**Indicator**	**CRA**	**Factor Loading**				
			6	**7**			
PEU	PEU1	0.918		0.628			
	PEU2			0.878			
	PEU3			0.881			
	PEU4			0.885			
PU	PU1	0.904	0.807				
	PU2		0.794				
	PU3		0.887				
	PU4		0.775				
KMO = 0.878; $Sig_{Bartlett's\ Test}$ = 0.000; Eigenvalue = 1.371; TVE = 74.625%							
Dependent Variable							
Factor	**Indicator**	**CRA**	**Factor Loading**				
			8				
BI	BI1	0.948	0.902				
	BI2		0.897				
	BI3		0.927				
	BI4		0.927				
KMO = 0.860; $Sig_{Bartlett's\ Test}$ = 0.000; Eigenvalue = 3.336; TVE = 83.393%							

The reliability assessment, based on the CRA coefficients presented in Table 3, demonstrates a high level of reliability, with all CRA values exceeding 0.8 and inter-item correlations above 0.3. Consequently, no observed variables were excluded from the model [52]. All 32 observed variables were retained for the subsequent EFA. The criteria for factor analysis were met, with a Kaiser-Meyer-Olkin (KMO) index greater than 0.5 and a statistically significant Bartlett's test ($p < 0.05$). These results confirm the adequacy of the data for factor analysis and sufficient intercorrelations among the variables [53].

The results from Table 3 satisfy these criteria, indicating that the data meet the conditions for factor analysis. Subsequently, separate EFAs were conducted for each type of variable (PM, SI, SE, LA, PE), mediating variable (PEU, PU), and dependent variable (BI) using PCA with Varimax orthogonal rotation. The TVE values in Table 3 are all above 50%, meeting the requirement and demonstrating that the factors account for more than 50% of the data variance [54]. All factor loadings exceed 0.5, indicating practical significance [55]. Additionally, the differences between the component variables of the two factors are above 0.3 [56], ensuring convergence and discrimination of the factors during EFA. Furthermore, there is no overlap of observed variables between the factors, indicating that the observed variables of one factor are not mixed with those of another. Therefore, the proposed factors were retained after conducting the EFA.

4.3 Confirmatory factor analysis

Convergent validity and reliability. An evaluation was conducted using CRA and CR coefficients to assess the reliability of the measurement scale [57]. Table 3 indicates that all CRA coefficients exceed the value of 0.8, demonstrating high internal consistency of the measurement scales. Additionally, based on the findings in Table 4, the CR coefficients for all constructs are greater than 0.7, with the lowest being the PM factor with $CR_{PM} = 0.840$. Therefore, the study results indicate that the measurement scales meet the reliability requirements.

Table 4. Convergent validity and reliability analysis

Variable	Factor Loadings	CR	AVE
PM	0.654–0.786	0.842	0.571
SI	0.605–0.807	0.822	0.546
SE	0.695–0.867	0.878	0.644
LA	0.750–0.867	0.870	0.628
PE	0.796–0.879	0.936	0.786
PEU	0.628–0.885	0.895	0.682
PU	0/775–0.887	0.874	0.636
BI	0.897–0.927	0.934	0.780

The factor loading column of the confirmatory factor analysis results is presented in Table 4 and Figure 2, indicating the standardized factor loadings of the component variables of the scales. The coefficients within this column range from 0.605 to 0.927, all exceeding the threshold of 0.5 [54]. Moreover, the average variance extracted (AVE) values satisfy the requisite criteria, with all values surpassing 0.5 [55]. Notably, the lowest AVE value is attributed to factor SI, with $AVE_{SI} = 0.546$. Consequently, the scales demonstrate convergence validity by the established criteria.

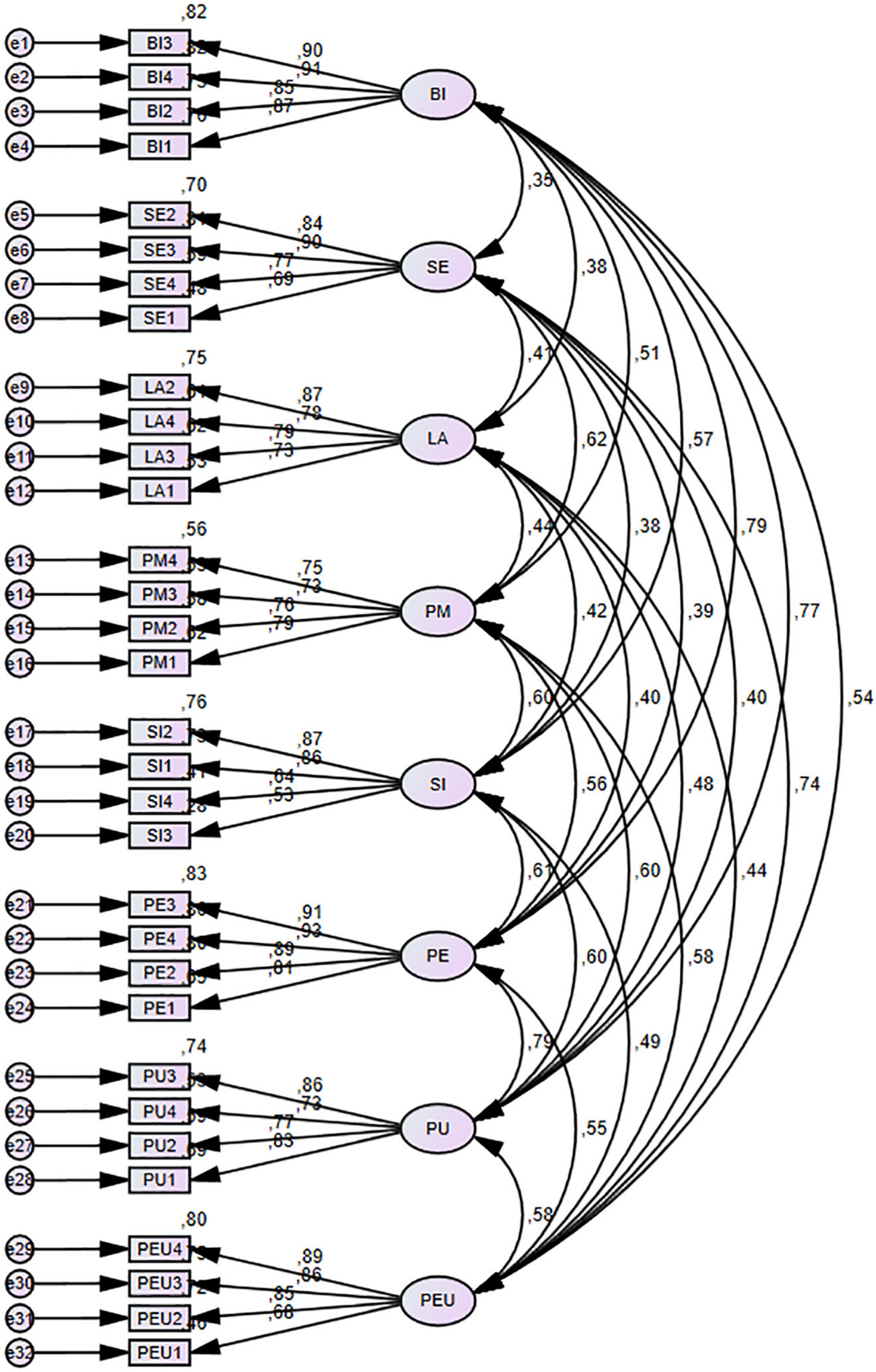

Fig. 2. Confirmatory factor analysis results

Discriminant validity. As depicted in Table 5, the discriminant validity assessment indicates that the scale's discriminant validity has been achieved. This is evidenced by the fact that the square root of the AVE values (bold diagonal) exceeds the inter-construct correlations [58]. For example, the PM scale possesses an AVE value of $AVE_{PM} = 0.571$ (see Table 4), with its square root reaching 0.756. The value of 0.756 surpasses both the within-row correlations (0.515, 0.621, 0.444, and 0.561) and the within-column correlations (0.579, 0.596, and 0.602). Furthermore, the inter-construct correlations are all below 0.85, and the AVE of the constructs [59] exceeds the maximum shared variance (MSV) of the constructs, ranging from 0.234 to 0.624. This compliance with the requirement that the MSV should be less than the AVE of the constructs indicates that the scale meets the criteria for construct discriminant validity.

Table 5. Discriminant validity analysis

Variable	BI	SE	LA	PE	PM	PU	SI	PEU
BI	**0.883**							
SE	0.347	**0.802**						
LA	0.381	0.407	**0.792**					
PE	0.787	0.387	0.404	**0.887**				
PM	0.515	0.621	0.444	0.561	**0.756**			
PU	0.773	0.405	0.484	0.790	0.602	**0.797**		
SI	0.570	0.382	0.424	0.605	0.596	0.598	**0.739**	
PEU	0.537	0.739	0.441	0.549	0.579	0.579	0.489	**0.826**
MSV	0.620	0.547	0.234	0.624	0.385	0.624	0.366	0.547

4.4 Full analysis of the final model

Model fit. The evaluation of the measurement model's fit reveals that the majority of fit indices satisfy the criteria for model adequacy, as outlined by [49]. As a result, the model is deemed suitable for the dataset under analysis (refer to Table 6). In terms of the model's explanatory power, as demonstrated by the R^2 values, the independent variables collectively explain 68.9% of the variance in BI, 63.8% in PEU, and 69.4% in PU, as illustrated in Figure 3.

Table 6. Model fit indices for the final structural model

Model Fit Criteria	Parameter Fit	Fit	Output	Decision
Absolute fit	p-value	≥ 0.05	0.000	–
	df	the smaller, the better	436	–
	χ^2/df	≤ 5.00	2.409	Acceptable
	GFI	≥ 0.90	0.904	Good fit
	RMSEA	≤ 0.05	0.048	Good fit
Relative fit	IFI	≥ 0.90	0.957	Good fit
	TLI	≥ 0.90	0.951	Good fit
	CFI	≥ 0.95	0.957	Good fit
	RFI	≥ 0.05	0.919	Good fit

(Continued)

Table 6. Model fit indices for the final structural model *(Continued)*

Model Fit Criteria	Parameter Fit	Fit	Output	Decision
Parsimonious fit	PGFI	> 0.50	0.746	Good fit
	PNFI	> 0.50	0.816	Good fit
	PCFI	> 0.50	0.841	Good fit
R^2: PU (0.694), PEU (0.638), BI (0.689)				

Note: The R^2 value represents the proportion of variability in a given variable that can be attributed to the influence of the independent variables within the model. It indicates the extent to which the predictor variables account for the variance in the dependent variable.

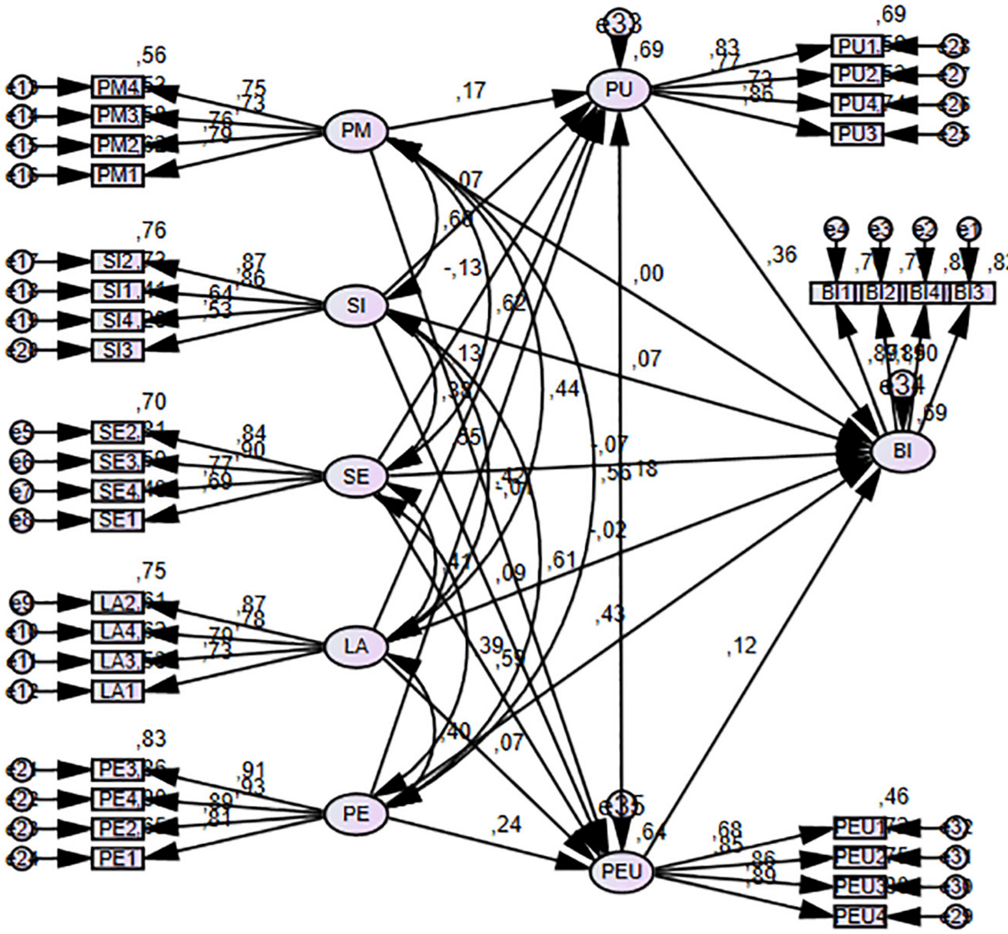

Fig. 3. Final structural model

Hypotheses testing

Table 7. Direct effects in the final structural model

Hypothesis		Unstandardized Estimate (B)	p-Value	Results	Standardized Estimate (β)	Effect Size
H1	PM → PU	0.217***	0.001	Supported	0.167	M
H2	SI → PU	0.077 NS	0.124	Not Supported	0.069	S
H3	SE → PU	–0.131*	0.022	Supported	–0.126	M

(Continued)

Table 7. Direct effects in the final structural model *(Continued)*

Hypothesis		Unstandardized Estimate (B)	p-Value	Results	Standardized Estimate (β)	Effect Size
H4	LA → PU	0.143***	0.000	Supported	0.129	M
H5	PE → PU	0.545***	0.000	Supported	0.551	L
H6	PM → PEU	−0.008 NS	0.890	Not Supported	−0.007	S
H7	SI → PEU	0.091*	0.042	Supported	0.093	S
H8	SE → PEU	0.532***	0.000	Supported	0.587	L
H9	LA → PEU	0.067 NS	0.064	Not Supported	0.069	S
H10	PE → PEU	0.209***	0.000	Supported	0.242	M
H11	PM → BI	−0.005 NS	0.939	Not Supported	−0.004	S
H12	SI → BI	0.084 NS	0.081	Not Supported	0.073	S
H13	SE → BI	−0.074 NS	0.177	Not Supported	−0.070	S
H14	LA → BI	−0.024 NS	0.540	Not Supported	−0.021	S
H15	PE → BI	0.433***	0.000	Supported	0.430	M
H16	PEU → PU	0.208***	0.000	Supported	0.181	M
H17	PEU → BI	0.138*	0.023	Supported	0.119	M
H18	PU → BI	0.370***	0.000	Supported	0.363	M

Notes: Not Significant: NS; Small: S; Medium: M; Large: L; →: Indicates the direction of the relationship; Significance levels: *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

The study employed CB-SEM to test the existing model and research hypotheses. The results of the structural model assessment (see Table 7) indicate that 11 hypotheses (H1, H3, H4, H5, H7, H8, H10, H15, H16, H17, H18) were supported at the 5% significance level, while the remaining seven hypotheses (H2, H6, H9, H11, H12, H13, H14) were not supported. The linear structural model estimation results reveal that all accepted relationships exhibit positive regression weights.

Table 8. Direct and indirect effects of seven variables in the final structural model

Variable	Effect	Intervening		Dependent
		PU	PEU	BI
PM	Direct	0.217** (0.167M)	−0.008NS (−0.007S)	−0.005NS (−0.004S)
	Indirect	PM → PEU → PU: −0.002NS (−0.001)		PM → PU → BI: 0.080** (0.061S)
				PM → PEU → PU → BI: −0.001NS (−0.001S)
				PM → PEU → BI: −0.001NS (−0.001S)
	Total Indirect	−0.002NS (−0.001)		0.079NS (0.059S)
	Total	0.216* (0.166M)	−0.008NS (−0.007S)	0.073NS (0.055S)

(Continued)

Table 8. Direct and indirect effects of seven variables in the final structural model *(Continued)*

Variable	Effect	Intervening		Dependent
		PU	PEU	BI
SI	Direct	0.077NS (0.069S)	0.091* (0.093S)	0.084NS (0.073S)
	Indirect	SI → PEU → PU: 0.019NS (0.017S)		SI → PU → BI: 0.028NS (0.025S)
				SI → PEU → PU → BI: 0.007NS (0.006S)
				SI → PEU → BI: 0.013NS (0.011S)
	Total Indirect	0.019NS (0.017S)		0.048NS (0.042S)
	Total	0.096NS (0.086S)	0.091NS (0.093S)	0.132* (0.115M)
SE	Direct	–0.131* (–0.126)	0.532*** (0.587L)	–0.074NS (–0.070)
	Indirect	SE → PEU → PU: 0.111* (0.106M)		SE → PU → BI: –0.049NS (–0.046S)
				SE → PEU → PU → BI: 0.041** (0.039S)
				SE → PEU → BI: 0.074NS (0.070S)
	Total Indirect	0.111* (0.106M)		0.066NS (0.063S)
	Total	–0.020NS (–0.020S)	0.532** (0.587L)	–0.008NS (–0.007S)
LA	Direct	0.143*** (0.129M)	0.067NS (0.069S)	–0.024NS (–0.021S)
	Indirect	LA → PEU → PU: 0.014NS (0.012S)		LA → PU → BI: 0.053NS (0.047S)
				LA → PEU → PU → BI: 0.005NS (0.005S)
				LA → PEU → BI: 0.009NS (0.008S)
	Total Indirect	0.014NS (0.012S)		0.067*** (0.060S)
	Total	0.157*** (0.142M)	0.067NS (0.069S)	0.043NS (0.039S)
PE	Direct	0.545*** (0.551L)	0.209*** (0.242M)	0.433*** (0.430M)
	Indirect	PE → PEU → PU: 0.043** (0.044S)		PE → PU → BI: 0.202*** (0.200M)
				PE → PEU → PU → BI: 0.016** (0.016S)
				PE → PEU → BI: 0.029* (0.029S)
	Total Indirect	0.043** (0.044S)		0.247*** (0.245M)
	Total	0.589*** (0.595L)	0.209*** (0.242M)	0.680*** (0.675L)

(Continued)

Table 8. Direct and indirect effects of seven variables in the final structural model *(Continued)*

Variable	Effect	Intervening		Dependent
		PU	PEU	BI
PU	Direct			0.370*** (0.363M)
	Indirect			
	Total Indirect			
	Total			0.370*** (0.363M)
PEU	Direct	0.208*** (0.181M)		0.138* (0.119M)
	Indirect			PEU → PU → BI: 0.077* (0.066S)
	Total Indirect			0.077* (0.066S)
	Total	0.208* (0.181M)		0.215** (0.185M)

Notes: Standardised effects are presented first, followed by an analysis of their effect sizes, classified as Small (S) for values < 0.1, Medium (M) for values between 0.1 and < 0.5, and Large (L) for values ≥ 0.5 [60]. →: Indicates the direction of the relationship. Significance levels: *: p < 0.05; **: p < 0.01; ***: p < 0.001; NS: Not Significant.

Table 8 emphasizes the need to determine the statistical significance of indirect effects as well as the overall influence of all variables in the model in order to fully understand the factors influencing BI. Although SI does not exhibit strong direct or indirect effects on its own, its total impact is significantly positive. In contrast, while PM and SE demonstrate some significant indirect effects, neither their direct nor total effects reach statistical significance.

Interestingly, the indirect effects of LA are considerably more pronounced than its direct effects, with a notable inverse relationship. Theoretically, PE stands out as the most impactful factor among the seven variables included in the final model for BI, as reflected by its high standardized coefficient of 0.675. Following PE, three factors, PU, PEU, and SI, show moderate effects, with total standardized effects ranging from 0.115 to 0.363, all statistically significant at or below the 0.05 level. The other variables, PM, LA, and SE, contribute minimally to BI, with standardized coefficients for total effects ranging from –0.007 to 0.055, none of which reach statistical significance at the 0.05 level. The resultant model explains 68.9% of the variation in BI, and the model fit indices are high, indicating that the model is well-suited to the data.

The results of this study further support previous discoveries regarding the direct impacts outlined in technology acceptance models. It is essential to highlight that the connections between BI and each of the seven studied variables consistently show positive correlations that are statistically significant at the 0.001 level or below. These results offer valuable contributions to the expanding knowledge base concerning the factors influencing BI in educational contexts.

Table 9. Model fit indices for moderating variables

Group	N	χ^2/df	RMR	GFI	AGFI	NFI	IFI	CFI	RMSEA
Male	236	785.081/436 = 1.801	0.049	0.832	0.796	0.887	0.946	0.946	0.058
R^2: PU (0.701), PEU (0.768), BI (0.698)									
Female	375	934.672/436 = 2.144	0.044	0.867	0.839	0.890	0.938	0.938	0.055
R^2: PU (0.700), PEU (0.553), BI (0.703)									

(Continued)

Table 9. Model fit indices for moderating variables *(Continued)*

Group	N	χ^2/df	RMR	GFI	AGFI	NFI	IFI	CFI	RMSEA
Less Experienced	348	898.097/436 = 2.060	0.040	0.862	0.833	0.899	0.945	0.945	0.055
R^2: PU (0.710), PEU (0.685), BI (0.682)									
More Experienced	263	860.688/436 = 1.974	0.050	0.835	0.800	0.872	0.932	0.932	0.061
R^2: PU (0.692), PEU (0.605), BI (0.711)									

Overall, Table 9 provides an overview of the model's fit statistics, revealing that, although the fit indices are within acceptable ranges, none of the groups achieve a goodness of fit index (GFI), adjusted goodness of fit index (AGFI), or normed fit index (NFI) above 0.9. This indicates that the model needs to exhibit a satisfactory level of fit with the data for any specific subgroup among the moderators.

Furthermore, Table 10 demonstrates the variability in the impact of various factors on BI when moderated by variables such as gender and mobile learning experience. These findings indicate that the influence of these factors could be more consistent. It varies significantly depending on the moderating variables considered.

Table 10. Influence of moderating variables

Gender	Male (N = 236)				Female (N = 375)			
	B	p-Value	β	Effect Size	B	p-Value	β	Effect Size
PM → BI	–0.022	NS	0.055	S	0.138	NS	0.104	M
SI → BI	0.126	NS	0.106	M	0.126	NS	0.111	M
SE → BI	0.169	NS	0.008	S	–0.064	NS	–0.066	S
LA → BI	0.019	NS	0.022	S	0.010	NS	0.009	S
PE → BI	0.697	**	0.685	L	0.663	***	0.680	L
PEU → BI	0.209	NS	0.162	M	0.198	**	0.176	M
PU → BI	0.293	*	0.355	M	0.434	**	0.412	M
Mobile Learning Experience	**Less Experienced (N = 348)**				**More Experienced (N = 263)**			
	B	**p-Value**	**β**	**Effect Size**	**B**	**p-Value**	**β**	**Effect Size**
PM → BI	–0.022	NS	0.055	S	0.138	NS	0.104	M
SI → BI	0.126	NS	0.106	M	0.126	NS	0.111	M
SE → BI	0.169	NS	0.008	S	–0.064	NS	–0.066	S
LA → BI	0.019	NS	0.022	S	0.010	NS	0.009	S
PE → BI	0.697	**	0.685	L	0.663	***	0.680	L
PEU → BI	0.209	NS	0.162	M	0.198	**	0.176	M
PU → BI	0.293	*	0.355	M	0.434	**	0.412	M

Notes: Not Significant: NS; Small: S; Medium: M; Large: L; →: Indicates the direction of the relationship; Significance levels: *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

5 DISCUSSION AND CONCLUSION

Understanding the factors influencing students' willingness to adopt new technologies is crucial, especially given institutions' significant investments in integrating these technologies [61] and the potential applications across various subjects, like mathematics [62]. While mobile learning offers numerous advantages, its success depends on proper adaptation and application, which are directly tied to student acceptance of mobile technologies [27]. If students and educators resist new technologies, institutions risk wasting resources and failing to reap the benefits of their investments. Therefore, prioritizing student acceptance is about ensuring the success of technological integration and maximizing the return on investment for educational institutions [32]. Research in this field may be valuable for researchers, educational policymakers, and teachers [6]. This study examined the factors influencing Vietnamese high school students' acceptance of mobile learning.

In Vietnam, research on the factors influencing high school students' adoption of mobile learning has been limited, with only two prior studies addressing this topic [7], [13]. Study [7] applied the UTAUT model and identified factors such as perceived expectancy, perceived playfulness, social influence, and attitude towards use affecting BI through EFA, but it focused solely on English language learning. Study [13] utilized the TAM model, similar to this study, identifying PU, PEU, FC, SE, and attitude and object impact as significant factors influencing mobile learning adoption through multiple regression analysis. Our research extends these works by incorporating a broader range of variables within the theoretical framework. We determine that PE, PEU, and PU influence BI; PM, LA, PE, and PEU impact PU; SI, SE, and PE affect PEU. Another significant contribution of our study is updating this study area within a more recent technological and educational context in Vietnam. The previous studies [7], [13] were conducted in 2021 when mobile learning was still novel in Vietnam's education system, and students were prohibited from bringing mobile devices to class before 2020. By the time of our study, the conditions for mobile learning adoption had shifted considerably. First, the Vietnamese government expanded mobile technology infrastructure, for instance, with widespread 5G coverage. Second, the implementation of Circular 32/2020/TT-BGDDT of the Ministry of Education and Training allowed secondary students to use mobile phones for educational purposes. Third, the EdTech sector in Vietnam has grown significantly, with increased investment in mobile-based educational applications. These contextual changes provide a unique backdrop for our study, making it one of the first to analyze mobile learning adoption among high school students under these evolving conditions. On the other hand, our study responds to the call by [32] for a comprehensive model for mobile learning adoption by adding additional information in developing countries.

The findings reaffirm the relationships within the TAM proposed by [45]. Specifically, PEU significantly influences PU, and both PU and PEU significantly influence BI. Our findings align with previous studies on high school students, such as those by [13] and [27].

Regarding the external variables considered in this study, we found that PE influences BI, consistent with previous research by [7], [27], [40], [46], [61]. Contrary to traditional beliefs that academic rigor outweighs enjoyment, gamification in the mobile learning environment can effectively motivate students in exam-oriented systems. In this study, PE strongly affected BI, suggesting that students value interactive and engaging learning experiences. This reflects a growing cultural shift—while academic achievement remains paramount, intrinsic motivation through game-like mechanics (e.g., rewards, competition, and progress tracking) enhances sustained engagement. Given that Vietnamese students are accustomed to structured learning, gamification in mobile learning may bridge traditional methods and student-centered, exploratory learning approaches. Future research should examine how cultural values modulate the motivational impact of gamification in mobile learning environments.

In our study, PU is influenced by PM, SE, LA, and PE. Despite the different target groups, this result aligns with the study [46] on university students. Moreover, our study also found that PU is influenced by PM, SE, LA, and PE, aligning with the findings of [46] on university students. Research by [22] and [46] has highlighted the impacts of SE and PE on PEU. Similarly, our study identified these influences on high school students, aligning with the results of [63] regarding SE and [9] regarding perceived enjoyment.

Among the external variables, the influence of SI in our study differs from previous research findings. For instance, we did not find SI to influence BI as noted in [7], [27], [46], nor did it influence PU as reported by [46]. Although SI did not directly affect BI in this study, its influence through PEU suggests an indirect yet meaningful impact, a result rarely observed in other studies. Students in Confucian education systems like Vietnam are more likely to adopt mobile learning if it is endorsed by authoritative figures such as teachers or if peer groups engage with these platforms. This finding reveals that students in collectivist cultures are more responsive to external validation and social norms when adopting new technologies. Future studies should further explore how teacher endorsement and peer collaboration mediate the relationship between social influence (SI) and technology acceptance.

Another finding is the limited influence of LA on BI. Self-directed learning seems less prevalent in Confucian-heritage cultures, where students rely on teacher guidance. Mobile learning platforms must, therefore, balance structured support with opportunities for autonomous exploration. Encouraging autonomy may require scaffolding interventions, such as adaptive learning pathways and real-time feedback, which allow students to exercise agency while remaining within the framework of teacher-defined objectives.

The above findings indicate that students need to actively and flexibly use mobile technologies inside and outside the classroom to plan their learning. Learning activities should be enjoyable and provide opportunities to effectively utilize mobile technologies to address academic challenges (e.g., see [64], [65]). These requirements are new and pose significant challenges for teachers. Therefore, institutions must develop regular training programs for in-service teachers and educate pre-service teachers about mobile learning. Studies on professional development in mobile learning, especially studies focusing on its adoption by key stakeholders like students and teachers, will be essential to realize the benefits of mobile learning.

A key dimension insufficiently explored in many TAM-based studies is the role of interactivity in mobile learning environments. Interactive mobile technologies, such as gamification, adaptive learning, and virtual collaboration, can significantly enhance PE and PU—two core determinants of technology acceptance. Integrating these interactive elements within mobile learning environments can address intrinsic and extrinsic motivational factors, thus fostering deeper student engagement.

Gamification strategies, such as reward systems, interactive quizzes, and achievement badges, have increased student motivation and engagement. By transforming passive learning experiences into dynamic, game-like tasks, gamification enhances PE and facilitates sustained participation in mobile learning platforms. Future research could explore how these mechanics influence SE and LA in Vietnamese high school contexts.

Adaptive mobile learning platforms leverage AI-driven feedback and personalized content delivery to cater to individual student needs. This personalization enhances PU by offering tailored learning pathways and PEU through intuitive interfaces that adjust to student performance. For instance, real-time assessments and automated progress tracking can improve students' confidence in managing their learning autonomy (LA) while addressing diverse learning needs.

Interactive mobile platforms enhance collaborative learning via peer discussion forums, virtual study groups, and shared knowledge spaces. This correlates with the SI variable, as peer support and collaborative efforts can promote technology adoption. Our research shows that while SI did not directly predict BI, its indirect effects through PEU suggest that peer-driven interactivity may support technology adoption acceptance.

The study provides important insights into the factors influencing the adoption of mobile learning among Vietnamese secondary school students; however, certain limitations should be noted. Focusing only on English-language literature might have left out essential studies written in other languages, which could have limited the cultural and contextual scope of the study [47]. The dataset only includes data from one cultural and educational setting, which means that the results can't be used in other places or with other school systems. This shows how important it is to do more comparative studies in the future. Although the study observed differences in students' familiarity with mobile learning technologies, it did not extensively examine how prior experience impacts acceptance, SE, or learning outcomes. Furthermore, the reliance on self-reported data raises concerns about potential response bias. To mitigate this, the study conducted rigorous sample screening, collecting data only from students confirmed to have exposure to the research problem. To enhance validity, future studies should incorporate data triangulation methods, such as student interviews or focus groups. Employing mixed-method or longitudinal approaches could provide deeper insights into student perceptions and behaviors, thereby improving the robustness of the findings [66]. Addressing these issues will make the results more reliable and applicable to other contexts, offering a more comprehensive understanding of how mobile learning is utilized across various types of schools.

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