



## An expert-validated model of student engagement in virtual engineering labs

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### ABSTRACT

This study proposes a theoretically grounded conceptual framework to enhance student engagement in virtual engineering laboratories. The framework is validated through expert review rather than empirical testing. To address the challenges of online and blended learning environments, the model integrates two established theories: the extended Technology Acceptance Model (TAM2) and Self-Determination Theory (SDT). TAM2 captures extrinsic motivational factors, including perceived usefulness and ease of use, while SDT focuses on intrinsic psychological needs, particularly autonomy and competence. This paper presents an initial theoretical model that has been validated by experts and is intended to precede future empirical testing with students. Expert validation was conducted using a mixed-methods approach involving eight specialists in engineering education and educational technology. Quantitative evaluation employed the content validity ratio (CVR) and item-level content validity index (I-CVI), while qualitative feedback was analyzed using inductive thematic coding. The results showed strong agreement among experts on key components such as system usability, learner engagement, and feedback processes. However, some conceptual overlap was identified between the gamification and enjoyment constructs, suggesting the need for further clarification. The validated framework provides a foundation for future empirical studies to examine the proposed relationships among its constructs. By linking pedagogical design with digital system features, the framework contributes to a deeper understanding of student motivation and engagement in virtual engineering learning environments.

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### 1. Introduction

Virtual laboratories have emerged as a pivotal component in contemporary engineering education, offering scalable, resource-efficient alternatives to conventional hands-on laboratory instruction (Alsaleh et al., 2021; Rukangu et al., 2021). Their pedagogical significance has grown markedly in tandem with the rise of online and blended learning modalities, particularly within science, technology, engineering, and mathematics (STEM) disciplines, where simulation-driven platforms facilitate the acquisition of applied competencies (Elmoazen et al., 2023; Hantoobi et al., 2021). However, maintaining a

high level of learner engagement in virtual environments remains a pressing concern. A critical limitation of current models is their tendency to treat usability and motivation as discrete constructs, thereby overlooking the pedagogical value of frameworks that holistically integrate technological affordances with psychological drivers of engagement (Talib et al., 2024).

To address this gap, this paper introduces an integrated engagement model that draws on two widely recognized theories: The extended technology acceptance model (TAM) and self-determination theory (SDT). The proposed model aims to capture both intrinsic motivators (e.g., autonomy and competence) and extrinsic factors (e.g., perceived ease of use and usefulness) that influence student behavior in virtual learning environments (VLEs) (Hang and Hong, 2025; Shambare and Jita, 2025; Yengkopiong, 2025).

The model was subjected to expert validation by eight professionals in educational technology, engineering education, e-learning, smart cities,

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EdTech validation, and multimodal learning analytics in higher education. Both qualitative (open-ended thematic analysis) and quantitative content validity ratio (CVR) and item-level content validity index (I-CVI) techniques were used to assess the theoretical reliability, clarity, and practical relevance of the model (Li and Liang, 2024).

Although previous studies have independently examined the extended TAM and SDT, efforts to synthesize these frameworks into a unified model tailored to VLEs have been limited. Recent research has begun to explore such integrations, indicating the value of combining usability constructs (e.g., perceived usefulness and perceived ease of use) with intrinsic motivational factors (e.g., autonomy and competence) to understand learner engagement more holistically (Talib et al., 2024).

In this study, existing foundations were built upon with the proposed extended, integrated TAM-SDT model designed explicitly for VLEs. Unlike previous frameworks, such as UTAUT or the classic TAM model, which primarily focus on external factors, the proposed model explicitly integrates technological and psychological dimensions, making an original and relevant contribution to the literature (Alnagrat et al., 2023).

The remainder of this paper is organized as follows. The next section presents the theoretical framework of the proposed model. The Methodology section explains the methodology and its expert validation. The Results section describes the experimental results. The Discussion section discusses these results in the context of previous methods. The Limitations and Future Work sections respectively outline the limitations of this study and future research directions. The final section concludes the paper with the key implications for practical virtual laboratory designs.

The TAM, a prominent theory in this research area, was first introduced by Davis (1989), who argued that two primary constructs, perceived usefulness (PU) and perceived ease of use (PEOU), affect an individual's intention to adopt technology. Throughout the years, the TAM has been broadly used in educational environments to study the impact of usability on typical trends in student engagement with digital learning tools (Davis, 1989).

The extended TAM expands the TAM with external variables, such as system quality, user satisfaction, and social influence, making it more appropriate for complex settings, such as online or blended learning (BL) platforms (Mustafa and Garcia, 2021). This model adopts a perspective that emphasizes internal motivation. It highlights the significance of fulfilling individuals' basic psychological needs, such as autonomy, competence, and relatedness, that underpin sustained effort and enriched learning. Satisfaction of these needs is likely to lead learners to become more motivated, persistent, and cognitively involved (Talib et al., 2024; Ryan and Deci, 2020).

In this study, extended TAM and SDT were combined into a comprehensive engagement model

developed for virtual engineering laboratories. Integration offers an opportunity for a double-sided view that addresses both intrinsic (autonomy and competence) and extrinsic (usability and usefulness) motivations. This holistic model contributes to a better understanding of student engagement through an explanation of the system design and motivational aspects (Talib et al., 2024). In this study, a theoretical integration of TAM2 and SDT was developed and validated by experts as a first step toward student-based empirical testing.

Previous research demonstrated that aligning system functions with learner needs (often known as technology fit success) correlates with increased student engagement in online environments (Alnagrat et al., 2023). The current model expands on this foundation by providing a research-based learner-focused framework for creating viable and effective virtual laboratories for engineering education. The operational definitions of all model components and a complete set of hypotheses are provided in the next section.

The integrated TAM2-SDT engagement model comprises 16 constructs that explain both the technological and motivational factors that shape students' engagement in virtual engineering laboratories. Each construct was operationalized on the basis of validated literature and refined through expert review to ensure conceptual clarity and contextual alignment. System quality (SQ) represents the perceived reliability, stability, and responsiveness of the virtual laboratory platform. A higher SQ level is associated with a reduced cognitive load and stronger perceptions of usefulness and ease of use (Hair et al., 2022; Kemp et al., 2024). The virtual assistant (VA) refers to embedded digital guidance that provides contextual prompts, step-by-step hints, and formative feedback to support autonomous problem solving (Li and Liang, 2024). Assessment and feedback (AF) capture the immediacy and explanatory depth of evaluative responses, which help learners interpret errors and determine improvement strategies. Within AF, feedback specificity denotes the precision and contextual detail of such messages, linking outcomes to learner actions, and supporting mastery (Becker et al., 2023).

Personalized learning (PL) involves adaptive pacing and task sequencing that adjusts to learner performance and preferences, reinforcing autonomy and competence (Marikyan et al., 2023). Perceived realism (PR) reflects the degree to which a virtual laboratory replicates authentic engineering procedures, constraints, and reporting formats, thereby increasing situational relevance (Li and Liang, 2024). Collaborative learning (CL) represents the extent of interaction and shared responsibility among learners, strengthening their social presence and engagement (Talib et al., 2024).

Playfulness (PLY) denotes the intrinsic enjoyment and curiosity generated by exploratory or gamified activities that sustain motivation (Zeng et al., 2024). Cognitive engagement (CE) describes the

sustained mental effort and strategic thinking directed toward solving laboratory tasks (Ryan and Deci, 2020). Perceived usefulness (PU) is the belief that a virtual laboratory enhances learning efficiency and conceptual understanding (Alnagrat et al., 2023; Davis, 1989). Perceived ease of use (PEOU) indicates the extent to which interacting with the virtual lab is intuitive and requires minimal effort (Mustafa and Garcia, 2021). Perceived competence (PC) expresses the learner’s confidence in successfully completing the laboratory tasks successfully (Ryan and Deci, 2020). Perceived autonomy (PA) reflects the sense of control and self-direction over task selection, pacing, and approach (Talib et al., 2024).

Behavioral intention to use (BIU) captures the learner’s willingness to continue using virtual laboratories in future learning contexts (Marikyan et al., 2023). Student engagement (SE) encompasses behavioral, emotional, and cognitive involvement in laboratory activities (Hair et al., 2022). Finally, gamification elements (GAM) refer to structured motivational features, such as progress indicators and achievement badges, that foster persistence when aligned with meaningful learning goals (Zeng et al., 2024). Drawing on these definitions and the theoretical links derived from the TAM2 and SDT, 16 hypotheses were formulated to explain the expected interrelationships between the constructs. Assessment and feedback are proposed to influence PU, PEOU, and PC (H1a–H1c). PL is expected to enhance PC and autonomy (H2a, H2b). Gamification is proposed to increase cognitive engagement and playfulness (H3a and H3b). SQ is hypothesized to

affect perceived usefulness and ease of use (H4a, H4b), whereas the VA is expected to influence the same variables (H5a, H5b). Perceived usefulness and ease of use are predicted to strengthen BIU (H6 and H7), which subsequently drives SE (H8). Finally, PA, competence, playfulness, and realism were hypothesized to positively influence SE (H9–H12). Collectively, these relationships formed an integrated theoretical model validated by experts using the content validity ratio (CVR) and item-level content validity index (I-CVI) to assess conceptual soundness and practical relevance.

**2. Methodology**

A synthesis of quantitative trends and qualitative expert judgments confirmed this model. The validation was conducted by a panel of eight domain specialists, including academics and industry practitioners with expertise in both educational technology and engineering education. Table 1 presents the experts’ profiles, including their disciplines, academic ranks, institutions, countries, and years of experience, to demonstrate diversity and domain coverage. We selected expert contributors for several reasons: Their practical experience in developing virtual laboratories, their backgrounds in e-learning and content authoring, and their authorship in the field. Participation was voluntary under informed consent, and all responses were anonymized to maintain confidentiality and adhere to ethical standards.

**Table 1:** Profile of the expert review panel

Expert ID	Discipline	Years of experience
E1	Educational technology validation, multimodal learning analytics	13
E2	Remote laboratories, engineering education	19
E3	Engineering education, virtual laboratories	28
E4	E-learning, smart cities	15
E5	Engineering education, remote laboratories	15
E6	Instructional and learning technologies	44
E7	Civil engineering, engineering education, IT	52
E8	Educational technology	15

The panel collectively represented experts across engineering pedagogy, instructional design, remote laboratories, and educational technology, ensuring the triangulation of perspectives for content validity.

An expert-reviewed structured questionnaire with a five-point Likert scale (1 = not important, 5 = essential) was used to assess the importance and relevance of each model component. Given the ordinal nature of Likert responses and the small panel size, both medians and interquartile ranges were reported alongside means and standard deviations to better characterize the level of agreement. Descriptive statistics were used to examine the degree of agreement among respondents and identify potentially ambiguous items (Cooksey, 2020).

For content validity, the analysis of Lawshe’s (1975) CVR and I-CVI was based on the number of experts (NE) who rated an item as essential (4 or 5), with a minimum accepted value of 0.75 (Lawshe,

1975; Yusoff, 2019). For an eight-member panel, CVR ≥ 0.75 was adopted as the retention threshold; items below this level were marked for revision or clarification. The I-CVI values were calculated per construct to complement the CVR results and identify items requiring refinement.

In the qualitative assessment, open-ended comments were analyzed both deductively and inductively through thematic coding. The emergent themes were categorized into strengths and weaknesses of concepts and suggestions for refinement. Coding was conducted independently by two reviewers, and disagreements were resolved through discussion while maintaining an audit trail to ensure reliability and transparency.

Both the quantitative measures and thematic findings provide strong evidence-based validation of the model’s precision, theoretical relevance, and practical applications in engineering education (Marshall and Jonker, 2010). Because the sole focus

of this study was expert validation, student data were not collected. The next phase will involve empirical testing with student participants to examine the predictive relationships of the model.

### 3. Results

#### 3.1. Component evaluation

Statistical analysis of the 16 components of the proposed engagement model was performed. Both the central tendency (mean and median) and dispersion (standard deviation, variance, and interquartile range) were reported to accurately represent expert ratings on an ordinal Likert scale. Indices of content validity, such as CVR and I-CVI, were calculated for expert ratings. These indicators served to evaluate the degree of expert consensus and identify constructs that require further improvement. The results are summarized in Table 2. High consensus was observed for components such as system quality and usability, VA, SE, and BIU (CVR = 1.00; SD ≤ 0.52), suggesting strong agreement on their importance and clarity. Conversely, components such as GAM, enjoyment, and feedback specificity received lower CVR values (≤ 0.50) and higher variability, indicating conceptual ambiguity or differing interpretations across contexts. This result suggests the need for more precise definitions and future empirical testing of these elements. Overall, the results support the

theoretical structure of the model, affirming the robustness of most components and identifying areas for future enhancement, particularly within motivational constructs.

#### 3.2. Hypothesis evaluation

Table 3 presents an evaluation of the 16 hypothesized relationships among the constructs in the engagement model. Medians and interquartile ranges were reported alongside means and standard deviations to reflect the ordinal scale and a small expert panel. Using the same metrics as in the component evaluation (CVR, I-CVI, mean, SD, and variance), the experts assessed the clarity and theoretical grounding of each relationship. For an eight-expert panel, CVR ≥ 0.75 was adopted as the retention threshold, and relationships below this level were flagged for revision before student testing. Of the 16 hypotheses, 12 met or exceeded the CVR threshold of 0.75, indicating a strong expert agreement. Hypotheses H5a and H8 achieved perfect validation scores (CVR = 1.00), suggesting exceptional clarity and relevance in the context of virtual laboratories. Alignment with the component-level results was observed. The paths involving system quality, virtual assistants, and intention to use showed a higher consensus, which is consistent with the strong component ratings for these constructs.

**Table 2: Descriptive statistics for model components**

Component	NE	I-CVI	CVR	Decision	Mean	Median	SD	Variance
Assessment and feedback	8	1.00	1.00	Accept	4.88	5.00	0.35	0.13
Gamification elements	6	0.75	0.50	Review	3.75	4.00	1.16	1.36
Personalized learning paths	7	0.88	0.75	Accept	4.50	5.00	0.76	0.57
System quality and usability	8	1.00	1.00	Accept	4.63	5.00	0.52	0.27
Virtual assistant	8	1.00	1.00	Accept	4.63	5.00	0.52	0.27
Perceived realism	7	0.88	0.75	Accept	4.38	4.50	0.74	0.55
Collaborative use	6	0.75	0.50	Review	4.00	4.00	0.76	0.57
Feedback specificity	6	0.75	0.50	Review	4.00	4.00	0.76	0.57
PU	7	0.88	0.75	Accept	4.63	5.00	0.74	0.55
PEOU	7	0.88	0.75	Accept	4.38	4.50	0.74	0.55
Enjoyment	5	0.63	0.25	Review	3.63	4.00	0.92	0.84
Cognitive engagement	7	0.88	0.75	Accept	4.50	5.00	0.76	0.57
Perceived competence	7	0.88	0.75	Accept	4.25	4.50	1.04	1.07
Perceived autonomy	7	0.88	0.75	Accept	4.13	4.00	0.64	0.41
Student engagement	8	1.00	1.00	Accept	4.75	5.00	0.46	0.21
Behavioral intention to use	8	1.00	1.00	Accept	4.63	5.00	0.52	0.27

**Table 3: Descriptive statistics for hypotheses**

Hypothesis	NE	I-CVI	CVR	Decision	Mean	Median	SD	Variance
H1a	7	0.88	0.75	Accept	4.63	5.00	0.74	0.55
H1b	6	0.75	0.50	Review	4.38	5.00	0.92	0.84
H1c	7	0.88	0.75	Accept	4.13	4.00	0.64	0.41
H2a	7	0.88	0.75	Accept	4.13	4.00	0.64	0.41
H2b	6	0.75	0.50	Review	3.88	4.00	0.99	0.98
H3a	6	0.75	0.50	Review	4.25	5.00	1.16	1.36
H3b	7	0.88	0.75	Accept	4.38	4.50	0.74	0.55
H4a	7	0.88	0.75	Accept	4.38	4.50	0.74	0.55
H4b	7	0.88	0.75	Accept	4.50	5.00	0.76	0.57
H5a	8	1.00	1.00	Accept	4.38	4.00	0.52	0.27
H5b	7	0.88	0.75	Accept	4.25	4.00	0.71	0.50
H6	7	0.88	0.75	Accept	4.63	5.00	0.74	0.55
H7	7	0.88	0.75	Accept	4.50	5.00	0.76	0.57
H8	8	1.00	1.00	Accept	4.75	5.00	0.46	0.21
H9	5	0.63	0.25	Review	3.63	4.00	0.92	0.84
H10	7	0.88	0.75	Accept	4.38	4.50	0.74	0.55

However, four hypotheses (H1b, H2b, H3a, and H9) scored below the acceptable threshold and showed relatively high standard deviations, indicating the need to refine the construct definitions and item wording for these links prior to empirical testing with students.

Overall, the results confirm the model's theoretical foundation, while pointing to areas for improvement. Grouping hypotheses by expert agreement level may help guide future empirical testing. These outcomes are expected to guide the next phase by prioritizing confirmatory testing of high-consensus paths and treating low-consensus links as exploratory in the student study.

#### 4. Discussion

According to the theoretical model and corresponding research, and based on the statistical results presented in the previous section, the results of the expert validation are explained as follows. The substantial agreement among the experts regarding the integrated theoretical model (extended TAM and SDT) suggests the theoretical validity and relevance of the integrated developmental model in a virtual-laboratory context. Because this research represents an expert validation phase rather than an empirical testing phase, the findings should be interpreted as theoretical evidence of conceptual clarity and readiness for subsequent student-based validation.

This integration captures student engagement by incorporating external factors (perceived usefulness and ease of use) and intrinsic motivations (autonomy and competence) (Talib et al., 2024). This approach addresses the evolving pedagogical requirements for models that effectively integrate usability design with motivational theory.

Expert assessments revealed a strong consensus on constructs such as assessment and feedback, system quality and usability, VA, SE, and BIU. These factors not only exceeded the CVR threshold (CVR = 1.0) but also exhibited low variances, supporting their significant influence on promoting student engagement and usability in digital learning. These findings align with earlier research, suggesting that immediate feedback, user-friendly interfaces, and learner-centered support systems contribute to sustained motivation.

Conversely, the constructs of gamification, enjoyment, and feedback specificity show greater divergence in expert ratings. This result can be attributed to variations in the interpretation or contextual applications. The literature suggests that when these factors are not closely aligned with the learning goals, their motivational effects may be minimal or even negative (Roca and Gagné, 2008).

Qualitative responses further enriched the results, suggesting new applications of the model in other engineering specialties. Several studies have proposed the implementation of metacognitive dashboards to support self-regulated learning, social dynamics of learning, and instructor facilitation approaches. These observations provide promising

directions for refining the model and expanding its application.

The combined extended TAM and SDT establishes a robust and flexible foundation for modeling learner engagement in VLEs. Although most constructs are well theorized, certain motivational aspects require more precise operationalization or adaptation to the instructional context. These findings directly inform the design of the forthcoming empirical phase in which the predictive validity of the model is tested with engineering students in authentic virtual-laboratory environments.

#### 4.1. Limitations

Although rigorous validation must be considered, this study has some limitations. First, the expert panel was relatively small with only eight members. Although this sample size exceeded the methodological criteria for the CVR analysis (Yusoff, 2019), it restricted the diversity of perspectives, particularly considering that the design of virtual laboratories is an interdisciplinary activity. In addition, the panel composition may limit generalizability across institutional and regional contexts, and future work will purposefully broaden disciplinary and geographic representation to mitigate potential selection bias. Second, expert judgment is subjective, even when appraising abstract concepts, such as 'enjoyment' or 'engagement', which can depend on the expert's disciplinary and cultural background. Inter-rater agreement in qualitative coding was ensured through double coding, but formal coefficients were not estimated. Subsequent studies will report reliability indices, such as Cohen's kappa or Krippendorff's alpha, to quantify coder agreement (Hair et al., 2022). Third, the model was not empirically tested on real student users in a virtual-laboratory setting. Thus, its predictive strength and teaching efficacy have not yet been validated by practical evaluation. The next phase will conduct a pre-registered, student-level study with an a priori power analysis, multi-institution sampling, tests of measurement quality (e.g., AVE, CR, and HTMT), and out-of-sample predictive validity (Hair et al., 2022; Li and Liang, 2024).

Moreover, the use of measurement levels (e.g., mean and standard deviation) in the analysis of Likert-scale data in a small sample should be considered carefully because these indices presuppose normality, which is unlikely to be met in this case (Norman, 2010). To address this limitation, the expert-level results report medians and interquartile ranges alongside means and standard deviations. Future studies will prioritize robust estimators and non-parametric inferences where appropriate (Hair et al., 2022). Finally, the minor conceptual overlap observed between gamification and enjoyment indicates a need for sharper operational boundaries; forthcoming empirical work will test discriminant validity and refine item

wording before confirmatory modeling (Li et al., 2024). Future work should focus on increasing the sample size of domain experts, conducting student-centered empirical trials, and testing the model in different engineering education contexts. These steps are critical for enhancing the generalizability of the model and evaluating its practical instructional utility.

#### 4.2. Future work

Future studies should focus on empirical validation and the applicability of the proposed engagement model across various virtual learning environments. The adaptation of the model to various engineering programs and institutional contexts will allow the testing of its predictive power with respect to likely student engagement, satisfaction, and learning outcomes. The next phase will be a pre-registered, multi-site student study with a priori power analysis targeting small-to-moderate effects and an anticipated total sample of approximately 300 undergraduate engineering students. Sampling will follow a stratified approach across at least three programs to ensure disciplinary and regional diversity with clear inclusion criteria and pre-specified stopping rules.

In addition, when optimizing a model using iterative methods, model refinement involves focusing on several essential yet underexplored dimensions. These include the supporting role of instructional mediation, the impact of AI personalization on engagement trajectories, the process of social learning, and the expansion of engagement patterns across long learning episodes (Talib et al., 2024). The empirical study will deploy validated short-form scales for PU, PEOU, BIU, autonomy, competence, playfulness, cognitive engagement, system quality, and perceived realism, followed by measurement diagnostics (indicator reliability, AVE, CR, and HTMT) and an out-of-sample predictive assessment using PLSpredict (Hair et al., 2022). We will examine the mediating paths (PU and PEOU to BIU to SE) and moderators, such as prior digital experience and perceived realism, using multi-group or interaction tests with bootstrap confidence intervals (Hair et al., 2022; Ringle et al., 2023). To address interpretive subjectivity, qualitative comments will be double-coded, and inter-rater agreement will be reported with coefficients such as Cohen's kappa.

Model refinement will prioritize low-consensus links (e.g., H1b, H2b, H3a, H9) through item rewording and targeted pilots before inclusion in confirmatory models, whereas high-consensus paths (e.g., SQ→PU, PEOU→BIU, BIU→SE) will receive confirmatory testing. Planned analyses include invariance checks across sites using measurement invariance of composite model (MICOM) procedures and sensitivity analyses with robust estimators; all materials, code, and anonymized data will be shared via a registered repository, with preregistration details provided upon acceptance.

Cumulatively, these lines of enquiry present valuable prospects for increasing the generalizability of the model and underscore its value for designing personalized, socially networked, and future-ready virtual learning environments. They will also provide a definitive test of predictive validity in authentic virtual laboratory settings and specified actionable design levers for system quality, feedback, and virtual assistance.

#### 5. Conclusion

This paper presents a theoretically integrated model that combines TAM2 and SDT to conceptualize student acceptance and engagement in virtual engineering laboratories, validated through expert reviews rather than student-level experiments. The premise for this integration was to examine not only external factors, such as how helpful or easy the system is to use, but also internal drivers, such as students' feelings of autonomy and competence. Using feedback from domain experts, we identify a set of factors that appear to be fundamental to how students work on these platforms. These include feedback quality, system performance, and overall engagement. Expert ratings and qualitative comments (CVR, I-CVI, thematic analysis) indicated high agreement on these core dimensions, whereas divergence around gamification and enjoyment suggests the need for sharper definitions and targeted piloting before broad use. By combining quantitative expert ratings with structured qualitative analysis, the model is theoretically grounded and oriented toward practical design choices.

Given the continued growth of digital and blended education, this model offers a structured basis for educators, designers, and policymakers in engineering education. It is designed to transfer across programs and institutions, with a planned next phase that will test the model with approximately 300 undergraduate engineering students across multiple programs to evaluate the predictive validity using partial least squares structural equation modeling (PLS-SEM) and refine lower-consensus links. This empirical step provides a definitive assessment of the predictive performance of the model and provides concrete design levers for system quality, feedback, and virtual assistance in authentic virtual laboratory settings.

#### List of abbreviations

AF	Assessment and feedback
AI	Artificial intelligence
AVE	Average variance extracted
BIU	Behavioral intention to use
BL	Blended learning
CE	Cognitive engagement
CL	Collaborative learning
CR	Composite reliability
CVR	Content validity ratio
GAM	Gamification elements

HTMT	Heterotrait–Monotrait ratio
I-CVI	Item-level content validity index
IT	Information technology
MICOM	Measurement invariance of composite model
NE	Number of experts
PA	Perceived autonomy
PC	Perceived competence
PEOU	Perceived ease of use
PL	Personalized learning
PLS-SEM	Partial least squares structural equation modeling
PLSpredict	Partial least squares predict procedure
PLY	Playfulness
PR	Perceived realism
PU	Perceived usefulness
SD	Standard deviation
SDT	Self-determination theory
SE	Student engagement
SQ	System quality
STEM	Science, technology, engineering, and mathematics
TAM	Technology acceptance model
TAM2	Extended technology acceptance model
UTAUT	Unified theory of acceptance and use of technology
VA	Virtual assistant
VLEs	Virtual learning environments

## Compliance with ethical standards

### Ethical considerations

Ethical approval for this study was obtained from the Research Excellence Centre, Universiti Tenaga Nasional (Reference No. REC/Ethics/2026/002). All participants served as expert evaluators on a fully voluntary basis and provided informed consent prior to participation. The questionnaire did not collect any identifying information, ensuring anonymity and data confidentiality. The study adhered to approved ethical research standards and posed no foreseeable risk to participants.

### Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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