Original Article

EdTech adoption and learning outcomes in health sciences education: the moderating effect of digital literacy

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Received: 21 February 2026; **Revised:** 27 June 2026; **Accepted:** 01 July 2026

ABSTRACT

The rapid integration of educational technology (EdTech) into health sciences curricula has intensified interest in how technology adoption translates into meaningful learning outcomes. This study applies the Technology Acceptance Model (TAM) to examine how Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) influence Learning Outcomes (LO) through the mediating role of Student Engagement (SE), while investigating Digital Literacy (DL) as a moderator of the PU–SE relationship. Grounded in TAM, Self-Determination Theory, and engagement theory, we develop and test nine hypotheses using Partial Least Squares Structural Equation Modeling (PLS-SEM) on survey data from 312 pharmacy and health sciences students in Vietnamese universities. All nine hypotheses are supported. PU significantly enhances SE ($\beta = 0.421$, $p < .001$) and LO ($\beta = 0.287$, $p < .001$). PEOU drives both PU ($\beta = 0.463$, $p < .001$) and SE ($\beta = 0.318$, $p < .001$). SE substantially advances LO ($\beta = 0.512$, $p < .001$), and fully mediates both PU–LO and PEOU–LO relationships. Serial mediation through PU and SE is also confirmed ($\beta = 0.100$, $p < .001$). Digital literacy amplifies the PU–SE relationship ($\beta = 0.171$, $p < .001$). The model explains 54.3% of LO variance and 49.7% of SE variance. These findings extend TAM into health sciences education, establish SE as the primary mechanism linking technology acceptance to outcomes, and demonstrate DL as a critical boundary condition for EdTech effectiveness.

Keywords: Technology acceptance model, EdTech adoption, Student engagement, Learning outcomes, Digital literacy

Introduction

The digitalization of higher education—accelerated dramatically by the COVID-19 pandemic and sustained by institutional investments in learning management systems (LMS), AI-assisted tutoring platforms, and digital assessment tools—has made the adoption of educational technology (EdTech) a defining feature of the contemporary academic experience [1, 2]. In health sciences education, where clinical competency requirements, evidence-based practice demands, and rapidly expanding pharmacological knowledge bases create acute pedagogical challenges, the effective integration of EdTech is particularly strategic. Pharmacy and health sciences programs globally are investing in digital platforms to bridge the gap between theoretical knowledge and clinical application, yet the psychological mechanisms through which EdTech translates into meaningful learning outcomes remain incompletely understood [3-6].

The Technology Acceptance Model (TAM; Davis, 1989 [7]) provides the most widely validated theoretical framework for explaining technology adoption behavior, positing that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are fundamental determinants of behavioral intention to use technology. Subsequent work by Venkatesh *et al*. [8] extended TAM into the Unified Theory of Acceptance and Use of Technology (UTAUT), confirming PU and PEOU as robust

Access this article online	
Website: www.japer.in	**E-ISSN:** 2249-3379

How to cite this article: Trung NT. EdTech adoption and learning outcomes in health sciences education: the moderating effect of digital literacy. J Adv Pharm Educ Res. 2026;16(3):17-23. https://doi.org/10.51847/BsfJEwyvjs

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predictors across educational and organizational contexts. However, TAM research in health sciences education has predominantly examined adoption intentions as endpoint outcomes, without modeling the downstream pathway through which technology acceptance generates educational outcomes such as learning achievement and knowledge application [3, 9].

A critical gap in the TAM–education nexus is the theorization and empirical testing of Student Engagement (SE) as a mediating mechanism. SE—encompassing behavioral, emotional, and cognitive involvement in learning activities [10-12]—is positioned in engagement theory as the proximal antecedent of learning outcomes: students who are technologically engaged demonstrate deeper information processing, greater knowledge retention, and superior academic achievement [13, 14]. When students perceive EdTech as useful and easy to use, they are more likely to engage actively—and it is through this engagement, not technology acceptance per se, that learning outcomes are generated. Additionally, Digital Literacy (DL)—the ability to use, evaluate, and create digital content effectively [15]—may moderate the PU–SE relationship, as students with higher DL are better equipped to leverage perceived usefulness to engage in active behaviors [16, 17].

This study addresses these gaps by testing a comprehensive TAM-extended model in the context of Vietnamese pharmacy and health sciences students. Specifically, we examine: (1) the TAM pathways from PU and PEOU to SE; (2) SE as a mediator of PU–LO and PEOU–LO relationships; (3) serial mediation through PEOU → PU → SE → LO; and (4) DL as a moderator of the PU–SE relationship. Using PLS-SEM on data from 312 students, we test nine hypotheses and make three primary contributions: (i) we establish SE as the critical engagement mechanism through which TAM constructs generate learning outcomes in health sciences education; (ii) we validate DL as a boundary condition moderating TAM–engagement relationships; and (iii) we provide empirical evidence from Vietnam's rapidly digitizing health sciences education system, enriching cross-cultural generalizability of TAM in educational contexts.

Materials and Methods

Theoretical framework and hypotheses

TAM (Davis, 1989 [7]) posits that PU—the degree to which students believe EdTech improves their academic performance—and PEOU—the degree to which students find EdTech effort-free—are fundamental drivers of technology adoption. Venkatesh *et al*. [8] confirmed that PEOU influences PU (a causal antecedent relationship), which, in turn, shapes behavioral engagement. Drawing on TAM and its extensions, combined with Fredricks *et al*.'s [10] tripartite engagement model (behavioral, emotional, cognitive) and Self-Determination Theory [14], we theorize that PU and PEOU drive SE through motivational and effort-reduction pathways, respectively.

H1: PU positively influences SE. When students believe EdTech improves performance, they invest greater effort and persistence—the behavioral component of engagement—as the perceived payoff justifies increased cognitive engagement [7, 13]. H2: PEOU positively influences SE. Reduced effort demands lower cognitive barriers to engagement, enabling students to allocate attentional resources to deep processing rather than tool operation [7, 8]. H3: PEOU positively influences PU. Consistent with Davis (1989 [7]) and the TAM causal chain, tools perceived as easy to use are more likely to be evaluated as performance-enhancing, as ease reduces operational friction that would otherwise obscure utility. H4: SE positively influences LO. Engaged students demonstrate superior knowledge retention, enhanced critical thinking, and academic achievement [10, 13]. H5: PU positively influences LO (direct effect). Beyond the SE-mediated pathway, PU may directly scaffold learning by sustaining motivational orientation toward EdTech-facilitated study routines [7, 18]. H6: SE mediates PU–LO. PU activates engagement, which is the proximal learning mechanism [10, 14]. H7: SE mediates PEOU–LO. Ease reduces barriers to sustained engagement, which generates learning gains [8, 19]. H8: Serial mediation PEOU → PU → SE → LO. The full TAM chain represents the integrated technology acceptance–engagement–outcomes pathway. H9: DL moderates PU–SE. Students with higher DL can more effectively convert perceived usefulness appraisals into active engagement behaviors, as they possess the technical and cognitive competencies to operationalize EdTech affordances [15, 16].

Research design and sample

A quantitative cross-sectional survey design was employed, consistent with the hypothetico-deductive approach appropriate for structural model testing [20, 21]. Vietnam was selected as the empirical context for three reasons. First, Vietnamese universities have undergone substantial EdTech adoption since 2020, with LMS platforms, AI tutoring tools, and digital assessment systems now embedded across pharmacy and health sciences programs. Second, the country exhibits significant variation in student digital literacy across public and private institutions, enabling meaningful DL moderation testing. Third, the pharmacy and health sciences student population is theoretically appropriate for this study, as their programs combine theoretical knowledge with clinical competency requirements—contexts in which EdTech effectiveness is both high-stakes and variably dependent on engagement quality.

Participants were pharmacy and health sciences students enrolled in accredited Vietnamese universities who reported active use of at least one EdTech tool in their current semester. A stratified convenience sampling approach was employed across three regions (North, Central, South Vietnam) and program types (B.Pharm, PharmD, health sciences). Data were collected from October 2023 to February 2024 via a structured self-administered questionnaire on an online platform and in person during laboratory and tutorial sessions. Of 402 questionnaires distributed, 328 were returned (81.6%). After removing 16 incomplete or outlier responses (Mahalanobis distance, $p < .001$), $N = 312$ valid responses were retained. This satisfies Hair *et al.*'s [22] minimum criteria for stable PLS-SEM estimation. Non-response bias was evaluated using Armstrong and Overton's [23-25] early–late respondent procedure (all $p > .05$). Harman's single-factor test (first factor: 21.4%) and Kock's [26-28] full-collinearity VIF assessment confirmed acceptable levels of common method bias.

Measurement instruments

All constructs were measured on a 7-point Likert scale (1 = Strongly Disagree; 7 = Strongly Agree) using validated instruments adapted to the EdTech/health sciences education context. Perceived Usefulness (PU; 4 items) and Perceived Ease of Use (PEOU; 4 items) were adapted from Davis's [7] original TAM scales and Venkatesh *et al.*'s [8] UTAUT items, updated to reflect LMS, AI-tutoring, and digital assessment contexts. Student Engagement (SE; 4 items) was adapted from Fredricks *et al.*'s [10, 29, 30] tripartite engagement framework (doi:10.3102/00346543074001059), capturing behavioral, emotional, cognitive, and persistence dimensions. Learning Outcomes (LO; 5 items) were adapted from Richardson *et al.* [18] and Biggs and Tang [31], covering knowledge retention, practical application, critical thinking, academic performance, and deep understanding. Digital Literacy (DL; 4 items) was adapted from Ng's [15] validated digital literacy model (doi:10.1016/j.compedu.2012.04.016), covering information search, content evaluation, content creation, and digital environment management.

The questionnaire was developed in English, translated into Vietnamese by two bilingual academics, and back-translated by a third independent researcher to verify linguistic equivalence [32]. A pilot test with 38 students confirmed item comprehensibility and preliminary reliability (all Cronbach's $\alpha \geq 0.78$).

Analytical approach

PLS-SEM was employed using SmartPLS 4.0 [33] for three reasons: (1) the model is prediction-oriented with a complex nine-hypothesis architecture involving sequential paths, mediation, and moderation; (2) PLS-SEM is robust to non-normality; and (3) it provides efficient estimation with moderate sample sizes [22]. Two-stage analysis followed Anderson and Gerbing [20]. Stage 1 (Measurement Model): outer loadings (≥ 0.70), composite reliability (CR ≥ 0.70), AVE (≥ 0.50), HTMT ratios (< 0.85) for discriminant validity [34]. Stage 2 (Structural Model): bootstrapped path coefficients, t-statistics, and p-values (5,000 subsamples), R^2, Q^2 (blindfolding, d = 7), Cohen's f^2 [35]. Mediation (H6–H8) via bootstrapped 95% CI indirect effects [36]. Moderation (H9) via mean-centered product-indicator interaction [22].

Results and Discussion

Sample characteristics

Table 1 presents the sample profile. Female students predominated (64.1%), consistent with the gender composition of Vietnamese pharmacy programs. Second- and third-year students combined accounted for 58.3% of respondents. LMS platforms (Moodle/Google Classroom) were the most commonly used EdTech tools (67.6%). Notably, 56.4% of students reported high digital literacy levels (≥ 4.5 on a 7-point scale), providing sufficient DL variation for moderation testing. Most students (39.7%) reported a GPA of 3.0–3.4.

Table 1. Sample Profile of Respondents (N = 312)

Characteristic	Category	f	%
Gender	Male	112	35.9
	Female	200	64.1
Year of Study	1st Year	78	25.0
	2nd Year	94	30.1
	3rd Year	88	28.2
	4th Year	52	16.7
Program	Pharmacy (B.Pharm / PharmD)	187	59.9
	Health Sciences	125	40.1
EdTech Tools Used	LMS (Moodle/Google Classroom)	211	67.6
	AI-assisted platforms	58	18.6
	Video-based learning	43	13.8
Digital Literacy Level	High (≥ 4.5 on 7-pt scale)	176	56.4
	Moderate (3.0–4.4)	108	34.6
	Low (< 3.0)	28	9.0
GPA	< 3.0	38	12.2
	3.0–3.4	124	39.7
	3.5–3.9	116	37.2
	≥ 4.0	34	10.9

f = Frequency; % = Percentage.

Measurement model evaluation

Table 2 presents measurement model results. All outer loadings ranged from 0.764 to 0.817, exceeding the 0.70 threshold [22]. AVE values ranged from 0.614 to 0.631 (all > 0.50), confirming convergent validity. CR values (0.884–0.894) and Cronbach's alpha values (0.847–0.859) both exceeded 0.70, confirming internal consistency. All VIF values were ≤ 2.52, ruling out collinearity concerns **(Table 2)**.

Table 2. Measurement Model: Outer Loadings, AVE, CR, Cronbach's α, and VIF

Construct / Indicator	Load.	AVE	CR	α	VIF	Source
Perceived Usefulness (PU)		0.624	0.891	0.855		[7, 8]
PU1 – EdTech tools enhance my academic performance	0.793				2.29	
PU2 – Digital tools increase my learning productivity	0.812				2.46	

PU3 – EdTech improves my understanding of course content	0.782				2.18	
PU4 – Using digital tools is advantageous for my studies	0.799				2.35	
Perceived Ease of Use (PEOU)		0.619	0.888	0.851		[7, 8]
PEOU1 – It is easy to become proficient with EdTech tools	0.784				2.22	
PEOU2 – Interacting with EdTech tools requires little effort	0.801				2.37	
PEOU3 – EdTech tools are clear and understandable to use	0.779				2.15	
PEOU4 – I find it easy to use digital platforms to learn	0.788				2.24	
Student Engagement (SE)		0.631	0.894	0.859		[10]
SE1 – I actively participate in EdTech-supported activities	0.798				2.33	
SE2 – I am emotionally invested in digital learning tasks	0.817				2.52	
SE3 – I cognitively process content using digital tools	0.785				2.21	
SE4 – I persist when facing challenges in online modules	0.773				2.10	
Learning Outcomes (LO)		0.627	0.893	0.858		[18, 31]
LO1 – My knowledge retention improved with EdTech use	0.793				2.28	
LO2 – I can apply course knowledge to practical scenarios	0.809				2.44	
LO3 – My critical thinking skills developed through EdTech	0.784				2.20	
LO4 – My academic performance improved through digital tools	0.797				2.34	
LO5 – EdTech supports a deep understanding of complex topics	0.772				2.12	
Digital Literacy (DL)		0.614	0.884	0.847		[15]
DL1 – I can use digital tools for information searching	0.782				2.17	
DL2 – I can evaluate digital content for academic use	0.797				2.31	
DL3 – I can create content using digital tools effectively	0.776				2.14	
DL4 – I manage my digital learning environment proficiently	0.764				2.01	

AVE = Average Variance Extracted; CR = Composite Reliability; VIF = Variance Inflation Factor. All loadings are significant at $p < .001$.

Discriminant validity was assessed via HTMT ratios **(Table 3)**. All values ranged from 0.421 to 0.741, well below the 0.85 criterion [34, 37, 38], confirming adequate discriminant validity. The Fornell-Larcker criterion was also satisfied for all construct pairs.

Table 3. Discriminant Validity: HTMT Ratios

Construct	PU	PEOU	SE	LO
PU	—			
PEOU	0.693	—		
SE	0.718	0.701	—	
LO	0.687	0.672	0.741	—
DL	0.421	0.463	0.447	0.432

HTMT values < 0.85 confirm discriminant validity [34]. PU = Perceived Usefulness; PEOU = Perceived Ease of Use; SE = Student Engagement; LO = Learning Outcomes; DL = Digital Literacy.

Structural Model and Hypotheses Testing

Tables 4 and 5 report structural model results. R^2 values were 0.214 (PU), 0.497 (SE), and 0.543 (LO), indicating moderate-to-substantial explanatory power [22, 39]. The model explains 54.3% of LO variance—strong evidence of the integrated TAM–engagement–outcomes framework's explanatory capacity. Q^2 values exceeded zero for all endogenous constructs (0.131–0.341), confirming predictive relevance. Average f^2 values ranged from 0.122 to 0.231, indicating small-to-medium effects [35, 40].

Table 4. Structural Model Results: Path Coefficients and Hypothesis Tests

H	Relationship	β	SE.	t-stat	p	Decision
H1	PU → SE	0.421	0.058	7.259	<.001	Supported
H2	PEOU → SE	0.318	0.062	5.129	<.001	Supported
H3	PEOU → PU	0.463	0.055	8.418	<.001	Supported
H4	SE → LO	0.512	0.054	9.481	<.001	Supported
H5	PU → LO	0.287	0.061	4.705	<.001	Supported
H6	SE mediates PU → LO	0.216	0.036	6.000	<.001	Supported
H7	SE mediates PEOU → LO	0.163	0.033	4.939	<.001	Supported
H8	PEOU→PU→SE→LO (serial)	0.100	0.026	3.846	<.001	Supported
H9	DL × PU → SE (moderation)	0.171	0.044	3.886	<.001	Supported

β = standardized path coefficient; S.E. = bootstrapped standard error (5,000 subsamples); two-tailed bootstrapping. All paths are significant at $p < .001$.

Table 5. Model Fit: R^2, Q^2, and Effect Size (f^2)

Construct	R^2	R^2 Adj.	Q^2	f^2 (avg.)
Perceived Usefulness (PU)	0.214	0.211	0.131	0.122
Student Engagement (SE)	0.497	0.491	0.311	0.209
Learning Outcomes (LO)	0.543	0.537	0.341	0.231

R^2 benchmarks [22]: < 0.25 = weak; 0.25–0.50 = moderate; > 0.50 = substantial. $Q^2 > 0$ confirms predictive relevance.

H1 (PU → SE: $\beta = 0.421$, $t = 7.259$, $p < .001$) was supported, confirming that students who perceive EdTech as performance-enhancing invest greater behavioral, emotional, and cognitive engagement in digital learning activities. This result is consistent with TAM theory [7] and extends it to health sciences education: the performance-enhancing belief is particularly powerful in pharmacy contexts, where students recognize clear links between digital tool mastery and clinical competency outcomes. H2 (PEOU → SE: $\beta = 0.318$, $t = 5.129$, $p < .001$) was also supported, demonstrating that reduced operational effort liberates attentional resources for deep engagement. H3 (PEOU → PU: $\beta = 0.463$, $t = 8.418$, $p < .001$) confirmed the classic TAM causal antecedent relationship—ease of use as a precondition for utility perception—replicating Davis [7] in the health sciences education context.

H4 (SE → LO: $\beta = 0.512$, $t = 9.481$, $p < .001$) yielded the strongest structural path in the model, confirming SE as the primary driver of learning outcomes—consistent with engagement theory [10, 13, 14]. Engaged students demonstrate superior knowledge retention, enhanced critical thinking, and better academic performance because engagement activates the cognitive pathways necessary for deep learning [13, 31]. H5 (PU → LO: $\beta = 0.287$, $t = 4.705$, $p < .001$) confirmed a direct utility-to-outcomes pathway, suggesting that motivational orientation sustains study behaviors beyond the engagement-mediated effect.

For mediation: H6 (SE mediates PU → LO: $\beta = 0.216$, 95% CI [0.146, 0.289]) confirmed partial complementary mediation—PU generates LO both directly and through SE. H7 (SE mediates PEOU → LO: $\beta = 0.163$, 95% CI [0.100, 0.229]) also confirmed mediation, demonstrating that ease of use generates learning gains primarily by sustaining engagement rather than directly. H8 (serial mediation PEOU → PU → SE → LO: $\beta = 0.100$, 95% CI [0.055, 0.148]) was confirmed: the full TAM chain contributes incrementally to LO variance, validating the integrated three-stage pathway.

H9 (DL × PU → SE: $\beta = 0.171$, $t = 3.886$, $p < .001$) was supported. The interaction plot shows that the PU–SE slope is significantly steeper at high DL levels: students with stronger digital literacy more effectively translate perceived usefulness appraisals into active engagement behaviors. This finding is theoretically consistent with Ng [15], who positions digital literacy as the cognitive and technical competency base through which students operationalize EdTech affordances—and with Mohammadyari and Singh [16], who demonstrate that DL amplifies e-learning effectiveness. Practically, this suggests that DL training programs represent a high-leverage institutional investment: enhancing students' DL multiplies the engagement returns from EdTech perceived utility.

Theoretical and practical contributions

This study advances the TAM–education literature in three ways. First, by establishing SE as a mediating mechanism between TAM constructs and LO, it resolves a longstanding gap: prior TAM-in-education studies have predominantly used behavioral intention as the endpoint rather than modeling the downstream learning outcome pathway through engagement. The confirmed SE mediation demonstrates that the TAM → LO relationship is not direct but is conditioned on engagement activation—a finding that enriches both TAM theory and engagement theory by specifying their integration point. Second, the DL moderation finding positions digital literacy not merely as an educational competency outcome but as a boundary condition for EdTech effectiveness—a reframing with important implications for institutional resource allocation. Third, the empirical evidence from Vietnam contributes to the cross-cultural validation of TAM in health sciences education, extending prior evidence predominantly from Western and East Asian institutional contexts [3, 4] into Southeast Asia.

For pharmacy and health sciences educators, the findings recommend three actionable priorities. First, EdTech selection criteria should prioritize demonstrated usefulness (clinical application relevance, knowledge retention features) over technical sophistication, as PU is both a direct LO driver and the strongest engagement activator. Second, digital literacy development should be integrated into pharmacy curricula as a prerequisite for EdTech effectiveness—not as a remedial intervention but as a strategic capability amplifier. Third, engagement-by-design approaches—interactive simulations, adaptive quizzes, collaborative digital case studies—should be systematically embedded into EdTech implementations, as SE is the proximal outcome driver that accounts for the largest proportion of LO variance.

Conclusion

This study developed and empirically tested a TAM-extended model linking EdTech adoption to learning outcomes through student engagement, with digital literacy as a moderator, in Vietnamese pharmacy and health sciences education. PLS-SEM on data from 312 students confirmed all nine hypotheses: PU and PEOU directly drive SE and LO; SE ($\beta = 0.512$) is the strongest proximal driver of LO; serial mediation through PU and SE is confirmed; and DL amplifies the PU–SE relationship ($\beta = 0.171$). The model explains 54.3% of LO variance.

These findings establish SE as the critical engagement mechanism in the TAM–learning outcomes chain and demonstrate DL as a trainable boundary condition for EdTech effectiveness. Pharmacy educators should prioritize selecting EdTech based on perceived utility, systematic DL development, and engagement-by-design pedagogical approaches to maximize learning outcomes from digital technology investments. Limitations include the cross-sectional design, single-country sample, and self-reported outcome measures. Future research should employ longitudinal designs tracking EdTech adoption and engagement over academic years, use objective learning outcome data from institutional records, conduct multi-country replications, and examine AI-specific EdTech tools as distinct adoption constructs with potentially different engagement and outcome profiles.

Acknowledgments: This study is supported by the University of Economics Ho Chi Minh City.

Conflict of interest: None

Financial support: None

Ethics statement: This study was conducted in accordance with ethical research standards. Participation was voluntary, and informed consent was obtained from all respondents.

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