# Cultural and Technological Factors Influencing the Use of Digital Devices in Learning Among Multicultural High School Students in Vietnam's Central Highlands

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***Abstract*—This article explores factors shaping the uptake of digital learning among high school students in Vietnam's Central Highlands, a region rarely examined despite its multicultural context and limited resources. To the best of our knowledge, this constitutes the first empirical inquiry in the region that expands the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) through the integration of Self-Efficacy (SE), Facilitating Conditions (FC), and Perceived Safety (PS). In doing so, the research contributes a comprehensive perspective on how psychological, socio-cultural, and contextual elements shape technology acceptance in under-resourced schools. Data were gathered from a sample of 926 students representing various ethnic backgrounds, utilizing Structural Equation Modeling (SEM) for hypothesis testing. The research indicates that Perceived Usefulness (PU), Perceived Ease of Use (PEU), Social Influence (SI), and Self-Efficacy (SE) are important predictors of Behavioral Intention (BI). FC has both direct influences on BI and indirect influences through PU and PEU, while PS does not appear as a major predictor. These outcomes challenge conventional infrastructure-focused perspectives by demonstrating that provision of access alone is insufficient; instead, digital confidence, peer influence, and cultural embeddedness serve as critical enablers of sustained engagement. From a theoretical standpoint, the study extends UTAUT by emphasizing the pivotal role of SI within collectivist and resource-constrained contexts, thereby problematizing integration models that privilege infrastructure as the primary determinant. From a practical perspective, the findings underscore the necessity of culturally responsive interventions—including peer mentoring and community-based digital literacy initiatives—to foster inclusive digital participation. Collectively, these insights generate timely implications for policymakers, educators, and technology developers in Vietnam as well as in other multicultural and low-resource settings.**

***Keywords*—cultural diversity, digital learning devices, mobile learning, multicultural high school students, Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT)**

## I. Introduction

In the era of globalization and rapid technological advancement, digital devices have become central to modern educational practices [1–4]. These tools not only increase students' engagement but also help them develop essential digital competencies needed in a technology-driven world [5, 6]. The successful integration of technology depends on the readiness of learners, educators, and the broader community to adopt and use these tools [7]. Therefore, learners' acceptance of digital technologies is a critical condition for implementing educational innovations [8–10].

Within the literature, the Technology Acceptance Model (TAM) [11, 12] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [13] are the most widely applied frameworks for examining technology adoption. These models have been extensively validated across diverse educational contexts, including mobile-assisted [14–16], YouTube-based instruction, and internet-supported environments [17, 18]. Empirical studies consistently highlight the central role of Perceived Ease of Use (PEU) and Perceived Usefulness (PU) in predicting Behavioral Intention (BI), while extended models emphasize the importance of Social Influence (SI) and Facilitating Conditions (FC). Recent research also underscores the relevance of cultural dimensions and technological accessibility, particularly in marginalized or resource-limited settings [19–21].

Despite this progress, most existing studies have been conducted in technologically advanced or urban environments [22, 23]. Limited research has focused on disadvantaged, multicultural contexts such as Vietnam's Central Highlands, where Hofstede's cultural dimensions [24–26] provide a useful yet underutilized analytical lens [7, 21, 23]. Prior findings suggest that collectivism and power distance may shape learners' technology perceptions, implying that conventional adoption models may not fully capture behavioral variation in non-Western contexts [21, 27]. However, cultural influences have not been systematically integrated into TAM or UTAUT in Vietnam, leaving a significant empirical gap in understanding how sociocultural factors shape technology acceptance in secondary education.

Vietnam's cultural landscape is characterized by high power distance, collectivist orientations, and moderate uncertainty avoidance [28], all of which may influence learners' perceptions of authority, collaboration, and technological risk [29, 30]. The Central Highlands—particularly Dak Lak province—is one of the most culturally diverse yet underserved regions of the country, home to 47 of Vietnam's 54 ethnic groups, many living in matrilineal communities with strong communal traditions [31, 32]. However, infrastructural disparities remain substantial: only 63% of students have internet access, and just 27% of individuals aged 3–24 own personal computers [33].

Although the region is home to multiple ethnic groups, this study focuses on the broader cultural and contextual factors affecting students' adoption of digital learning technologies rather than conducting cross-ethnic comparisons. These conditions underscore the need to examine technology acceptance in culturally diverse, low-resource learning environments.

Building on TAM and UTAUT, this study investigates the key determinants of high school students' acceptance and BI toward digital learning in Vietnam's Central Highlands. Specifically, it examines how PU, PEU, SI, FC, Perceived Safety (PS), and Self-Efficacy (SE) influence technology acceptance within the region's cultural and educational context. By integrating cultural and contextual perspectives, the study provides evidence-based implications for policymakers, educators, and technology developers in designing inclusive digital literacy programs and equitable educational policies that support sustainable digital transformation in under-resourced regions.

## II. Literature Review

### A. TAM and Its Extensions

Since its introduction by Davis [11], TAM has been widely applied to explain Behavioral Intention (BI) and Usage Behavior (UB) in technology acceptance research. It emphasizes PU and PEU as the central predictors of BI, which subsequently shapes UB. Extensive meta-analyses and empirical research have confirmed the validity of these constructs across diverse technological domains [34, 35].

Despite its robustness, most applications of TAM have been carried out in technologically advanced and urban contexts. Its explanatory capacity in under-resourced or multicultural settings, where socio-economic inequalities and cultural diversity are prevalent, remains limited. In such contexts, digital adoption is shaped not only by perceptions of utility and ease of use but also by infrastructural constraints, psychological readiness, and socio-cultural dynamics. Conventional TAM, therefore, may overlook essential determinants of adoption.

Recent research indicates the necessity of expanding TAM to fill these deficiencies. This research incorporates FC, PS, and SE into the model to enhance its explanatory scope. FC reflects infrastructural and institutional readiness, PS captures concerns about security and privacy, and SE reflects learners' confidence in using digital technologies effectively. These additions provide a more comprehensive perspective for understanding digital adoption among high school students in Vietnam's Central Highlands.

### B. UTAUT and Contextual Factors

The Unified Theory of Acceptance and Use of Technology (UTAUT) [13] synthesizes key determinants from earlier models and emphasizes four central predictors: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Since its introduction, UTAUT has been extensively used in educational technology studies, offering strong predictive validity for BI and UB [36, 37].

In resource-constrained environments, FC plays a critical role. Evidence from Ghana, Jordan, and El Salvador demonstrates that FC significantly shape PU, PEU, and BI [38–40]. These findings indicate that infrastructure, technical support, and institutional capacity may weigh more heavily in disadvantaged regions compared to technologically advanced contexts. In Vietnam's Central Highlands, where device ownership and internet access are uneven, FC are expected to exert substantial influence on adoption processes.

However, UTAUT has primarily been validated with university students and faculty, populations with higher levels of digital autonomy and competence. High school students in disadvantaged multicultural regions face distinct developmental, infrastructural, and socio-cultural challenges that necessitate adapting UTAUT to the local context.

In this study, only selected UTAUT constructs were retained to ensure theoretical parsimony and contextual appropriateness. SI was included because learners' decisions in collectivist and hierarchical settings are strongly shaped by teachers, peers, and family members. FC was also retained due to its heightened relevance in environments characterized by infrastructural inequality. In contrast, PE and EE were excluded because they are conceptually redundant with PU and PEU in TAM. Adding both sets of variables could cause multicollinearity and make the model more complicated. Likewise, within TAM, constructs such as Attitude and other external variables were excluded due to conceptual overlap with PU and PEU and minimal added explanatory value. This selective integration reflects a theory-driven choice to retain only the constructs most relevant to the cultural and infrastructural characteristics of the Central Highlands context.

### C. Integrating Perceived Safety and Self-Efficacy

While TAM and UTAUT explain much of technology adoption behavior, scholars increasingly recognize the relevance of psychological and socio-emotional constructs [20, 41]. Among these, PS and SE have been identified as critical in shaping digital adoption, especially in marginalized and low-literacy environments.

PS means having faith in the safety, privacy, and dependability of digital platforms [42]. Concerns regarding data protection, content accuracy, and misuse of personal information have been shown to influence BI indirectly through PU and PEU [43]. In under-resourced settings such as Vietnam's Central Highlands, where awareness of digital risks is limited and privacy protections are weak, PS is likely to act as a salient moderator of adoption. Learners who lack faith in the safety of digital platforms may refuse to use them, even if they think they will be useful.

SE, rooted in Bandura's social cognitive theory, reflects confidence in the ability to effectively use digital technologies. Empirical evidence indicates that SE positively influences both PU and PEU, thereby strengthening BI [44–46]. In contexts where digital competencies vary significantly, SE often determines whether learners can overcome infrastructural barriers and engage productively with technology [47]. Low SE may exacerbate inequalities in access and outcomes, while high SE can enable adoption even in resource-poor environments.

Incorporating PS and SE extends existing adoption frameworks by addressing non-infrastructural determinants of behavior. These constructs are especially relevant in culturally diverse and resource-limited educational environments, where psychological readiness is as crucial as technical capacity.

### *D. Cultural Compatibility and Comparative Dimensions*

Although not always explicitly modeled, Cultural Compatibility (CC) has been recognized as a critical contextual moderator in technology adoption. Grounded in Hofstede's cultural dimensions [25, 28, 48] and subsequent extensions [49], CC refers to the degree of alignment between technology-related practices and the prevailing cultural norms and values of a community.

Recent empirical studies reinforce the explanatory role of cultural factors. Fan and Wang [50] and Hatlevik *et al.* [51] demonstrate that digital competence and learning behaviors are shaped by cultural capital and social environments. Ullah *et al.* [52] further highlight that in collectivist societies, Facilitating Conditions (FC) and Social Influence (SI) tend to exert stronger effects on technology use than Perceived Ease of Use (PEU). Similarly, Faqih [53] and Kudjo and Chiweshe [54] show that cultural values such as Power Distance and Uncertainty Avoidance condition the strength of relationships among cognitive factors, suggesting that culture functions as an indirect and contextual determinant. UNESCO (2023) likewise emphasizes that digital transformation in education must be culturally grounded to ensure inclusiveness, equity, and social relevance [55].

In multicultural educational contexts such as Vietnam's Central Highlands, CC plays a pivotal role. The region is home to 47 of Vietnam's 54 ethnic groups, characterized by high cultural diversity, collectivist traditions, and hierarchical social structures. Such cultural dynamics may shape interpretations of PU, PEU, and BI. For example, collectivism may heighten the influence of SI, while high power distance may amplify the effects of authority and institutional endorsement on adoption.

This study does not conduct direct cross-ethnic comparisons but situates its findings within the broader cultural and technological landscape of Vietnam's Central Highlands. The analysis interprets how cultural compatibility helps explain the observed adoption behaviors among high school students and how these patterns align with or diverge from international studies in other collectivist or resource-limited contexts. While this study focuses primarily on contextual and theoretical interpretation, future research could extend the framework to explore cross-ethnic variations in digital behavior and cultural moderation effects.

The literature indicates that digital adoption is shaped by multiple factors. PU and PEU remain central in TAM, while UTAUT broadens the framework by integrating constructs such as SI and FC. However, in under-resourced and culturally diverse contexts, these models require further adaptation. By incorporating socio-influential, infrastructural, and psychological dimensions–particularly SE and PS–the present study extends TAM and UTAUT to capture determinants of adoption more comprehensively. This multidimensional framework is particularly suited for analyzing high school students in Vietnam's Central Highlands, where infrastructural limitations intersect with cultural diversity. The approach enhances explanatory power and offers practical insights for designing inclusive, context-sensitive interventions in educational technology.

## III. Materials and Methods

### *A. Proposed Research Model and Hypotheses*

Based on the integration of TAM, UTAUT, and the additional constructs of PS and SE, the proposed research model (Fig. 1) captures the multifaceted determinants of digital learning adoption in multicultural and underserved educational settings, such as Vietnam's Central Highlands. As illustrated in Fig. 1, the model comprises 15 hypotheses linking SI, FC, SE, PS, PEU, PU, and BI.

This extended framework underscores the need to consider psychological safety, user confidence, and local infrastructural realities when modeling technology adoption in culturally diverse and under-resourced contexts. By integrating individual, environmental, and cultural dimensions, the proposed model offers a comprehensive lens for understanding digital learning behavior among multicultural high school students in Vietnam's Central Highlands.

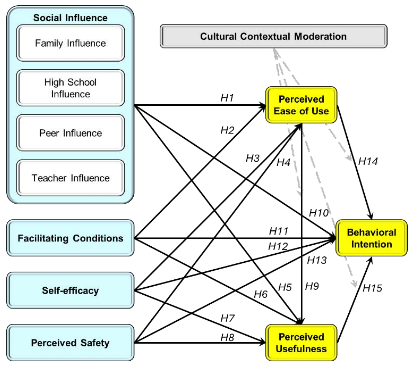


Fig. 1. Theoretical framework of the study (TAM–UTAUT integration with contextual moderation by cultural factors).

### *B. Research Design*

A sequential mixed-methods design was employed to investigate the technological and cultural factors influencing students' adoption of digital-learning tools. Qualitative insights were first used to contextualize constructs and language, followed by quantitative testing to assess relationships statistically.

Ethical approval for all phases was obtained from the Scientific Committee of Tay Nguyen University. Participation was voluntary, with informed consent, anonymity, and confidentiality guaranteed.

The study was implemented through four successive phases to ensure methodological rigor and internal validity: development of the conceptual framework, a preliminary qualitative exploration, a pilot survey, and a large-scale main survey.

### *C. Research Procedure*

#### *1) Development of the theoretical measurement framework*

Drawing on TAM [11, 12], UTAUT [13], and cultural dimension theories [28], the study built its conceptual model through a thorough review of prior scholarship. This model provided the conceptual basis for designing research instruments and formulating hypotheses.

#### *2) Preliminary qualitative study*

The qualitative phase comprised semi-structured interviews with 20 students representing diverse ethnic backgrounds (Ede, Muong, Jrai, and Kinh–the majority ethnic group in Vietnam). This phase aimed to elicit contextual meanings associated with technology use, perceptions of cultural identity, and school-level digital practices [56]. The sampling approach was intentionally narrow and purposive, consistent with the objective of generating preliminary and exploratory insights rather than achieving demographic representativeness.

*3) Pilot quantitative study*

A pilot survey ($n$ = 832) was administered online via snowball sampling to test the reliability and clarity of the preliminary questionnaire [57]. Although large, this sample reflected uncontrolled viral diffusion inherent in online distribution and was used only to evaluate reliability and language clarity, not for inferential analysis. Cognitive interviews and item analyses (using Cronbach's α and corrected item–total correlations) guided revisions to ensure cultural appropriateness and comprehensibility across groups.

*4) Main quantitative study and sampling strategy*

The main quantitative phase was conducted among high school students in Dak Lak province—the central and most culturally diverse province within Vietnam's Central Highlands region. Dak Lak was selected for its demographic representativeness of the region, where educational access and digital infrastructure remain uneven.

A stratified random sampling approach was employed to ensure balanced representation across gender and residential location (urban vs. rural). Eight high schools, encompassing both public and private institutions, were selected in collaboration with local educational authorities. Within each school, classes were randomly chosen, and all students in those classes were invited to participate. Coordination with the authorities facilitated school access and ensured full ethical compliance throughout the data collection process.

The survey was administered in person during class hours by trained enumerators fluent in local dialects, who provided explanations and assisted students as needed. Participation was voluntary and anonymous, and informed consent was obtained from both students and their teachers prior to data collection.

A total of 1,261 questionnaires were distributed, of which 926 valid responses were retained for final analysis after excluding incomplete and duplicate entries. The final sample comprised 54.2% female and 45.8% male students, with 61.3% residing in urban areas and 38.7% in rural areas. Regarding cultural background, 95.1% identified as Kinh, while 4.9% belonged to ethnic minority groups including Ede, Muong, Jrai, Dao, Tay, Thai, Hoa, Nung, Chut, and Hmong. Although ethnicity was not a stratification variable, this distribution broadly reflects the demographic structure of the Central Highlands. The main survey further expanded ethnic representation to enhance demographic alignment for large-scale validation.

The achieved sample size exceeds the minimum requirements for Partial Least Squares Structural Equation Modeling (PLS-SEM), meeting the 10:1 sample-to-indicator ratio and power-based guidelines proposed by Hair *et al.* [58] and Henseler *et al.* [59]. This ensured sufficient statistical power and robustness for subsequent measurement and structural model estimations.

## D. Measurement Instrument

To provide greater transparency regarding instrument design, the final questionnaire consisted of 42 items distributed across seven constructs. Behavioral Intention (BI) was measured using three items; Perceived Usefulness (PU) and Perceived Ease of Use (PEU) each used four items; Social Influence (SI) included 17 items capturing multiple layers of interpersonal and institutional influence; Facilitating Conditions (FC) and Perceived Safety (PS) each comprised four items; and Self-Efficacy (SE) was measured using six items. All items were adapted from validated scales and contextualized for cultural appropriateness in Vietnam's Central Highlands. These item counts correspond to the reliability and validity analyses presented in the following tables.

Responses were recorded using a seven-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree). The instrument was originally developed in English and subsequently translated into Vietnamese following the Brislin back-translation procedure [60]. To ensure semantic accuracy and cultural equivalence, independent bilingual experts reviewed the translations, and discrepancies were resolved through iterative discussion. Cultural and linguistic appropriateness was further verified through cognitive interviews conducted during the pilot phase.

Table 1 presents the variables, operational definitions, sample items, and theoretical foundations.

Table 1. Definitions of variables, sample Item, and theoretical support

| Variable | Code | Definition / Sample Item | Theoretical Support |
|---|---|---|---|
| Behavioral Intention | BI | Indicates students' intention and readiness to incorporate digital devices into their learning activities. (e.g., "I intend to use digital devices for learning in the future".) | [11, 18, 61–64] |
| Perceived Usefulness | PU | The degree to which students perceive that utilizing digital devices improves their learning outcomes (e.g., "Using digital devices helps me complete learning tasks faster".) | [11, 18, 61, 63, 64] |
| Perceived Ease of Use | PEU | Students' perceptions of the ease with which digital devices can be utilized for learning tasks (e.g., "I can easily learn how to use digital devices for learning".) | [11, 18, 61, 63, 64] |
| Social Influence | SI | Influence of significant others (e.g., teachers, parents, peers) on students' attitudes and behaviors toward digital learning (e.g., "People who influence my learning encourage me to use digital devices for learning".).<br>Multi-layered support perceived from school, teachers, family, and peers encouraging digital device use (e.g., "My school encourages the use of digital devices for learning"; "My teachers' use of digital devices motivates me".) | [18, 61, 62, 65, 66] |
| Facilitating Conditions | FC | Availability of resources, support, and infrastructure that enable digital learning (e.g., "I have a digital device for my learning.") | [18, 61, 62] |
| Self-Efficacy | SE | Students' self-assessed ability to design, produce, and innovate using digital tools (e.g., "I can use software (e.g., Canva, PowerPoint) to create engaging presentations".) | [41, 42] |
| Perceived Safety | PS | Awareness and application of safe and ethical digital practices in online environments (e.g., "I ensure the safety of my personal data and protect my privacy"; "I apply energy-saving measures to protect the environment".) | [38, 42, 67–69] |

### E. Data Analysis Strategy

Data analysis employed PLS-SEM (SmartPLS 4), chosen for its suitability in theory-building contexts and its capacity to handle both reflective and formative indicators when modeling complex behavioral dynamics [58].

#### 1) Measurement model

The measurement model was assessed following established SEM conventions. Model adequacy was established using conventional SEM diagnostics, including SRMR ($< 0.08$) [70] and reliability indices ($\alpha > 0.70$; CR $> 0.60$) [58, 71], which jointly confirmed consistency across constructs. The reliability of indicators was mainly determined by factor loadings, with values exceeding 0.70 being preferred; however, loadings ranging from 0.40 to 0.70 were accepted if theoretically justified [72]. Convergent validity was verified through AVE values greater than 0.50 [73], while discriminant validity was checked using the HTMT ratio, with values under 0.85 indicating sufficient distinctiveness across constructs [59]. Multicollinearity was monitored through VIF values, which remained well below the recommended ceiling of 10 [74]. Overall, these diagnostics confirmed that the measurement model provided a reliable and valid basis for structural testing.

#### 2) Structural model

Once the measurement model was validated, the structural model was evaluated to examine explanatory power and predictive relevance. The coefficient of determination ($R^2$) was evaluated against standard benchmarks, with values approximately 0.75, 0.50, and 0.25 indicating substantial, moderate, and weak explanatory strength, respectively [58]. Bootstrapping (5,000 resamples, bias-corrected intervals) was applied to estimate path coefficients, with significance inferred from conventional thresholds ($t > 1.96$; $p < 0.05$). Complementary indicators such as effect sizes ($f^2$) and predictive relevance ($Q^2$), derived through blindfolding procedures, offered additional evidence of the substantive contribution of predictors and the adequacy of the model's predictive performance.

## IV. Result and Discussion

### A. Evaluation of the Measurement Model

Analysis of the measurement model confirmed that the employed scales demonstrated acceptable levels of reliability and validity for subsequent testing. As reported in Table 2, all outer loadings exceeded the recommended cut-off value of 0.70, suggesting that the observed indicators contribute meaningfully to their corresponding latent constructs.

The internal consistency of the constructs was also verified. $\alpha$ values ranged between 0.864 and 0.968, while CR values varied from 0.871 to 0.968. Both sets of coefficients surpass the conventional threshold of 0.70, confirming robust reliability. Similarly, the AVE scores, which fell between 0.692 and 0.887, were well above the 0.50 benchmark. This provides evidence of convergent validity, indicating that the items adequately represent their respective constructs.

Table 2. Reliability and convergent validity of the measurement scales

| Construct | Number of Items | Outer Loading | $\alpha$ | CR | AVE |
|---|---|---|---|---|---|
| BI | 3 | 0.873–0.894 | 0.855 | 0.856 | 0.775 |
| FC | 4 | 0.845–0.906 | 0.901 | 0.905 | 0.771 |
| PEU | 4 | 0.750–0.856 | 0.835 | 0.850 | 0.667 |
| PS | 4 | 0.831–0.888 | 0.879 | 0.884 | 0.733 |
| PU | 4 | 0.863–0.890 | 0.897 | 0.898 | 0.764 |
| SE | 6 | 0.737–0.871 | 0.896 | 0.897 | 0.659 |
| SI | 17 | 0.720–0.810 | 0.959 | 0.959 | 0.603 |

### B. Discriminant Validity

Discriminant validity was assessed using both the Fornell–Larcker criterion and the HTMT ratio to ensure robustness. Table 3 shows that all HTMT coefficients are below the recommended threshold of 0.85, thereby confirming that the constructs are statistically distinct [59]. Additionally, Table 4 demonstrates that the square root of each construct's AVE (diagonal values) exceeded its correlations with other constructs (off-diagonal values). This further reinforces the conceptual distinctiveness of the latent variables.

Table 3. Discriminant validity based on HTMT ratios

| Construct | BI | FC | PEU | PS | PU | SE | SI |
|---|---|---|---|---|---|---|---|
| BI | | | | | | | |
| FC | 0.487 | | | | | | |
| PEU | 0.756 | 0.733 | | | | | |
| PS | 0.518 | 0.471 | 0.642 | | | | |
| PU | 0.839 | 0.599 | 0.836 | 0.517 | | | |
| SE | 0.612 | 0.487 | 0.616 | 0.597 | 0.668 | | |
| SI | 0.694 | 0.797 | 0.842 | 0.551 | 0.787 | 0.555 | |

Table 4. Fornell–Larcker criterion

| Construct | BI | FC | PEU | PS | PU | SE | SI |
|---|---|---|---|---|---|---|---|
| BI | 0.880 | | | | | | |
| FC | 0.434 | 0.878 | | | | | |
| PEU | 0.654 | 0.635 | 0.817 | | | | |
| PS | 0.453 | 0.422 | 0.556 | 0.856 | | | |
| PU | 0.736 | 0.543 | 0.741 | 0.461 | 0.874 | | |
| SE | 0.537 | 0.441 | 0.541 | 0.531 | 0.600 | 0.812 | |
| SI | 0.632 | 0.741 | 0.757 | 0.508 | 0.733 | 0.517 | 0.777 |

### C. Multicollinearity Assessment

Table 5. VIF values of the constructs

| Construct | BI | PEU | PU |
|---|---|---|---|
| FC | 2.317 | 2.248 | 2.293 |
| PEU | 3.158 | N/A | 2.721 |
| PS | 1.650 | 1.558 | 1.642 |
| PU | 2.937 | N/A | N/A |
| SE | 1.811 | 1.583 | 1.628 |
| SI | 3.770 | 2.588 | 3.284 |

VIF statistics were computed to assess multicollinearity. As presented in Table 5, VIF values ranged from 1.000 to 3.770, remaining well below the conservative threshold of

5 [58]. These results suggest that collinearity among predictors is not problematic in the present model.

### *D. Model fit Assessment Using SRMR*

With a SRMR of 0.048, the model meets the criteria for adequate fit, as it falls below the 0.08 threshold [70]. This result supports the overall appropriateness of the proposed model structure.

### *E. Coefficient of Determination and Predictive Relevance*

The explanatory power of the model was examined through $R^2$ values, which ranged from 0.588 to 0.660 for the endogenous variables. According to established benchmarks, these values indicate moderate explanatory capacity [58]. Moreover, all $Q^2$ values were greater than zero, confirming that the model demonstrates acceptable predictive relevance. Detailed results are presented in Table 6.

Table 6. $R^2$ and $Q^2$ values for the dependent constructs

| Construct | $R^2$ | Adjusted $R^2$ | Explanatory Power | $Q^2$ | Predictive Relevance |
|---|---|---|---|---|---|
| BI | 0.588 | 0.586 | Moderate | 0.449 | Strong |
| PEU | 0.633 | 0.631 | Moderate | 0.416 | Strong |
| PU | 0.660 | 0.658 | Moderate | 0.499 | Strong |

### *F. Hypothesis Testing*

Hypotheses were tested using a non-parametric bootstrapping procedure with 5,000 resamples. As displayed in Table 7 and illustrated in Fig. 2, thirteen of the fifteen proposed hypotheses were supported, with statistically significant path coefficients ($p < 0.05$). These findings provide empirical confirmation of most of the theorized relationships in the research framework.

Table 7. Bootstrapping results for direct effects

| Hypothesis | Path | *β* | *p*-value | $f^2$ | Result | Effect Level |
|---|---|---|---|---|---|---|
| H1 | SI → PEU | 0.506 | <0.001*** | 0.269 | Supported | Medium |
| H2 | FC → PEU | 0.129 | 0.001*** | 0.020 | Supported | Small |
| H3 | SE → PEU | 0.129 | <0.001*** | 0.029 | Supported | Small |
| H4 | PS → PEU | 0.176 | <0.001*** | 0.054 | Supported | Small |
| H5 | SI → PU | 0.407 | <0.001*** | 0.148 | Supported | Medium |
| H6 | FC → PU | −0.090 | 0.006** | 0.010 | Supported | Small (near negligible) |
| H7 | SE → PU | 0.249 | <0.001*** | 0.112 | Supported | Small |
| H8 | PS → PU | −0.054 | 0.084ns | 0.005 | Not Supported | Negligible |
| H9 | PEU → PU | 0.386 | <0.001*** | 0.160 | Supported | Medium |
| H10 | SI → BI | 0.174 | <0.001*** | 0.019 | Supported | Small (near negligible) |
| H11 | FC → BI | −0.123 | <0.001*** | 0.016 | Supported | Small (near negligible) |
| H12 | SE → BI | 0.103 | 0.001*** | 0.014 | Supported | Small (near negligible) |
| H13 | PS → BI | 0.053 | 0.120ns | 0.004 | Not Supported | Negligible |
| H14 | PEU → BI | 0.174 | <0.001*** | 0.023 | Supported | Small |
| H15 | PU → BI | 0.460 | <0.001*** | 0.175 | Supported | Medium |

Note: ***, **, and * indicate significance levels at 0.001, 0.01, and 0.05, respectively. "ns" indicates non-significant results ($p > 0.05$)

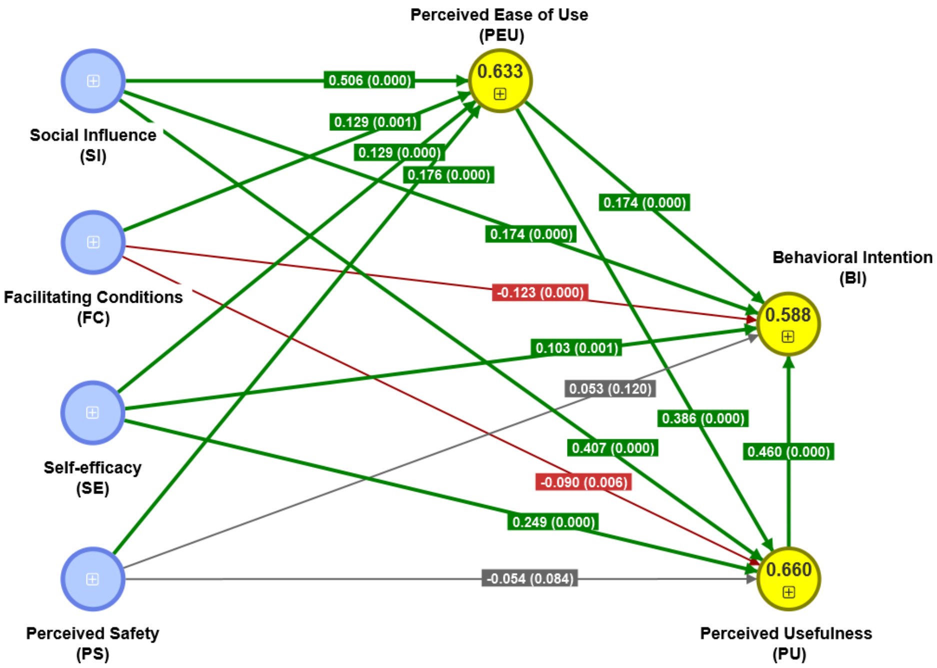


Fig. 2. Final structural model with 7 constructs and 15 hypotheses.

### *G. Indirect and Total Effects*

Table 8 presents the significant indirect and total effects. Notably, SI has an indirect effect on BI through PEU and PU, highlighting the mediating role of technological factors in the model.

Table 8. Bootstrapping results for indirect and total effects

| Path | *β* | Result |
|---|---|---|
| SI → … → BI | 0.539*** | Supported |
| SI → PU → BI | 0.187*** | Supported |
| SI → PEU → BI | 0.088*** | Supported |
| SI → PEU → PU → BI | 0.090*** | Supported |

| Path | $\beta$ | Result |
|---|---|---|
| FC → … → BI | −0.119*** | Supported |
| FC → PU → BI | −0.041** | Supported |
| FC → PEU → BI | 0.023* | Supported |
| FC → PEU → PU → BI | 0.023** | Supported |
| SE → … → BI | 0.263*** | Supported |
| SE → PU → BI | 0.115*** | Supported |
| SE → PEU → BI | 0.023** | Supported |
| SE → PEU → PU → BI | 0.023*** | Supported |
| PS → … → BI | 0.090* | Supported |
| PS → PU → BI | −0.025ns | Not Supported |
| PS → PEU → BI | 0.031** | Supported |
| PS → PEU → PU → BI | 0.031*** | Supported |

Note: ***, **, and * indicate significance levels at 0.001, 0.01, and 0.05, respectively. "ns" indicates non-significant results ($p$ > 0.05).

## V. Discussion

### A. Digital Integration in a Multicultural and Underserved Educational Context

The findings underscore the need to contextualize technology adoption within socio-cultural and infrastructural realities. In Vietnam's Central Highlands–where students experience both ethnic diversity and technological inequities–digital integration presents opportunities for inclusion but also exposes systemic gaps. Applying TAM [11] and UTAUT [13], the results reveal that Perceived Usefulness (PU), Perceived Ease of Use (PEU), and Social Influence (SI) operate differently for learners in resource-constrained environments.

Specifically, PU exerted a stronger influence on Behavioral Intention (BI) ($\beta$ = 0.460, $p$ < 0.001) compared with PEU ($\beta$ = 0.174, $p$ < 0.001), indicating that students are primarily outcome-driven, valuing tangible academic benefits (e.g., access to learning materials, efficiency gains) over ease of use. This pattern is consistent with findings from Indonesia [16, 75], Turkey [64], and Somalia [4], where technology serves as a compensatory tool to overcome structural barriers. By contrast, in digitally mature contexts, ease of use typically initiates adoption behavior [76]. These results align with Fan and Wang [50], who argue that digital competence reflects the cultural and social values of specific learning environments.

Perceived Safety (PS) significantly influenced PEU ($\beta$ = 0.176, $p$ < 0.001) but not BI, reflecting the "privacy paradox" [68, 69]—where learners continue to adopt technology despite potential security concerns. While some studies (e.g., Almaiah *et al.* [38]) report a direct relationship between PS and usage, this study aligns more closely with Wang *et al.* [50], showing that PS primarily shapes perceptions of ease rather than behavioral intent x.

### B. Social Influence, Self-Efficacy, and Cultural Context

The findings reveal that Social Influence (SI) plays a particularly strong role in shaping Behavioral Intention (BI) among high school students in Vietnam's Central Highlands. SI exerted both direct effects ($\beta$ = 0.174, $p$ < 0.001) and indirect effects via Perceived Usefulness (PU) and Perceived Ease of Use (PEU), resulting in a substantial total effect ($\beta$ = 0.539, $p$ < 0.001). This magnitude is higher than those reported in China ($\beta$ = 0.244) and Iraq ($\beta$ = 0.188) [3, 77], indicating that peer endorsement and social support exert greater behavioral influence in this cultural context. The result aligns with previous studies emphasizing the salience of collectivist norms in Asian educational settings [78].

This pattern is consistent with Hofstede [25] cultural framework and the propositions of Srite and Karahanna [48], suggesting that values such as collectivism and high power distance can amplify the role of SI and Facilitating Conditions (FC) in technology acceptance. Complementing this view, Faqih [53] demonstrated that the cultural dimensions of Individualism–Collectivism and Uncertainty Avoidance do not directly determine behavior but rather moderate the strength of relationships among cognitive variables. These findings collectively underscore that technology adoption in collectivist, hierarchical societies is not purely an individual decision but one deeply embedded in social structures, including peer mentoring, family expectations, and teacher endorsement. Leveraging these collective influences can thus serve as an effective strategy to foster digital learning in underserved regions.

Self-Efficacy (SE) also emerged as a significant predictor of both Perceived Usefulness (PU) ($\beta$ = 0.249, $p$ < 0.001) and Perceived Ease of Use (PEU) ($\beta$ = 0.129, $p$ < 0.001). This finding supports earlier meta-analyses [79], which identified SE as a central determinant of technology acceptance across diverse contexts. Students with higher confidence in their digital abilities are more likely to perceive technology as both valuable and manageable. However, the influence of SE may vary according to the pedagogical environment. In teacher-centered, passive learning environments, SE generally has diminished effects [9]; conversely, in learner-centered contexts, SE can substantially facilitate technology adoption. These findings are consistent with Hatlevik *et al.* [51] and Aesaert *et al.* [80], who found that students' digital competence and self-belief are strongly shaped by cultural capital and learning environment.

Overall, the results suggest that digital integration strategies should not only strengthen technical competence but also cultivate autonomy, confidence, and social support. In resource-constrained, collectivist environments such as the Central Highlands, maximizing the combined effects of Social Influence and Self-Efficacy can create more equitable and sustainable digital learning ecosystems.

### C. Facilitating Conditions and the Paradox of Infrastructure

The role of FC in this study revealed a complex relationship with PEU and PU. Although FC positively influenced PEU ($\beta$ = 0.129, $p$ = 0.001), it negatively affected PU ($\beta$ = −0.090, $p$ = 0.006) and ultimately reduced BI ($\beta$ = −0.123, $p$ < 0.001). This suggests that infrastructural support, while improving ease of use, may not always translate into perceptions of usefulness or effectiveness. In the Central Highlands, where 63% of students have internet access and only 27% own computers [33], unreliable infrastructure may make people less likely to trust digital tools. This finding is consistent with Self-Determination Theory [81], which posits that poorly implemented external support can weaken intrinsic motivation and autonomy, particularly when students perceive inadequate support.

These findings are also aligned with studies from Turkey [82] and Saudi Arabia [19], where infrastructural issues and digital readiness varied significantly across schools and regions. Furthermore, prior research [39, 40] indicates that FC may have limited impact if support mechanisms are not tailored to learners' specific needs, especially in resource-constrained contexts.

### D. Theoretical Contributions, Limitations, and Future Directions

This study offers several significant contributions to theory. First, it extends UTAUT by emphasizing SI as a meta-construct that shapes both PU and PEU, particularly in collectivist cultures. Second, it challenges traditional assumptions about FC, showing that access to technology alone is insufficient without context-specific support and tailored interventions. Finally, the integration of Self-Determination Theory with TAM/UTAUT provides a more complex overview of how motivation and autonomy impact technology adoption.

Nevertheless, several limitations should be acknowledged. The cross-sectional design constrains the ability to draw causal conclusions [83], and the sample, being limited to the Central Highlands, may not fully represent other regions of Vietnam [84]. Furthermore, the absence of in-depth qualitative data restricts insights into the potential negative effects of FC [85]. Future studies could overcome these limitations by employing longitudinal designs, comparative analyses with urban regions, and exploring the influence of ethnic minority cultures on SI.

Finally, these findings reinforce UNESCO [55] recommendations that digital transformation in education must be interpreted within specific cultural contexts, as learners' perceptions, beliefs, and digital behaviors are deeply intertwined with community norms and local social structures.

## VI. Conclusion

This study offers actionable insights for educational policymakers, school leaders, and practitioners aiming to promote inclusive and sustainable digital transformation in resource-constrained and multicultural environments.

First, schools should regularly assess and develop students' digital competence through periodic evaluations aligned with Vietnam's National Digital Competence Framework (MOET). Understanding variations in infrastructure and digital confidence across regions can guide differentiated support and ensure that interventions remain equitable and responsive to learners' needs.

Second, improving technical and infrastructural support is essential. Investments should prioritize long-term maintenance, training, and system reliability rather than one-time hardware procurement. Schools may establish local or inter-school technical support teams to manage device upkeep, connectivity, and troubleshooting. In remote areas, hybrid or offline solutions can reduce dependence on unstable internet connections. Partnerships involving schools, local authorities, and telecommunications providers can further expand digital inclusion.

Third, fostering digital self-efficacy and learner autonomy is crucial. As Self-Efficacy (SE) emerged as a strong determinant of Perceived Usefulness (PU) and Perceived Ease of Use (PEU), teacher professional development and student training should emphasize experiential, project-based, and learner-centered activities that build confidence through authentic digital practice.

Fourth, leveraging Social Influence (SI) through community-based engagement can enhance student motivation in collectivist cultural contexts. Peer mentoring programs, parent involvement initiatives, and community learning clubs may serve as culturally aligned mechanisms for sustaining digital engagement and reinforcing shared responsibility for learning.

Collectively, these implications highlight that effective digital transformation requires a socio-cultural, participatory, and context-responsive approach–one that values local realities as much as technological innovation.

This study advances understanding of how technological, psychological, and cultural factors jointly influence students' acceptance of digital learning technologies in Vietnam's Central Highlands. The findings confirm that PU remains the strongest predictor of Behavioral Intention (BI), while SI and SE exert significant reinforcing effects in collectivist and resource-limited settings. The paradoxical relationship observed between Facilitating Conditions (FC) and PU suggests that infrastructure alone does not guarantee perceived usefulness without corresponding levels of competence, trust, and pedagogical alignment.

Theoretically, the study extends the TAM–UTAUT framework by integrating cultural and motivational dimensions, demonstrating that contextual adaptation is essential when applying global models in non-Western, disadvantaged environments. Practically, the findings inform the design of equitable, culturally sensitive digital education policies and learner-centered implementation strategies.

Future research should broaden the scope beyond the Central Highlands, employ longitudinal or comparative designs, and incorporate qualitative approaches to deepen understanding of digital learning behavior across diverse ethnic and socio-economic groups.

Ultimately, this research underscores that digital transformation in education must move beyond access alone–toward empowerment, equity, and cultural alignment.

## Conflict of Interest

The authors declare no conflict of interest.

## Author Contributions

T.T.T. was primarily responsible for conceptualization, methodology, formal analysis, and preparation of the original draft. L.T.T.A. carried out investigation and data collection. Both authors contributed to validation, review and editing, supervision, and project administration, and jointly approved the final version of the manuscript.

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