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PAPER

Undergraduate Engineering Students' Engagement in Blended Learning: Insights from the Two-Factor Theory and the Mediating Role of Learning Motivation

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ABSTRACT

This study explains undergraduate engineering students' engagement in blended learning through the lens of Herzberg's Two-Factor Theory and the mediating role of learning motivation. Survey data from 656 engineering students enrolled in blended courses at Hanoi University of Science and Technology were analyzed using PLS-SEM. Results indicated that motivator factors strongly influenced learning motivation, which in turn significantly predicted learning engagement, while hygiene factors had only a small direct effect on learning motivation but an indirect role through motivator factors. Mediation analysis confirmed a sequential path (hygiene factors → motivator factors → motivation → engagement), explaining 58% of motivation and 78% of engagement variance. The findings highlight that stable course conditions enable pedagogy-centered motivators to activate motivation and sustain engagement. Practical implications emphasize the need for designing blended courses that combine reliable technical environments with intrinsically motivating learning designs.

KEYWORDS

blended learning, undergraduate engineering students, hygiene factors (HF), motivator factors (MF), learning motivation (LM), learning engagement (LE)

1 INTRODUCTION

In the twenty-first century, blended learning has become a central trend in the innovation of higher education and engineering education [1], [2], [3]. The rapid development of technology, along with the need for flexible learning of learners [4], has prompted global universities to convert the traditional face-to-face classroom model to blended learning [5]. The COVID-19 pandemic further reinforced this necessity, forcing educational institutions to restructure their training programs to maintain continuity and quality [6]. By combining human interaction with the

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flexibility of digital technology, blended learning not only diversifies instructional methods but also enables students to control their own time, space, and pace of learning [7]. This flexibility has positioned blended learning as a highly suitable approach for higher education in the digital era [5], [8], [9]. Previous studies have also widely confirmed that university students engaged in blended learning achieve higher academic performance than those who study entirely face-to-face or fully online [8], [10], [11], [12], [13]. However, these studies also emphasized that students' attitudes toward blended learning are decisive factors in the success of its implementation [14].

A conceptual study has shown that implementing blended learning does not automatically yield positive outcomes if students lack learning engagement (LE) [15]. LE is the central factor determining the success of blended learning because it reflects the level of energy, concentration, and emotion that learners invest in the learning process [16], [17]. Students' LE is directly related to their academic performance and satisfaction and is a key indicator of blended learning effectiveness rather than the mixing ratio of online to face-to-face components [15]. When students exhibit low engagement, blended learning can be ineffective even with advanced technologies in place [18]. Moreover, the impact of blended learning on engagement and academic achievement is inconsistent across countries and contexts [18]. In some cases, in the United States, academic outcomes between students in blended learning and traditional face-to-face instruction were not significantly different, suggesting that if student engagement is not enhanced, the effectiveness of blended learning is limited [18]. Meanwhile, when blended learning is designed to emphasize interaction and timely instructor feedback on students' online activities, student engagement can be significantly improved, particularly when online content aligns with the curriculum [19]. Student engagement with lecture videos and online discussion forums also positively predicts their final course outcomes [20]. Among the three dimensions, emotional engagement is considered the strongest predictor of academic success in blended learning courses, and instructors can promote student engagement by maintaining personal connections with students in the classroom, using collaborative learning strategies, and aligning learning activities with course objectives [21]. Overall, blended learning can enhance student engagement by increasing opportunities for interaction, feedback, and personalized learning, but the extent of effectiveness depends on the design and conditions of the blended learning environment [22]. Collectively, these studies emphasize that student engagement is the decisive link between blended learning design and its learning outcomes.

Building on this rationale, it is important to identify which environmental components strongly shape student engagement. In some initial empirical evidence, elements of blended learning environments play an important role in shaping and maintaining LE [22]. Prominent elements include the presence of the instructor in the online setting, the quality of the learning management system (LMS), and the appropriate connection between online and offline sessions [22]. Prompt feedback, well-aligned content, and clear course organization have been identified as essential conditions for enhancing LE [19]. These factors can be categorized as *hygiene factors* (HFs) under Herzberg's Two-Factor Theory, which prevents students from disengaging from learning [23]. In contrast, motivator factors (MFs) include intrinsic elements such as self-directed learning experiences [24] and authentic or gamified learning activities [25], which stimulate internal motivation and foster active engagement. When a blended learning course harmoniously integrates both HFs and MFs, students are not only protected from disengagement but also encouraged to participate more deeply in learning activities [26].

Additionally, *learning motivation* (LM) is considered the psychological mechanism linking the elements of the blended learning environment and students' LE [27]. LM has a direct effect on LE in online courses, and along with self-monitoring and self-efficacy, it can explain up to 78% of the variance in engagement [28]. LM also indirectly influences academic achievement through LE [29], [30]. Consequently, LM is considered a psychological mechanism that mediates the influence of HFs and MFs on students' LE behavior [31]. Therefore, the purpose of this study is to examine a structural model explaining undergraduate students' LE in blended learning environments through analyzing the direct and indirect effects of environmental factors, including HFs and MFs, with LM functioning as a mediating variable that links these environmental conditions to student engagement.

2 LITERATURE REVIEW

2.1 Student engagement in blended learning in higher education

Blended learning is defined as the convergence between traditional face-to-face (F2F) teaching and online learning that leverages the strengths of both modes to improve the effectiveness of classroom management and learning outcomes [7], [12]. In undergraduate engineering education, blended learning is becoming an increasingly popular teaching method, as it allows educational institutions to maintain face-to-face classroom interactions while providing the learning flexibility of digital technology [32].

Empirical studies suggest that blended learning can improve students' learning engagement when courses are well designed and implemented. A quasi-experimental study using survey and interview data revealed that undergraduate students in the experimental group who participated in blended learning reported higher levels of overall LE in both online and in-class activities compared with those in traditional courses [33]. These results highlight that the blended format encourages not only online interaction but also more active participation during face-to-face sessions. Furthermore, a quantitative study involving 196 undergraduate students further demonstrated that participation in face-to-face sessions had a significant positive influence on engagement in LMS activities, while the amount of time spent using LMS tools was positively associated with academic performance in blended settings [34]. These results suggest that the interplay between physical and digital dimensions can strengthen students' LE [34].

Learning engagement has also been recognized as a strong predictor of academic success in blended learning courses. A survey of students in science courses converted to blended learning at a Canadian university found that LE was a strong indicator of academic success [21]. Additionally, a longitudinal study of 68 undergraduates in six blended courses showed that students' views of the blended learning environment strongly predicted both cognitive and emotional engagement [35]. Overall, these studies confirm that the effectiveness of blended learning largely depends on the extent to which it promotes student engagement across behavioral, cognitive, and emotional dimensions. Students' LE does not arise automatically from the use of technology but must be cultivated by intentional instructional design, instructor presence, and meaningful learning experiences that integrate online and offline components into a coherent and supportive environment [36].

2.2 Blended learning environment: from hygiene factors to motivator factors

The distinction between HFs and MFs in blended learning environments offers a useful framework for understanding how courses can be designed to be both technically effective and pedagogically motivating. This perspective helps explain why the effectiveness of blended learning often depends not only on technological infrastructure but also on the psychological conditions that support learning [37].

Based on *Herzberg's Two-Factor Theory* [23], HFs refer to the basic conditions that prevent frustration in learning among students. In a blended learning environment, HFs typically include the basic conditions that ensure the smooth operation of a course, such as the quality of the LMS, the accessibility of learning materials, the clarity of the course structure, and the responsiveness of the instructor [5], [38], [39], [40], [41]. When these factors are adequately provided, students are able to focus on learning rather than being distracted by technical difficulties or disorganization. However, when these foundational elements are missing, students tend to experience dissatisfaction and disengagement [42]. By contrast, motivator factors represent the intrinsic nature of learning activities that stimulate curiosity, excitement, and persistence among students. These factors include opportunities for active learning, authentic learning tasks, personalized feedback, self-directed learning experiences, and the use of interactive tools such as gamification and virtual simulations [24], [25], [43], [44]. When MFs are effectively integrated, students perceive their learning as meaningful, which enhances their intrinsic motivation and promotes deeper engagement in blended courses [45].

Previous studies have shown that HFs and MFs together form both the foundation and the driving force for LE in blended courses. A survey of 398 students from a comprehensive university in China found that the quality of the online learning environment had a significant and positive effect on both students' behavioral LE and LM [46]. Interview data from students enrolled in a blended *neuropharmacology* course revealed that maintaining a manageable workload, providing individual supervision during online learning, and organizing direct classroom sessions for interaction and clarification all contributed to enhancing LE [36]. Students expressed high appreciation for interactive components such as animations and quizzes, which increased their interest and comprehension [36]. An experimental design involving 152 postgraduate students revealed that prompt instructor responses to online inquiries significantly increased LE, particularly when the online content was closely aligned with the course curriculum [19]. These results demonstrate that HFs, such as clear course organization and responsive communication, and MFs, such as developmental interaction and authentic activities, work together to create a positive learning experience.

A systematic literature review identified three predominant factors influencing the effectiveness of blended learning in higher education: instructor presence in online environments, the degree of interaction among students, instructors, and learning content, and the integration between online and face-to-face activities [22]. These dimensions align with HFs (connection and technical support) and MFs (pedagogical interaction and meaningfulness), reflecting the interdependent nature of the two groups of factors. A longitudinal analysis involving 68 students from two universities found that course design and students' perceptions of the blended learning environment had significant positive effects on both cognitive and emotional LE; while multitasking behavior had a strong negative effect [35]. This finding suggests that a well-structured environment (reflecting HFs) combined with stimulating learning activities (reflecting MFs) is essential to sustain students' LE. Another survey involving 79 undergraduate students who experienced blended learning showed that students rated the courses as engaging and effective (mean = 4.47) [47]. Their positive perceptions of blended learning effectiveness also indirectly influenced learning outcomes through LE [47]. Instructor behaviors that fostered personal connections, used collaborative learning strategies, and linked learning activities with course objectives were associated with improved student LE [21].

Overall, these findings confirm that HFs and MFs are complementary and interdependent components of an effective blended learning environment. HFs provide the basic conditions for smooth course operation and reduce learning barriers, while MFs generate intrinsic motivation and sustain active participation. Without HFs, students may face frustration and disengagement, while without MFs, learning may become passive and lacking in meaning. Therefore, understanding and balancing these two sets of factors is crucial for designing effective blended learning experiences.

2.3 Learning motivation as a psychological mechanism linking the blended learning environment and student engagement

Learning motivation is defined as the internal disposition, energy, emotion, and drive that guide individuals to learn effectively and achieve their goals [48]. Motivation represents an internal psychological process, while engagement reflects the degree to which learners actively participate in a task or learning activity [49]. LM plays a pivotal mediating role that connects environmental conditions with students' behavioral, cognitive, and emotional engagement [50]. This subsection summarizes empirical studies that examined LM as a mediating mechanism between environmental conditions and student engagement.

Empirical evidence has increasingly confirmed the mediating function of LM in the relationship between the learning environment and engagement. A survey of 398 students from a comprehensive university in China found that the quality of the online learning environment significantly and positively affected both behavioral engagement and learning motivation [46]. Moreover, LM mediated the relationship between the online learning environment and behavioral engagement, suggesting that a supportive environment enhances motivation, which in turn fosters engagement [46]. Interview data from students participating in blended courses indicated that they felt motivated when they could control their own pace, time, and place of learning, highlighting the role of autonomy in sustaining both motivation and engagement [33]. A study of 437 university students in Pakistan also demonstrated that LM serves as an important psychological mechanism in online and blended contexts [51]. Structural equation modeling indicated positive correlations between teacher–student relationships, LM, and online LE [51]. Furthermore, LM played a significant mediating role in the relationship between teacher–student relationships and online engagement, underscoring the importance of integrating motivational elements into course design [51]. Consistently, LM has been shown to transmit the effects of environmental factors to engagement by enhancing students' sense of competence, autonomy, and relatedness within the online learning process [46].

Regarding the link between students' LM and LE, survey data from 508 university students majoring in science, technology, and management during a sudden shift to technology-enabled distance education showed that LM exerted a positive influence on student LE in online learning environments [52]. Similarly, a large-scale cross-sectional study of 1,638 Vietnamese university students found that LM had a direct positive impact on LE in higher education in general [53]. Analysis of data from 354 students in Taiwanese universities also demonstrated that LM significantly predicted LE in online learning [28]. Together with learning self-efficacy and self-monitoring, LM explained between 76% and 78% of the variance in LE [28]. Another regression-based study with 331 high school students engaged in online learning found that LM accounted for 55% of the variance in LE, indicating its substantial predictive power [54].

Structural equation modeling using survey data from 745 Chinese university students revealed that LM had a strong and direct positive effect on emotional engagement in blended learning courses [55]. Evidence from a non-experimental correlation design with 79 undergraduate students who had experienced BL showed that students' perceptions of course effectiveness indirectly influenced academic outcomes through engagement, and LM moderated the relationship between perceived effectiveness and learning outcomes [47]. In general learning contexts, findings from 251 Chinese university students confirmed that LM had a significant positive effect on LE, while engagement in turn positively influenced learning outcomes [30].

Overall, these findings highlight LM as a key psychological mechanism that connects external environmental conditions in blended learning, such as HFs and MFs, with LE. A well-designed blended learning environment provides the necessary conditions (reflecting HFs) and stimulating activities (reflecting MFs) that enhance LM, which in turn promotes sustained engagement. This mechanism reinforces the view that engagement does not emerge automatically from technological integration but rather through motivation-driven participation shaped by meaningful blended learning design, supportive instruction, and a sense of self-determination among learners.

2.4 Conceptual model and research hypotheses

Drawing from these theoretical and empirical insights, the following conceptual model was developed, as detailed in Figure 1.

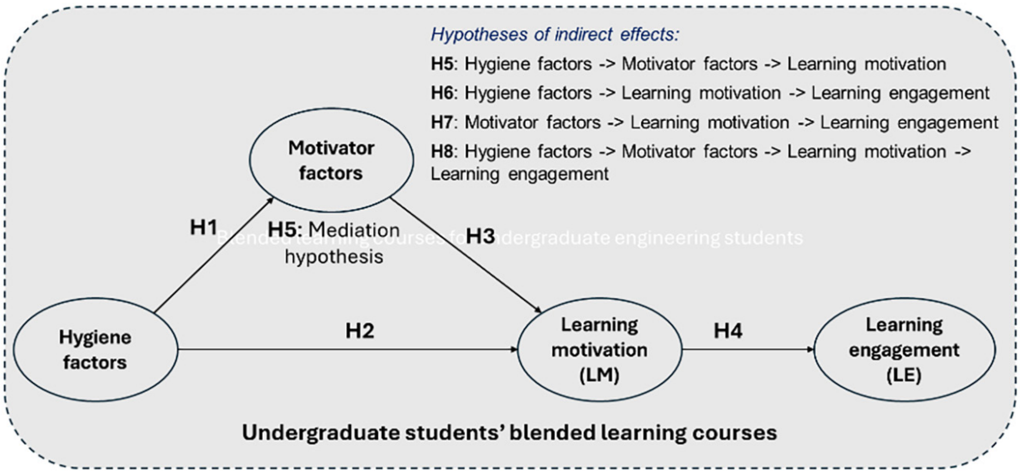

Fig. 1. Proposed research model

As shown in Figure 1, in the context of undergraduate students' blended learning courses, we proposed five research hypotheses:

Hypothesis 1 (H1): HFs in blended learning courses positively predict MFs of undergraduate engineering students.
Hypothesis 2 (H2): HFs in blended learning courses positively predict LM of undergraduate engineering students.
Hypothesis 3 (H3): MFs in blended learning courses positively predict LM of undergraduate engineering students.
Hypothesis 4 (H4): LM of undergraduate engineering students positively predicts their LE in blended learning courses.
Hypothesis 5 (H5): MFs in blended learning courses mediate the relationship between HFs in those courses and LM of undergraduate engineering students.
Hypothesis 6 (H6): LM of undergraduate engineering students mediates the relationship between HFs in blended learning courses and students' LE.
Hypothesis 7 (H7): LM of undergraduate engineering students mediates the relationship between MFs in blended learning courses and students' LE.
Hypothesis 8 (H8): The sequential path through MFs in blended learning courses and LM of undergraduate engineering students mediates the relationship between HFs in those courses and students' learning engagement.

3 METHODOLOGY

3.1 Background of the study site

The study took place in blended learning courses at Hanoi University of Science and Technology (HUST) in Vietnam. HUST is one of Vietnam's leading institutions in engineering and technology education [56], [57]. Since joining the ASEAN Cyber University project in 2010, HUST has invested heavily in digital infrastructure and faculty training to develop blended learning/e-learning courses. The first courses were officially implemented in 2012, marking the shift from traditional face-to-face teaching toward technology-enhanced instruction. Blended learning has become a strategic priority at HUST, aiming to improve learning flexibility, student autonomy, and instructional efficiency. To date, HUST is still making continuous efforts to systematically convert all traditional face-to-face theoretical courses to a blended format. Within this institutional context, understanding what keeps undergraduate students engaged in blended learning courses is essential for sustaining the effectiveness of HUST's digital transformation and ensuring high-quality learning experiences.

3.2 Research design

A quantitative cross-sectional survey was used to examine the factors influencing undergraduate engineering students' engagement in blended learning. Quantitative data were collected in September 2025. The study aimed to confirm a structural model in which MFs and HFs indirectly predict LE through LM. The data were analyzed using PLS-SEM. This method was selected because it is particularly suitable for predictive and theory-building research, handles complex models with multiple latent variables, and performs robustly even under non-normal data distributions [58].

3.3 Instrument development

1. **Motivator factors and hygiene factors:** When no validated instrument existed for assessing motivator and HFs in blended learning contexts, these two constructs were developed inductively from semi-structured interviews with 24 undergraduate engineering students (18 males, six females) across six engineering disciplines: Chemical Engineering (4), Electronics and Telecommunications (4), Control and Automation (5), Mechanical and Mechatronics Engineering (3), Information Technology (4), and Applied Mathematics (4). The interview data were analyzed thematically following the orientation of Herzberg's Two-Factor Theory [23], resulting in 11 items representing MFs and 15 items representing HFs. All items were converted into declarative statements measured on a five-point Likert scale from "1 = Strongly Disagree" to "5 = Strongly Agree."
2. **Learning motivation and learning engagement:** The two variables "learning motivation" and "learning engagement" were measured using established and validated instruments from previous international studies, which were adapted to fit the context of blended learning courses for undergraduate students.
   - Learning motivation: This construct consisted of 11 items adapted from the *Motivation for Online English Language Education Scale* developed by a previous study [59]. The original instrument measures learners' motivation in online English courses and includes three subdimensions: *language skills*, *responsibilities*, and *attitudes* [59]. In this study, the *responsibilities* and *attitudes of* subscales were selected and modified to align with the blended learning environment in engineering education. Each statement was rated on a five-point Likert scale, ranging from "1 = Strongly Disagree" to "5 = Strongly Agree," with higher scores reflecting stronger learning motivation.
   - Learning engagement: This construct was developed from the University Student Engagement Inventory (USEI) proposed by a previous study [60]. The USEI conceptualizes engagement across three dimensions: behavioral, cognitive, and emotional engagement [60]. Given the specific characteristics of blended learning, the original 15 items were reviewed and contextually adapted for relevance and clarity. After expert consultation, 12 items were retained for the final version, representing the breadth and coherence of engagement behaviors in blended environments. Participants responded using the same five-point Likert scale, with higher scores indicating higher engagement.

3.4 Participants and sampling

The study sample consisted of 656 undergraduate engineering students enrolled at HUST. Convenience sampling was used to recruit participants from blended learning courses in the first semester of the 2024–2025 academic year. The inclusion criterion required that students had completed or were currently enrolled in at least one blended learning course. Data was collected online via Microsoft Forms in September 2025. The questionnaire was configured so that all questions were mandatory, ensuring that there were no missing responses. All participants were between 19- and 23-years old. Table 1 summarizes the demographic characteristics of the sample. The proportion of female and male students in the sample is consistent with the actual population ratio at HUST [3], [6]. The majority of respondents were second-year students (73.6%), reflecting the core population of blended courses at HUST. All respondents had experienced at least one blended learning course or more.

Table 1. Participant characteristics (n = 656)

Characteristic	Frequency	%
Gender		
Female	161	28.5
Male	404	71.5
Year of study		
Year 1	5	0.9
Year 2	416	73.6
Year 3	101	17.9
Year 4	40	7.1
Year 5 or above	3	0.6
Number of blended courses previously completed		
1 course	465	82.3
2 courses	71	12.6
3 or more courses	29	5.1

3.5 Data analysis

Data were analyzed using SmartPLS 3.0 software employing the PLS-SEM method, with a significance level of $\alpha = 0.05$. Data analysis followed the standard two-step procedure of PLS-SEM [58], [61].

1. **Evaluation of the reflective measurement model:** Indicator reliability was assessed through outer loadings, with a threshold of ≥ 0.70 [61]. Composite reliability (CR) should be higher than 0.70, while between 0.60 and 0.70 is considered acceptable for exploratory research [61]. Convergent validity was established when average variance extracted (AVE) ≥ 0.50 [58], [61]. Discriminant validity was evaluated using two criteria: (i) the Heterotrait–Monotrait ratio (HTMT), which should be below 0.85 (strict) or 0.90 (lenient) [58], and (ii) the Fornell–Larcker criterion, which requires the square root of each construct's AVE to exceed its correlations with other constructs [61].
2. **Evaluation of the structural model:** Collinearity was assessed using variance inflation factor (VIF), with thresholds of < 3 for testing common method bias and < 5 for predictive collinearity [58]. The standardized root mean square residual (SRMR) was used as an overall model-fit index, with acceptable values below 0.08. Path coefficients were estimated via bootstrapping with 5000 subsamples, using a two-tailed significance level of 5%, and reporting t-values, p-values, and 95% confidence intervals (CIs) [61]. Coefficient of determination (R^2) for endogenous latent variables (indicating the variance explained in each of the endogenous constructs) was interpreted as 0.75 (substantial), 0.50 (moderate), and 0.25 (weak) [58], [61]. Effect size (f^2) values of 0.02, 0.15, and 0.35 were considered small, medium, and large, respectively. Predictive relevance (Q^2) values greater

than zero indicated satisfactory predictive capability of the structural model, indicating that the exogenous constructs are predictively related to the endogenous construct [61]. A larger Q^2 value indicates a greater predictive relevance of the model for a particular dependent variable.

3. **Mediation analysis:** Mediating effects were examined using bootstrapping to determine the significance following the guidelines of a previous study [58]. The variance accounted for (VAF) was also calculated to determine the extent to which the indirect effect explained the total effect. VAF values under 20% indicate no mediation, 20%–80% indicate partial mediation, and over 80% indicate full mediation [58], [62].

4 RESULTS

4.1 Reflective measurement model

We first assessed the reflective measurement model to verify the reliability and validity of HFs, MFs, LM, and LE before testing the structural relationships. Indicator reliability, internal consistency, and discriminant validity were examined, and the results were presented in Tables 2, 3, and 4.

Table 2. Measurement model results

Code	Item	λ	α	CR	AVE
HF	**Hygiene factors**		**0.982**	**0.984**	**0.803**
HF1	Poor video lecture quality	0.887			
HF2	Overloaded content	0.912			
HF3	Weak teacher pedagogical skills	0.886			
HF4	Delayed feedback to online learners	0.906			
HF5	Unequal group participation	0.891			
HF6	Large class sizes	0.877			
HF7	Lengthy lecture slides	0.921			
HF8	Poor visual quality	0.923			
HF9	Unattractive LMS interface	0.911			
HF10	No online study reminder function	0.903			
HF11	Unstable internet connection	0.883			
HF12	Low configuration personal smartphones	0.856			
HF13	Inactive discussion forum	0.893			
HF14	Off-topic group chat	0.900			
HF15	Lack of instructor monitoring	0.892			
MF	**Motivator factors**		**0.984**	**0.986**	**0.865**
MF1	Situational learning (case/problem-based)	0.913			
MF2	Collaborative discussion	0.894			
MF3	Instructor feedback and support	0.939			
MF4	Instructor approachability	0.952			

(Continued)

Table 2. Measurement model results *(Continued)*

Code	Item	λ	α	CR	AVE
MF5	Rich learning materials	0.942			
MF6	Multimodal e-learning	0.941			
MF7	Information visualization/visual clarity	0.948			
MF8	Learning style-oriented e-learning	0.923			
MF9	Competition in learning	0.913			
MF10	Digital creativity tasks	0.928			
MF11	Interactive polling tools	0.935			
LM	**Learning motivation**		**0.984**	**0.985**	**0.860**
LM1	Attendance commitment	0.953			
LM2	Complying with classroom rules	0.950			
LM3	Actively studying online lessons	0.938			
LM4	Completing online tasks within deadlines	0.949			
LM5	Actively interacting in class	0.952			
LM6	Passion and self-commitment to learning	0.909			
LM7	Positive attitude toward blended learning	0.951			
LM8	Enjoying blended learning	0.918			
LM9	Paying attention to learning	0.932			
LM10	Proactive mindset for learning readiness	0.923			
LM11	Persistence in learning	0.817			
LE	**Learning engagement**		**0.989**	**0.990**	**0.893**
LE1	Class attendance	0.944			
LE2	Online participation	0.945			
LE3	Timely assignment submission	0.942			
LE4	Active discussion	0.936			
LE5	Learning enthusiasm	0.942			
LE6	Course interest	0.954			
LE7	Motivational enjoyment	0.953			
LE8	Social connectedness	0.941			
LE9	Cognitive effort	0.952			
LE10	Knowledge integration	0.955			
LE11	Self-directed learning	0.930			
LE12	Knowledge application	0.943			

Notes: λ = Factor loadings; α = Cronbach's α.

As shown in Table 2, all item loadings exceed the threshold of HFs = 0.856–0.923, MFs = 0.894–0.952, LM = 0.817–0.953, and LE = 0.930–0.955, indicating strong indicator reliability in every construct. Cronbach's α and CR were well above 0.70 for all constructs (e.g., HFs: α = 0.982, CR = 0.984; MFs: α = 0.984, CR = 0.986; LM: α = 0.984, CR = 0.985; LE: α = 0.989, CR = 0.990), evidencing excellent internal consistency. AVE values were comfortably above 0.50 (HFs = 0.803; MFs = 0.865; LM = 0.860;

LE = 0.893), supporting convergent validity. Overall, these results met the established measurement requirements and allowed for discriminant validity testing to be conducted.

Table 3. Discriminant validity (Fornell–Larcker criterion)

Dimensions	AVE	HFs	MFs	LM	LE
HFs	0.803	**0.896**			
MFs	0.865	0.337	**0.945**		
LM	0.860	0.351	0.884	**0.927**	
LE	0.893	0.379	0.715	0.756	**0.930**

Note: Bold diagonal values indicate the square roots of AVE; other values are inter-construct correlations.

As shown in Table 3, the square roots of AVE appeared on the diagonal cells (HFs = 0.896; MFs = 0.945; LM = 0.927; LE = 0.930), and each exceeded the corresponding inter-construct correlations in its row/column. The largest correlation occurred between MFs and LM ($r = 0.884$), but it remains smaller than the square root of AVE for both constructs (0.945 and 0.927, respectively), indicating that the Fornell–Larcker criterion is met for all pairs. These findings supported discriminant validity from a variance-extracted perspective.

Table 4. Discriminant validity (HTMT ratio of correlations)

Dimensions	HFs	LE	LM	MFs
HFs				
LE	0.340			
LM	0.355	0.896		
MFs	0.383	0.725	0.768	

As shown in Table 4, all HTMT ratios fell below the lenient threshold of 0.90: HFs–LE = 0.340; HFs–LM = 0.355; HFs–MFs = 0.383; MFs–LE = 0.725; MFs–LM = 0.768; LM–LE = 0.896. While LM–LE = 0.896 was close to the boundary (and slightly above the stricter 0.85 guideline), it was still acceptable to retain based on the less than threshold criterion of 0.90. Therefore, discriminant validity was met under the HTMT criterion.

Overall, the model demonstrated strong indicator quality, excellent internal consistency, clear convergent validity, and acceptable discriminant validity. In other words, the reflective measurement model was well-founded and suitable for evaluating the subsequent structural model.

4.2 Structural model

The structural model was then tested to examine the hypothesized relationships among HFs, MFs, LM, and LE. The results of structural modeling were shown in Tables 5, 6, and 7. Additionally, Figure 2, "PLS-SEM path model," illustrated the tested relationships and path coefficients among constructs.

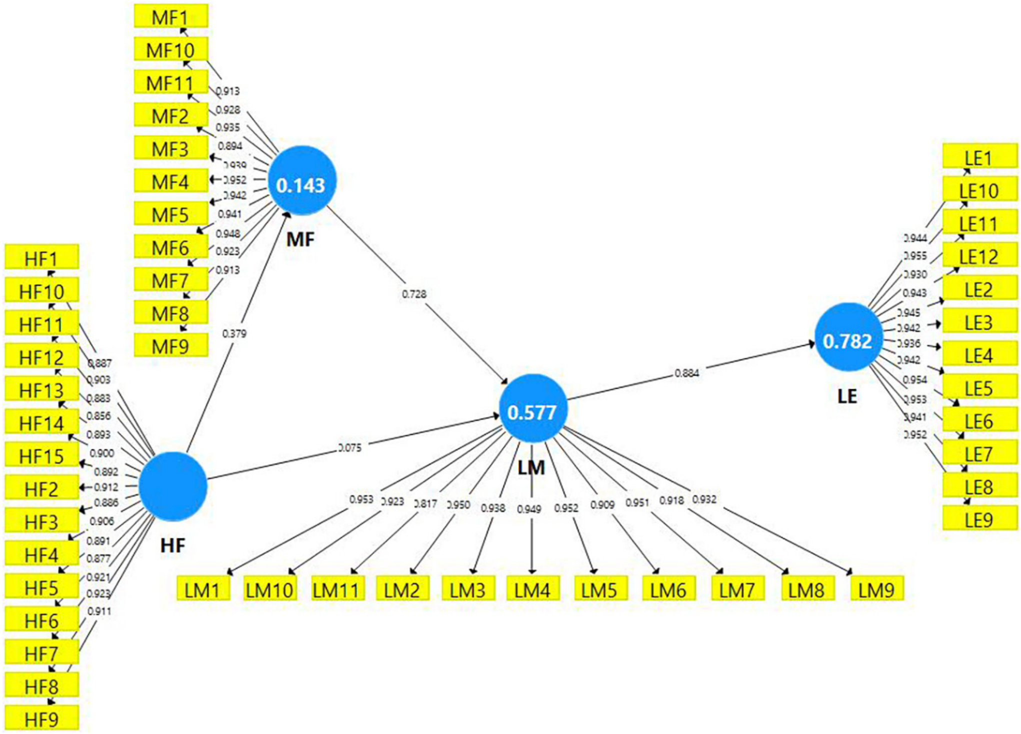

Fig. 2. PLS-SEM path model

Table 5. Collinearity and model fit result

Dimensional Correlation	VIF	Estimated Model Fit
HFs → MFs	1	SRMR = 0.030 Chi-square = 4733.950
HFs → LM	1.167	
MFs → LM	1.167	
LM → LE	1	

As shown in Table 5, before interpreting the path relationships, the model was examined for collinearity and overall fit. All VIF values were below 3, indicating no multicollinearity issues, while the SRMR value of 0.03 was lower than the threshold of 0.08, suggesting a good model fit.

Table 6. Path coefficients and hypothesis testing

Path	β	SD	t	p	95% CI	Hypothesis
HFs → MFs	0.379	0.047	7.998	<0.001	0.282 ÷ 0.468	H1 accepted
HFs → LM	0.075	0.034	2.202	0.028	0.012 ÷ 0.144	H2 accepted
MFs → LM	0.728	0.038	19.348	<0.001	0.648 ÷ 0.798	H3 accepted
LM → LE	0.884	0.021	42.743	<0.001	0.838 ÷ 0.919	H4 accepted

Note: SD = Standard Deviation; 95% CI = Confidence Intervals.

As shown in Table 6, all hypothesized path coefficients were positive and significant at the 5% level. Specifically, HFs → MFs ($\beta = 0.379$, $t = 7.998 > 1.96$, $p < 0.001$, 95% CI = 0.282 ÷ 0.468) and HFs → LM (β = 0.075, t = 2.202 > 1.96, p = 0.028, 95% CI = 0.012 ÷ 0.144) confirmed that HFs in blended learning courses contribute to both MFs and LM of undergraduate students in those courses. MFs → LM (β = 0.728, t = 19.348 > 1.96, p < 0.001, 95% CI = 0.648 ÷ 0.798) showed the strongest influence, underscoring the central role of MFs in shaping LM of undergraduate students. Finally, LM → LE (β = 0.884, t = 42.743 > 1.96, p < 0.001, 95% CI = 0.838 ÷ 0.919) revealed that higher motivation strongly enhances student engagement in blended learning courses. Therefore, all hypotheses related to direct effects from H1 to H4 were supported.

Table 7. Structural model quality indicators (R^2, f^2, and Q^2)

Path	R^2	R^2 Adjusted	Q^2	f^2
HFs → MFs	0.143	0.142	0.693	0.167
HFs → LM	0.577	0.575	0.491	0.011
MFs → LM				1.073
LM → LE	0.782	0.781	0.123	3.579

As shown in Table 7, the model explained 14.3% of the variance in MFs ($R^2 = 0.143$; adjusted $R^2 = 0.142$). Although this R^2 value was modest, $Q^2 = 0.693$ indicates large predictive relevance for MFs, and the local effect of HFs → MFs is medium ($f^2 = 0.167 > 0.15$). For LM, the explained variance was moderate ($R^2 = 0.577 > 0.5$; adjusted $R^2 = 0.575 > 0.5$) with $Q^2 = 0.491 > 0.35$ (large predictive relevance). Evaluation of the effect sizes showed that HFs → LM was small ($f^2 = 0.011 < 0.02$), while MFs → LM was large ($f^2 = 1.073 > 0.35$). For LE, the explained variance was substantial ($R^2 = 0.782 > 0.75$; adjusted $R^2 = 0.781 > 0.75$); $Q^2 = 0.123 < 0.15$, which remained positive, indicating small predictive relevance, and LM → LE produced a very large local effect ($f^2 = 3.579 > 0.35$). Overall, the model showed substantial explanatory power for LM and LE and clear predictive relevance.

4.3 Mediation analysis

Mediation effects were examined to test whether MFs and LM served as indirect pathways. Table 8 summarizes the results for the four hypothesized indirect paths (from H5 to H8).

Table 8. Mediation effect results

Path	β	SD	t	p	95% CI	Total β	VAF (%)	Hypothesis
HFs → MFs → LM	0.276	0.038	7.231	<0.001	0.200 ÷ 0.349	0.351	78.63	H5 accepted
HFs → LM → LE	0.066	0.030	2.194	0.028	0.011 ÷ 0.128	0.310	21.29	H6 accepted
MFs → LM → LE	0.644	0.038	17.036	<0.001	0.566 ÷ 0.714	0.644	100	H7 accepted
HFs → MFs → LM → LE	0.244	0.035	6.983	<0.001	0.175 ÷ 0.312	0.310	78.71	H8 accepted

Note: Total β = Total effects.

Table 8 showed a significant indirect effect of HFs → MFs → LM ($\beta = 0.276$, $t = 7.231 > 1.96$, $p < 0.001$, 95% CI = 0.200 ÷ 0.349), with a VAF = 78.63%, indicating partial mediation. For HFs → LM → LE, the indirect effect was also significant ($\beta = 0.066$, $t = 2.194 > 1.96$, $p = 0.028 < 0.05$, 95% CI = 0.011 ÷ 0.128) with VAF = 21.29%, indicating partial mediation. The path MFs → LM → LE showed the strongest mediation effect ($\beta = 0.644$, $t = 17.036 > 1.95$, $p < 0.001$, 95% CI = 0.566 ÷ 0.714), where the total and indirect effects were identical, yielding VAF = 100% and confirming full mediation. Finally, the sequential mediation HFs → MFs → LM → LE was significant ($\beta = 0.244$, $t = 6.983 > 1.96$, $p < 0.001$, 95% CI = 0.175 ÷ 0.312), with VAF = 78.71%, again indicating partial mediation. Overall, these results supported all four mediation hypotheses, from H5 to H8. The findings confirm that both MFs and LM serve as crucial mediators between HFs and LE, underscoring the sequential motivational process, where environmental conditions stimulate intrinsic motivators, enhance LM, and consequently strengthen engagement in blended learning courses.

5 DISCUSSION

This study enriches the theoretical understanding of LE in blended learning by integrating Herzberg's Two-Factor Theory with the concept of LM. The findings demonstrated a conceptual model explaining how HFs and MFs jointly shape LM and subsequently LE of undergraduate engineering students in blended learning courses.

First, the study advances theory by interpreting Herzberg's Two-Factor Theory in the context of blended learning-based undergraduate courses. HFs were conceptualized as extrinsic, technology- and environment-related conditions that prevent disengagement in blended learning courses, such as system usability, workload manageability, class size, and instructor monitoring, while MFs represented intrinsic pedagogical elements that foster engagement, including authentic learning tasks, feedback, autonomy, and creativity. This theoretical realignment clarifies how motivational and environmental components interact as pedagogical requirements for designing effective blended courses. The findings are consistent with earlier studies showing that well-structured blended environments improve students' LE through clear organization, feedback, and instructor presence [19], [22], [46]. Similarly, this study reaffirms that HFs, although extrinsic, are indispensable for maintaining students' participation and satisfaction [21], [36]. However, unlike previous applications of Herzberg's model that viewed HFs and MFs as separate influences, this study demonstrates a hierarchical relationship, where HFs create the conditions for MFs to operate effectively. This refinement extends Herzberg's original framework [23] from workplace settings to blended learning contexts, illustrating how technological stability and pedagogical quality jointly sustain learner engagement.

Second, the structural model reveals a causal hierarchy among environmental, motivational, and engagement constructs. Strong paths were observed from MFs to LM ($\beta = 0.73$, $p < 0.001$) and a very strong path from LM to LE ($\beta = 0.88$, $p < 0.001$), while the direct path from HFs to LM was positive but small ($\beta = 0.08$, $p < 0.05$), and the link from HFs to MFs is moderate ($\beta = 0.38$, $p < 0.001$). The sequential mediation HFs → MFs → LM → LE was significant (VAF = 78.7%), and the indirect path MFs → LM → LE constitutes full mediation (VAF = 100%), indicating that motivators affect engagement entirely through motivation, while HFs serve indirect, supportive roles. Overall, the pattern of both direct and indirect effects observed here provides a nuanced understanding of how blended learning environments shape students' engagement. The significant direct effect from MFs to LM supports extensive prior evidence that intrinsic task value, autonomy, and feedback-rich learning activities directly stimulate motivation [24], [25], [33], [34], [45]. Similarly, the direct effect from LM to LE corroborates numerous studies demonstrating that motivation serves as the most immediate and powerful driver of behavioral, emotional, and cognitive engagement [28], [30]. These robust direct relationships affirm that students' internalized motivation acts as the psychological "engine" of engagement in blended settings [31]. In contrast, the direct effect from HFs to LM, although statistically significant, is relatively small, suggesting that environmental conditions alone cannot energize LM unless they enable pedagogical motivators to function effectively. The findings are consistent with earlier studies showing that while system quality and instructor presence reduce dissatisfaction, they do not automatically generate engagement [22]. Instead, such HFs create the stability and predictability necessary for students to focus on meaningful learning tasks [36], [46]. Similarly, the direct path from HFs to MFs highlights that well-maintained learning environments can enhance the salience of motivators by supporting their implementation, such as reliable platforms that make authentic collaboration or peer review feasible [21]. Overall, these direct effects show that HFs provide the contextual foundation for blended learning, motivators supply the pedagogical impetus, and LM functions as the psychological bridge linking them to LE. The mediation analysis further reinforces this mechanism. The significant indirect effects through LM replicate earlier findings that LM mediates the impact of course design on engagement and achievement [28], [46], [51]. However, the current study goes beyond previous correlational evidence by empirically validating a sequential causal process that begins with environmental stability (reflecting HFs), transitions through pedagogical richness (reflecting MFs), and culminates in motivational activation (reflecting LM) leading to LE. This dual pattern of direct and mediated relationships strengthens Herzberg's Two-Factor Theory in the educational domain. It confirms that HFs are necessary but not sufficient. HFs prevent disengagement but do not generate motivation, while MFs produce meaningful engagement through the activation of learning motivation.

Finally, we add to the predictive theory of LE by demonstrating substantial explained variance for LM and LE ($R^2 \approx 0.58$ and 0.78, respectively) and meaningful predictive relevance (Q^2). These results affirm that a two-factor-derived model can parsimoniously account for engagement in blended environments. The mediation of LM validates motivation as the psychological bridge linking course design and engagement outcomes, consistent with previous studies emphasizing its centrality in online learning [28], [46]. Compared with foundational theories such as Self-Determination Theory or Expectancy-Value Theory, the present model refines theoretical understanding by suggesting that engagement arises not merely from autonomy or expectancy beliefs, but from the orchestrated interaction between reliable infrastructure and meaningful pedagogical design [19], [34].

6 CONCLUSION

This study integrated Herzberg's Two-Factor Theory to explain how environmental and motivational factors jointly influence students' LE through LM in undergraduate courses delivered through blended learning. Across a large student sample, HFs contributed to MFs and, to a smaller extent, directly to LM, while MFs exerted a strong influence on LM; LM, in turn, powerfully predicted LE. Mediation analysis confirmed a sequential pathway (HFs → MFs → LM → LE) and full mediation of MFs through LM. These findings suggest that student engagement is maintained primarily through intrinsic, pedagogy-centered motivators of learning tasks that activate learners' LM, rather than solely through improving the technical infrastructure and essential conditions for blended learning. The model explained substantial variance in LM and LE, providing an empirically grounded mechanism for why some blended courses engage students more effectively than others.

Theoretical implications: This study extends Herzberg's Two-Factor Theory to the context of blended learning, showing that HFs and MFs form a hierarchical sequence that sustains engagement. HFs create the necessary learning conditions, while MFs generate intrinsic value that, through LM, leads to active LE. This integration clarifies how environmental and psychological mechanisms jointly shape engagement in digitally mediated courses. The validated model offers a concise framework for future studies to compare or integrate alternative motivational theories, such as self-determination or expectancy-value, in explaining student engagement in blended learning research.

Practical implications: For course designers and instructors, the findings prioritize (a) maintaining sufficient HFs (e.g., clear structure, timely feedback channels, manageable workload) to prevent disengagement, and (b) deliberately enhancing MFs (e.g., problem/case-based tasks, collaborative activities, formative feedback, opportunities for autonomy and creativity) to stimulate LM and thereby sustain LE. Furthermore, institutions should invest not only in digital infrastructure but also in pedagogical training that helps faculty design motivation-driven blended courses capable of sustaining student engagement over time.

Limitations: The cross-sectional and self-reported nature of the data may limit causal interpretation of the relationships among HFs, MFs, LM, and LE. The study was conducted at a single engineering university, which may limit the generalizability of the findings to other disciplines or institutions. The relative strength of relationships and factor weights in the proposed model may differ across non-STEM disciplines, institutions with different levels of technological maturity, or distinct cultural and educational contexts. Finally, contextual variables, such as students' prior experience with blended learning, course difficulty, or instructor style, were not examined and may moderate the observed relationships. Future studies should adopt longitudinal or experimental designs and include multiple institutions, disciplines, and national contexts to strengthen causal interpretation and generalizability.

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9 REFERENCES

[1] L. A. Obukhova, V. G. Olga, O. B. Igor, V. B. Roman, A. K. Lyubov, and V. D. Tatyana, "Formation of organizational competence of future engineers by means of blended learning," *International Journal of Engineering Pedagogy (iJEP)*, vol. 10, no. 2, pp. 119–127, 2020. https://doi.org/10.3991/ijep.v10i2.12047

[2] R. Kandakatla, E. J. Berger, J. F. Rhoads, and J. DeBoer, "Student perspectives on the learning resources in an active, blended, and collaborative (ABC) pedagogical environment," *International Journal of Engineering Pedagogy (iJEP)*, vol. 10, no. 2, pp. 7–31, 2020. https://doi.org/10.3991/ijep.v10i2.11606

[3] N. T. Tuyet, N. T. Long, and N. Van Hanh, "The effect of positive learning culture in students' blended learning process," *Journal of E-Learning and Knowledge Society*, vol. 16, no. 3, pp. 68–75, 2020. https://doi.org/10.20368/1971-8829/1135218

[4] C. J. Bonk and C. R. Graham, *The Handbook of Blended Learning: Global Perspectives, Local Designs*. Wiley + ORM, 2012.

[5] L. M. Jeffrey, J. Milne, G. Suddaby, and A. Higgins, "Blended learning: How teachers balance the blend of online and classroom components," *Journal of Information Technology Education: Research*, vol. 13, pp. 121–140, 2014. https://doi.org/10.28945/1968

[6] H. T. Q. Lan, N. T. Long, and N. Van Hanh, "Validation of depression, anxiety and stress scales (Dass-21): Immediate psychological responses of students in the e-learning environment," *International Journal of Higher Education*, vol. 9, no. 5, pp. 125–133, 2020. https://doi.org/10.5430/ijhe.v9n5p125

[7] R. I. Platonova, N. A. Orekhovskaya, S. B. Dautova, E. V. Martynenko, N. I. Kryukova, and S. Demir, "Blended learning in higher education: Diversifying models and practical recommendations for researchers," *Front. Educ. (Lausanne)*, vol. 7, p. 957199, 2022. https://doi.org/10.3389/feduc.2022.957199

[8] M. Eryilmaz, "The effectiveness of blended learning environments," *Contemporary Issues in Education Research*, vol. 8, no. 4, pp. 251–256, 2015. https://doi.org/10.19030/cier.v8i4.9433

[9] N. T. Long and N. Van Hanh, "A structural equation model of blended learning culture in the classroom," *International Journal of Higher Education*, vol. 9, no. 4, pp. 99–115, 2020. https://doi.org/10.5430/ijhe.v9n4p99

[10] R. M. Bernard, E. Borokhovski, R. F. Schmid, R. M. Tamim, and P. C. Abrami, "A meta-analysis of blended learning and technology use in higher education: from the general to the applied," *J Comput. High. Educ.*, vol. 26, no. 1, pp. 87–122, 2014. https://doi.org/10.1007/s12528-013-9077-3

[11] C. Dziuban and P. Moskal, "A course is a course is a course: Factor invariance in student evaluation of online, blended and face-to-face learning environments," *Internet High Educ.*, vol. 14, no. 4, pp. 236–241, 2011. https://doi.org/10.1016/j.iheduc.2011.05.003

[12] A. Istenič, "Blended learning in higher education: The integrated and distributed model and a thematic analysis," *Discover Education*, vol. 3, no. 1, p. 165, 2024. https://doi.org/10.1007/s44217-024-00239-y

[13] P. Baepler, J. D. Walker, and M. Driessen, "It's not about seat time: Blending, flipping, and efficiency in active learning classrooms," *Comput. Educ.*, vol. 78, pp. 227–236, 2014. https://doi.org/10.1016/j.compedu.2014.06.006

[14] H. M. Selim, "Critical success factors for e-learning acceptance: Confirmatory factor models," *Comput. Educ.*, vol. 49, no. 2, pp. 396–413, 2007. https://doi.org/10.1016/j.compedu.2005.09.004

[15] L. R. Halverson and C. R. Graham, "Learner engagement in blended learning environments: A conceptual framework," *Online Learning*, vol. 23, no. 2, pp. 145–178, 2019. https://doi.org/10.24059/olj.v23i2.1481

[16] T. Roxana and B. Matthew, "What drives student engagement? A community engagement framework for online education," *International Journal of Advanced Corporate Learning*, vol. 17, no. 3, pp. 94–107, 2024. https://doi.org/10.3991/ijac.v17i3.45729

[17] K. Zaid and H. N. Fakhouri, "Impact of E-learning tools (Moodle, Microsoft Teams, Zoom) on student engagement and achievement at Jordan universities," *International Journal of Interactive Mobile Technologies*, vol. 18, no. 18, pp. 125–145, 2024. https://doi.org/10.3991/ijim.v18i18.49895

[18] W. Cao, "A meta-analysis of effects of blended learning on performance, attitude, achievement, and engagement across different countries," *Front Psychol*, vol. 14, p. 1212056, 2023. https://doi.org/10.3389/fpsyg.2023.1212056

[19] A. Dwivedi, P. Dwivedi, S. Bobek, and S. Sternad Zabukovšek, "Factors affecting students' engagement with online content in blended learning," *Kybernetes*, vol. 48, no. 7, pp. 1500–1515, 2019. https://doi.org/10.1108/K-10-2018-0559

[20] R. A. Green, L. Y. Whitburn, A. Zacharias, G. Byrne, and D. L. Hughes, "The relationship between student engagement with online content and achievement in a blended learning anatomy course," *Anat. Sci. Educ.*, vol. 11, no. 5, pp. 471–477, 2018. https://doi.org/10.1002/ase.1761

[21] S. Lane, J. G. Hoang, J. P. Leighton, and A. Rissanen, "Engagement and satisfaction: Mixed-method analysis of blended learning in the sciences," *Canadian Journal of Science, Mathematics and Technology Education*, vol. 21, no. 1, pp. 100–122, 2021. https://doi.org/10.1007/s42330-021-00139-5

[22] A.-M. Nortvig, A. K. Petersen, and S. H. Balle, "A literature review of the factors influencing e-learning and blended learning in relation to learning outcome, student satisfaction, and engagement," *Electronic Journal of E-learning*, vol. 16, no. 1, pp. 46–55, 2018.

[23] F. Herzberg, B. Mausner, and B. B. Snyderman, *The Motivation to Work*, Transaction publishers, vol. 1, 2011.

[24] A. H. S. Dzaiy and S. A. Abdullah, "The use of active learning strategies to foster effective teaching in higher education institutions," *Zanco Journal of Human Sciences*, vol. 28, no. 4, pp. 328–351, 2024. https://doi.org/10.21271/zjhs.28.4.18

[25] C. J. Hellín, F. Calles-Esteban, A. Valledor, J. Gómez, S. Otón-Tortosa, and A. Tayebi, "Enhancing student motivation and engagement through a gamified learning environment," *Sustainability*, vol. 15, no. 19, p. 14119, 2023. https://doi.org/10.3390/su151914119

[26] R. Fisher, Á. Perényi, and N. Birdthistle, "The positive relationship between flipped and blended learning and student engagement, performance and satisfaction," *Active Learning in Higher Education*, vol. 22, no. 2, pp. 97–113, 2018. https://doi.org/10.1177/1469787418801702

[27] D. H. Schunk and C. A. Mullen, "Self-efficacy as an engaged learner," in *Handbook of Research on Student Engagement*, Springer, 2012, pp. 219–235. https://doi.org/10.1007/978-1-4614-2018-7_10

[28] L. Alemayehu and H.-L. Chen, "The influence of motivation on learning engagement: The mediating role of learning self-efficacy and self-monitoring in online learning environments," *Interactive Learning Environments*, vol. 31, no. 7, pp. 4605–4618, 2023. https://doi.org/10.1080/10494820.2021.1977962

[29] J. M. Froiland and F. C. Worrell, "Intrinsic motivation, learning goals, engagement, and achievement in a diverse high school," *Psychol. Sch.*, vol. 53, no. 3, pp. 321–336, 2016. https://doi.org/10.1002/pits.21901

[30] H. Lei, C. Chen, and L. Luo, "The examination of the relationship between learning motivation and learning effectiveness: a mediation model of learning engagement," *Humanit. Soc. Sci. Commun.*, vol. 11, no. 1, p. 137, 2024. https://doi.org/10.1057/s41599-024-02666-6

[31] E. M. Anderman and H. Patrick, "Achievement goal theory, conceptualization of ability/intelligence, and classroom climate," in *Handbook of Research on Student Engagement*, Springer, 2012, pp. 173–191. https://doi.org/10.1007/978-1-4614-2018-7_8

[32] V.-M. Luis and G. Katherina, "Influence of self-regulated learning on the academic performance of engineering students in a blended-learning environment," *International Journal of Engineering Pedagogy (iJEP)*, vol. 13, no. 8, pp. 84–89, 2023. https://doi.org/10.3991/ijep.v13i8.38481

[33] J. Sahni, "Does blended learning enhance student engagement? Evidence from higher education," *Journal of E-learning and Higher Education*, vol. 2019, no. 2019, pp. 1–14, 2019. https://doi.org/10.5171/2019.121518

[34] R. S. Baragash and H. Al-Samarraie, "Blended learning: Investigating the influence of engagement in multiple learning delivery modes on students' performance," *Telematics and Informatics*, vol. 35, no. 7, pp. 2082–2098, 2018. https://doi.org/10.1016/j.tele.2018.07.010

[35] K. C. Manwaring, R. Larsen, C. R. Graham, C. R. Henrie, and L. R. Halverson, "Investigating student engagement in blended learning settings using experience sampling and structural equation modeling," *Internet High. Educ.*, vol. 35, pp. 21–33, 2017. https://doi.org/10.1016/j.iheduc.2017.06.002

[36] C. E. Morton *et al.*, "Blended learning: How can we optimize undergraduate student engagement?" *BMC Med Educ*, vol. 16, no. 1, p. 195, 2016. https://doi.org/10.1186/s12909-016-0716-z

[37] C. Nickerson, "Herzberg's two-factor theory of motivation-hygiene," *Simply Psychology*, 2023.

[38] A. K. M. N. Islam, "Sources of satisfaction and dissatisfaction with a learning management system in post-adoption stage: A critical incident technique approach," *Comput. Human Behav.*, vol. 30, pp. 249–261, 2014. https://doi.org/10.1016/j.chb.2013.09.010

[39] D. R. Garrison, *Blended Learning in Higher Education: Framework, Principles, and Guidelines*. Jossey-Bass, 2008. https://doi.org/10.1002/9781118269558

[40] G. Kurubacak, "Building knowledge networks through project-based online learning: A study of developing critical thinking skills via reusable learning objects," *Comput. Human Behav.*, vol. 23, no. 6, pp. 2668–2695, 2007. https://doi.org/10.1016/j.chb.2006.08.003

[41] C. T. Mart, "Commitment to school and students," *International Journal of Academic Research in Business and Social Sciences*, vol. 3, no. 1, p. 336, 2013.

[42] C. Dziuban, C. R. Graham, P. D. Moskal, A. Norberg, and N. Sicilia, "Blended learning: The new normal and emerging technologies," *International Journal of Educational Technology in Higher Education*, vol. 15, no. 1, p. 3, 2018. https://doi.org/10.1186/s41239-017-0087-5

[43] L. AlAbdulkarim and A. Albarrak, "Students' attitudes and satisfaction towards blended learning in the health sciences," in *International Conference on Advances in Education and Social Sciences*, 2015, p. 434.

[44] J. Ma, C. Li, and H.-N. Liang, "Enhancing students' blended learning experience through embedding metaliteracy," *Educ. Res. Int.*, vol. 2019, no. 1, p. 6791058, 2019. https://doi.org/10.1155/2019/6791058

[45] K.-C. Chen and S.-J. Jang, "Motivation in online learning: Testing a model of self-determination theory," *Comput. Human Behav*., vol. 26, no. 4, pp. 741–752, 2010. https://doi.org/10.1016/j.chb.2010.01.011

[46] Xiaoquan Pan, "Online learning environments, learners' empowerment, and learning behavioral engagement: The mediating role of learning motivation," *Sage Open*, vol. 13, no. 4, p. 21582440231205096, 2023. https://doi.org/10.1177/21582440231205098

[47] X. Han, "Associations between effectiveness of blended learning, student engagement, student learning outcomes, and student academic motivation in higher education," *Educ. Inf. Technol. (Dordr)*, vol. 30, no. 8, pp. 10535–10565, 2025. https://doi.org/10.1007/s10639-024-13246-1

[48] A. J. Martin, P. Ginns, and B. Papworth, "Motivation and engagement: Same or different? Does it matter?" *Learn. Individ. Differ.*, vol. 55, pp. 150–162, 2017. https://doi.org/10.1016/j.lindif.2017.03.013

[49] M. Ainley, "Students' interest and engagement in classroom activities," in *Handbook of Research on Student Engagement*, Springer: Boston, MA, 2012, pp. 283–302. https://doi.org/10.1007/978-1-4614-2018-7_13

[50] S. Zoya, B. Dmitrii, V. Ekaterina, R. Rodion, and E. Zhanna, "Motivation for mobile learning: Teacher engagement and built-in mechanisms," *International Journal of Interactive Mobile Technologies*, vol. 16, no. 1, pp. 78–93, 2022. https://doi.org/10.3991/ijim.v16i01.26321

[51] H. Akram and S. Li, "Understanding the role of teacher-student relationships in students' online learning engagement: Mediating role of academic motivation," *Percept. Mot. Skills*, vol. 131, no. 4, pp. 1415–1438, 2024. https://doi.org/10.1177/00315125241248709

[52] N. Aboobaker and K. H. Muneer, "Effectiveness of web-based learning environment: Role of intrinsic learning motivation, computer self-efficacy, and learner engagement," *Development and Learning in Organizations: An International Journal*, vol. 36, no. 4, pp. 13–16, 2021. https://doi.org/10.1108/DLO-07-2021-0139

[53] T. T. H. Pham, T. T. Q. Ho, B. T. N. Nguyen, H. T. Nguyen, and T. H. Nguyen, "Academic motivation and academic satisfaction: A moderated mediation model of academic engagement and academic self-efficacy," *Journal of Applied Research in Higher Education*, vol. 16, no. 5, pp. 1999–2012, 2024. https://doi.org/10.1108/JARHE-10-2023-0474

[54] L. Tara, I. Hidayati, and M. Susanti, "High school students' motivation and engagement in online learning," *Journal of Psychological Perspective*, vol. 4, no. 2, pp. 65–68, 2022. https://doi.org/10.47679/jopp.424062022

[55] Y. Liu, S. Ma, and Y. Chen, "The impacts of learning motivation, emotional engagement, and psychological capital on academic performance in a blended learning university course," *Front. Psychol.*, vol. 15, p. 1357936, 2024. https://doi.org/10.3389/fpsyg.2024.1357936

[56] N. Van Hanh and N. T. Long, "The ethical perception of engineering students who have never participated in the ethics curriculum," *International Journal of Engineering Pedagogy (iJEP)*, vol. 12, no. 1, pp. 4–20, 2022. https://doi.org/10.3991/ijep.v12i1.21781

[57] N. Van Hanh, N. T. Long, N. T. Duyen, P. T. T. Canh, N. T. Long, and M. D. Thang, "Teaching engineering ethics through a psychology course," *International Journal of Engineering Pedagogy (iJEP)*, vol. 11, no. 1, pp. 16–34, 2021. https://doi.org/10.3991/ijep.v11i1.14999

[58] J. F. Hair Jr., G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, "Evaluation of reflective measurement models," in *Partial Least Squares Structural Equation Modeling (PLS-SEM) using R: A Workbook*, Springer International Publishing Cham, 2021, pp. 75–90. https://doi.org/10.1007/978-3-030-80519-7_4

[59] O. F. Ipek and H. T. Mutlu, "Developing a scale of motivation for online english language education," *International Online Journal of Educational Sciences*, vol. 14, no. 5, pp. 1155–1166, 2022. https://doi.org/10.15345/iojes.2022.05.002

[60] J. Maroco, A. L. Maroco, J. A. D. B. Campos, and J. A. Fredricks, "University student's engagement: Development of the University Student Engagement Inventory (USEI)," *Psicologia: Reflexão e Crítica*, vol. 29, no. 1, p. 21, 2016. https://doi.org/10.1186/s41155-016-0042-8

[61] J. F. Hair, C. M. Ringle, and M. Sarstedt, "PLS-SEM: Indeed a silver bullet," *Journal of Marketing Theory and Practice*, vol. 19, no. 2, pp. 139–152, 2011. https://doi.org/10.2753/MTP1069-6679190202

[62] C. Nitzl, J. L. Roldan, and G. Cepeda, "Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models," *Industrial Management & Data Systems*, vol. 116, no. 9, pp. 1849–1864, 2016. https://doi.org/10.1108/IMDS-07-2015-0302

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