

PAPER

Beyond Points and Badges: How Mobile-Based Gamification Drives Multidimensional Engagement to Improve Learning Outcomes in Engineering Education

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ABSTRACT

Gamification and mobile-based learning have become popular innovative approaches in education. However, empirical evidence regarding their effectiveness in engineering education, particularly in electrical engineering, remains fragmented, with a critical gap in understanding the mediating mechanisms through which gamification drives outcomes in this uniquely demanding context. This study examines the impact of mobile-based gamification (MobGam) on learning engagement (LE) and learning outcomes (LO) among electrical engineering students. Research data were collected through standardized questionnaires from 121 students and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results demonstrate that the Usage Intensity of MobGam (UI) has a positive and significant effect on all dimensions of students' LE, namely Behavioral Engagement (BE), Cognitive Engagement (CE), and Emotional Engagement (EE). UI also positively associated with LO, as measured by perceived learning effectiveness (PLE) and perceived academic performance (PAP). Moreover, LE mediates the relationship between UI and LO. Crucially, EE emerged as the strongest mediating pathway, underscoring the paramount importance of affective factors in overcoming the cognitive demands of engineering coursework. Specifically, EE showed the most substantial mediating effect on PLE ($\beta = 0.326$) and PAP ($\beta = 0.314$). These findings extend beyond electrical engineering education by providing evidence that emotionally resonant gamification is associated with higher persistence and more positive perceived LO, particularly in contexts with high cognitive load. This study offers a theoretically grounded, empirically validated model that redefines the success of educational gamification in electrical engineering education, shifting focus from mere usage to the cultivation of deep, emotionally resonant engagement.

KEYWORDS

quality education, mobile-based gamification, learning engagement (LE), learning outcomes (LO), engineering education

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1 INTRODUCTION

The transformation of education in the digital era has driven the adoption of various innovative approaches aimed at enhancing student motivation, engagement, and learning outcomes (LO). One increasingly implemented approach is gamified learning, particularly when integrated with mobile learning [1], [2]. Gamification, through the incorporation of game elements such as points, badges, challenges, and leaderboards, has been shown to foster intrinsic motivation and create a more interactive learning experience [3], [4], [5]. In parallel, mobile learning provides students with access to learning materials anytime and anywhere, thereby supporting greater flexibility and autonomy in the learning process [6], [7], [8]. The combination of these two approaches is believed to strengthen students' LE and ultimately improve learning outcomes.

Although prior studies highlight positive outcomes, empirical evidence on the effectiveness of MobGam in engineering education remains scarce. Most existing research has been conducted in the fields of social sciences [2], [9], [10], general education [4], [5], [10], or health [11], [12], while studies specifically focusing on electrical engineering education are limited. Yet, engineering education has unique characteristics that demand both conceptual understanding and practical skills, making student engagement, behavioral, cognitive, and emotional, a critical factor in successful learning [1], [7], [13].

Moreover, while prior research has established correlations between gamification and motivation, a significant theoretical and empirical void exists in unpacking the causal pathway [4], [10], [14]. Specifically, there is a lack of robust, SEM-based evidence demonstrating how and through which specific dimensions of engagement gamification translate into tangible LO within the high-stakes, cognitively-taxing environment of core engineering courses like Electrical Machines. This represents a significant research gap, as engagement is widely recognized as the key mechanism connecting innovative learning experiences to improved academic achievement [7], [15]. Therefore, there is a need for more comprehensive empirical evidence on how MobGam influences LO through students' LE in the context of electrical engineering education, particularly in the Electrical Machines course, which requires both strong conceptual mastery and practical competence.

This study aims to analyze the relationships between Usage Intensity (UI) with electrical engineering education students' LE and LO in the Electrical Machines course. To guide this investigation, the following research questions are formulated: (RQ1) How does UI influence LE (Behavioral Engagement (BE), Cognitive Engagement (CE), and Emotional Engagement (EE)) among electrical engineering education students? (RQ2) How does UI influence the LO among electrical engineering education students? (RQ3) How do LE (BE, CE, and EE) influence LO among electrical engineering education students? And (RQ4) What is the mediating role of LE in the relationship between UI and LO among electrical engineering students?

This study examines the context of electrical engineering education by employing a comprehensive model that incorporates BE, CE, and EE as mediating variables. The findings extend the literature on gamification by highlighting the central role of students' LE in shaping LO within engineering education. From a practical perspective, the results offer guidance for educators and curriculum developers in designing effective digital learning strategies, particularly for courses with a high level of complexity. This study makes a threefold contribution: (1) It provides the first comprehensive SEM model testing the mediating role of multidimensional engagement

(BE, CE, EE) in the context of MobGam for electrical engineering education; (2) It empirically identifies EE as the dominant mediating pathway, challenging the prevailing cognitive-centric view in engineering education research; (3) It offers a validated, context-specific framework (using Gimkit) for designing effective gamified interventions in similar engineering education disciplines.

2 LITERATURE REVIEW

2.1 Theoretical framework

Self-Determination Theory (SDT) posits that learning motivation arises when the needs for autonomy, competence, and relatedness are fulfilled [16], [17]. In the context of MobGam, challenges, feedback, and reward systems can strengthen students' perceptions of competence, while the flexibility of mobile learning supports autonomy, and collaborative features foster relatedness. Consequently, students are more likely to develop intrinsic motivation and actively participate in learning activities [5], [7]. Building upon this motivational foundation, Constructivist Learning Theory (CLT) views learning as an active process of knowledge that is constructed through exploration, interaction, and reflection [18], [19]. Mobile-based gamification facilitates these processes by providing opportunities for experimentation, problem-solving, collaboration, and immediate feedback. As a result, students are encouraged to engage cognitively with learning materials rather than merely receiving information passively [2], [7], [20].

In addition to motivation and active knowledge construction, Flow Theory (FT) suggests that meaningful learning occurs when challenges are appropriately balanced with learners' abilities, creating a state of concentration, enjoyment, and immersion [7], [20]. This perspective is particularly relevant to electrical engineering education, where students frequently encounter abstract concepts and cognitively demanding tasks. Through elements such as missions, levels, leaderboards, and rewards, MobGam can create enjoyable learning experiences that reduce learning anxiety and sustain students' interest during complex learning activities.

These theoretical perspectives collectively suggest that the influence of MobGam on students' perceived LO is unlikely to occur directly. Instead, its effects are expected to be manifested through LE, which encompasses BE, CE, and EE [15], [21]. From the SDT perspective, the fulfillment of psychological needs stimulates students' willingness to participate in learning activities, thereby enhancing BE. CLT explains how active exploration and reflection strengthen CE, while FT highlights the importance of positive emotional experiences in fostering EE. Together, these dimensions represent the primary mechanisms through which students interact with learning experiences and achieve meaningful perceived LO [7], [22].

Among these dimensions, EE may play a particularly important role in engineering education. The demanding nature of electrical engineering courses often requires students to sustain effort despite cognitive complexity and learning difficulties. Positive emotional states, such as enjoyment, interest, confidence, and satisfaction, can help students maintain motivation, reduce cognitive fatigue, and persist in challenging learning situations. Therefore, while BE and CE remain essential, EE may provide a stronger pathway through which MobGam enhances perceived learning effectiveness (PLE) and perceived academic performance (PAP). Accordingly, this study proposes that the actual use of MobGam contributes to perceived LO both directly and indirectly through BE, CE, and EE [7], [15], [21].

2.2 LO

Learning outcomes is a key indicator of educational quality in higher education, reflecting both subjective and objective aspects of student success. In this study, LO was measured through two main dimensions: PLE and PAP. PLE represents students' perceptions of how compelling their learning experiences were in enhancing their understanding of course material, improving their thinking skills, and achieving academic goals [20], [21]. PLE is strongly associated with student motivation, satisfaction, and engagement in the learning process [10], [20]. Within the demanding context of electrical engineering education, students' PLE play a critical role in determining their engagement and persistence when completing complex tasks.

Meanwhile, PAP refers to students' PAP, namely their subjective perceptions of academic achievement after participating in MobGam learning. PAP extends beyond formal grades to include students' self-confidence in their academic abilities, their achievement of learning goals, and their success in applying acquired knowledge to assignments, examinations, and practical contexts [1], [22]. This study adopts the subjective perspective, as it aligns with evaluating the impact of MobGam learning on students' perceptions of their effectiveness and success [10], [20].

2.3 Students' engagement

Learning engagement is a multidimensional construct that reflects the quality of students' interaction with academic activities and serves as a strong predictor of LO. High engagement indicates students' psychological, cognitive, and emotional investment in learning [7], [10], [20]. LE typically comprises three interrelated dimensions: BE, CE, and EE. BE represents students' observable participation in academic activities such as attending classes, completing assignments on time, and contributing to group tasks [7], [15]. Within MobGam, BE is strengthened through game-based features like leaderboards, points, and digital rewards that promote active and consistent participation [7], [21]. Active learners tend to perceive their learning experiences as more valuable and demonstrate improved performance because consistent engagement deepens understanding and knowledge retention [7], [10], [20].

Cognitive engagement reflects students' mental effort in processing and understanding course material, applying deep learning strategies, and integrating new concepts with prior knowledge [7], [10]. Within MobGam learning, CE is stimulated through challenges requiring critical thinking, level-based tasks, and instant feedback that encourages students to evaluate their understanding continuously [7], [10]. Research shows that students with high CE report stronger perceptions of learning effectiveness, as they view the learning process as adding value to their conceptual understanding [10], [20], [23]. CE is also positively linked to academic achievement, since deeper cognitive strategies strengthen analytical and problem-solving skills [20], [23].

Emotional engagement encompasses students' affective responses toward learning, including enjoyment, interest, enthusiasm, and reduced anxiety [10], [20]. Emotional factors are particularly important in demanding subjects such as electrical engineering, as they influence persistence and motivation. MobGam enhances EE by providing a stimulating environment that combines competition and enjoyment

through challenges, feedback, and rewards [7], [20], [21]. Students experiencing positive emotions are more satisfied with their learning and tend to perform better academically, as EE promotes resilience and sustained effort [21], [22]. Drawing on the preceding literature review, this study formulates the following hypotheses: (H1) BE has a significant effect on PLE; (H2) BE has a significant effect on PAP; (H3) CE has a significant effect on PLE; (H4) CE has a significant effect on PAP; (H5) EE has a significant effect on PLE; and (H6) EE has a significant effect on PAP.

2.4 UI of MobGam

In the TAM, UI represents users' real behavior in utilizing technology after the acceptance process has taken place [24], [25]. In this study, UI refers to the intensity of students' use of Mobgam as part of their learning activities. Higher levels of UI encourage students to engage more frequently in digital activities, complete challenges, and respond to feedback, thereby strengthening BE [5], [7]. Intensive interaction with the application also promotes CE, as students are more likely to think critically, solve problems, and integrate new concepts [5], [20], [23]. Moreover, continued use creates a more enjoyable learning environment, fosters interest, and reduces boredom, which in turn enhances EE [7], [20]. Thus, this study formulates the following hypotheses: (H7) UI has a significant effect on BE; (H8) UI has a significant effect on CE; and (H9) UI has a significant effect on EE.

Beyond its effect on LE, UI also directly influences LO. Students who consistently use educational technologies are more likely to perceive their learning experiences as effective, as they benefit from repeated interactions, flexible access, and instant feedback [4], [7]. Furthermore, higher levels of UI contribute to improved PAP, since continuous exposure to digital materials helps students master concepts more effectively and apply them in practice [7], [14], [22]. Thus, this study formulates the following hypotheses: (H10) UI has a significant effect on PLE and (H11) UI has a significant effect on perceived academic performance.

2.5 MobGam using Gimkit

In this study, MobGam learning was developed and implemented using the Gimkit platform in the Electrical Machines course. Gimkit is an interactive digital quiz platform that enables students to answer questions via mobile devices either in real time or through independent assignments [1], [26]. The MobGam intervention was implemented throughout one semester (16 weeks) in the Electrical Machines course, with each session lasting 2×50 minutes. Gimkit was integrated into every class meeting and used at both the beginning and end of the lesson to activate prior knowledge, reinforce learning, and promote student participation. Learning activities combined individual and group-based game modes, incorporating conceptual quizzes, problem-solving tasks, and topic reviews related to electrical machines. Gamification elements, including points, energy systems, levels, leaderboards, rewards, and immediate feedback, were employed to enhance engagement and motivation. Throughout the intervention, the instructor served as a facilitator by guiding discussions, monitoring participation, providing clarification, and encouraging reflection on learning progress. The interface of the MobGam learning activity, utilizing the Gimkit platform, is presented in Figure 1.

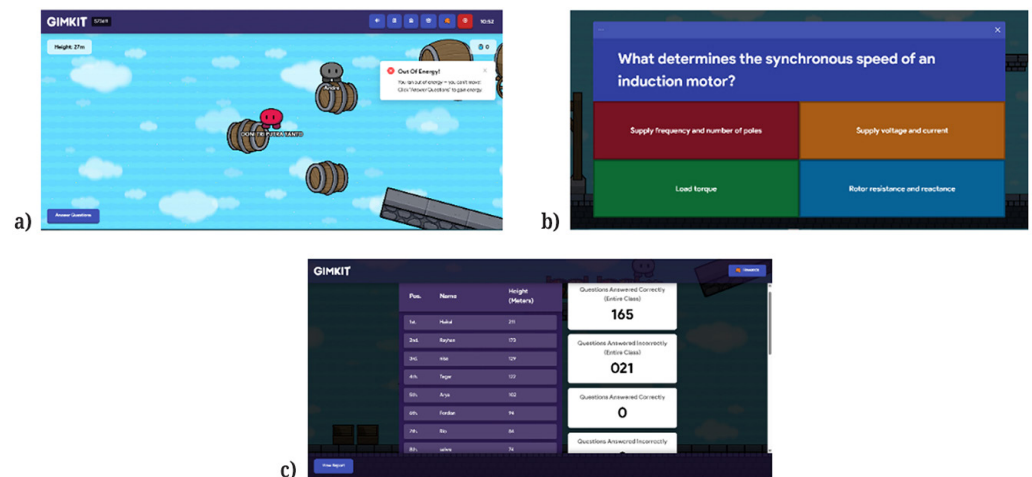


Fig. 1. MobGam learning display: (a) students compete to reach the highest level by answering questions, (b) a sample of questions, and (c) a live scoreboard

3 METHOD

3.1 Research design

This study employed a quantitative design with a survey approach. The survey design was selected because it is well-suited for examining relationships between latent psychological and behavioral variables, such as LE and LO, by collecting data on respondents' perceptions at a single point in time [22], [27]. This study design also allowed for the examination of both direct and indirect effects, as illustrated in the conceptual model presented in Figure 2.

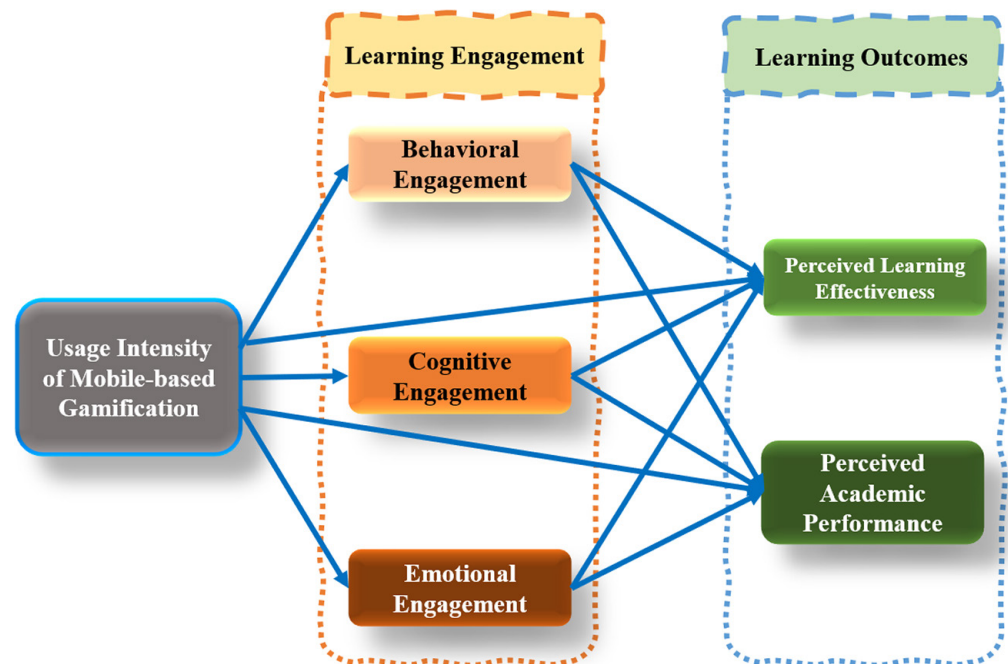


Fig. 2. The research design

3.2 Research instruments

The research instrument was a structured questionnaire developed using a five-point Likert scale, ranging from 1 to 5. The items were adapted from established theories and previous studies relevant to the research variables. Each variable was measured through multiple indicators to ensure comprehensive representation of the constructs under investigation. A summary of the research variables, their corresponding indicators, and the source for their development is presented in Table 1.

Table 1. Research instrument details

Construct	Indicators
UI	UI1. Frequency of using MobGam in lectures. UI2. Duration of MobGam use in each learning session. UI3. Consistency in completing gamification-based activities/tasks. UI4. Intensity of MobGam access outside class hours. UI5. Participation in various game modes in MobGam. UI6. Demonstrated personal initiative by utilizing MobGam as an additional learning tool. [5], [25], [28]
BE	BE1. Attendance and active participation in MobGam-based lectures. BE2. Perseverance in completing missions/questions in MobGam. BE3. Activeness in competitions or discussions triggered by MobGam. BE4. Consistency in following instructions and game rules. BE5. Discipline in completing MobGam assignments on time. [5], [7], [22], [23]
CE	CE1. Effort to understand the material through MobGam activities. CE2. Utilizing deep learning strategies for question answering in MobGam. CE3. Ability to connect prior knowledge with new questions in MobGam. CE4. Reflection on incorrect answers through feedback in MobGam. CE5. Efforts to solve challenges in MobGam using critical thinking. CE6. Trying various strategies to solve questions more effectively in MobGam. [5], [7], [20], [23]
EE	EE1. Enthusiasm when participating in MobGam-based learning. EE2. Feelings of joy and satisfaction when completing challenges in MobGam. EE3. Increased learning motivation in the game environment of MobGam. EE4. Confidence when achieving high scores. EE5. Reduced boredom/anxiety through enjoyable learning experiences. [5], [7], [21]
PLE	PLE1. Perception of improved conceptual understanding through MobGam learning. PLE2. Perception that MobGam learning is more effective than conventional methods. PLE3. Perception of improved analytical skills through repeated practice. PLE4. Perception of easier recall of studied material. [4], [20], [21]
PAP	AP1. Perception of improved academic abilities after gamification-based learning. AP2. Perception of improved ability to solve exam questions. AP3. Perception of improved quality of reports or academic assignments. AP4. Ability to apply concepts to new problems. AP5. Ability to integrate concepts into solving real-world problems. [1], [4], [20], [23]

This study instrument underwent a series of validation procedures to ensure the appropriateness of the items in measuring the intended constructs. Content validity was assessed by eight experts: four lecturers in electrical engineering education, two lecturers in learning technology, and two practitioners in digital learning. The experts evaluated the suitability of the indicators to the constructs, the clarity of wording, and their relevance in the context of engineering education. Subsequently, the instrument was piloted with 27 students who shared characteristics like those

of the study respondents but were excluded from the main sample. The pilot test results confirmed the validity of all items through Pearson's product-moment correlation analysis ($r = 0.42\text{--}0.71$, $p < 0.01$) [5], [7]. while Cronbach's alpha (CA) values ranging from 0.79 to 0.86 indicated satisfactory internal consistency (reliability) and exceeded the recommended threshold of 0.70 [1], [4].

3.3 Research participant

The research subjects were second-year students in the Electrical Engineering Education Study Program at the Faculty of Engineering, Universitas Negeri Padang, Indonesia, comprising 121 participants. The inclusion of the entire student cohort was based on both methodological and substantive considerations. Methodologically, involving the full study population ensured representative data while minimizing selection bias that could occur if only a subset of students were included [4], [20], [29]. Substantively, including all students was essential because they shared a uniform learning experience with the MobGam intervention in the same course, thereby strengthening the internal validity of the study. The sample size was considered adequate for PLS-SEM analysis. Following the widely adopted "*10-times rule*," the minimum required sample should be at least ten times the largest number of structural paths directed at a single endogenous construct in the model [30], [31]. The final participants exceeded the minimum threshold (> 60), and the sample was deemed sufficient to provide stable parameter estimates and reliable model evaluation.

3.4 Technique of data analysis

The research data were analyzed using the PLS-SEM approach with SmartPLS version 4.0. This technique was selected because it aligns with the research objectives, which focus on testing causal relationships among latent variables, including both direct and indirect effects through mediating variables [30], [32]. PLS-SEM is also recommended for studies with relatively small to medium sample sizes, as well as for both predictive and exploratory models [28], [32]. The analysis was conducted in three main stages. First, assumptions and model fit were examined to ensure that the data met the basic analytical requirements. Multicollinearity was tested using the Variance Inflation Factor (VIF) [24], [32]. Model fit was further evaluated using the Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), and Chi-Square. Second, the outer model was evaluated to test construct validity and reliability. Convergent validity (CV) was assessed using outer loading (OL), Average Variance Extracted (AVE), and Composite Reliability ($CR \geq 0.70$). Discriminant validity (DV) was examined using the Heterotrait-Monotrait Ratio (HTMT) [27], [32]. Construct reliability was further confirmed through CA. Finally, the inner model was evaluated to assess the structural relationships among latent variables, including direct effects, indirect effects, total effects, and effect size/ f square (f^2). The simultaneous effects of the model were determined by the coefficient of determination (R^2) and the Q square (Q^2) values obtained through the blindfolding procedure (cross-validated redundancy) to assess the model's predictive relevance. [24], [32]. Path significance was tested using a bootstrapping procedure to generate p -values. Because all constructs were measured using self-reported questionnaires collected from the same respondents, an additional collinearity assessment was conducted to evaluate the potential influence of Common Method Bias (CMB). VIF values below the recommended threshold of 3.3 indicate that CMB is unlikely to substantially affect the relationships among the constructs [30], [31].

4 RESULTS

The initial model, based on the research design in Figure 2, was evaluated to ensure compliance with the basic assumptions and analytical requirements. As shown in Table 2, all constructs had VIF values below the threshold of 5 ($VIF < 5$), indicating the absence of multicollinearity among the endogenous and exogenous variables [27], [32]. All VIF values ranged from 1.417 to 1.991, which are substantially below the recommended threshold. These results suggest that CMB is unlikely to pose a serious threat to the validity of the findings. Consequently, the observed relationships among the constructs are unlikely to be primarily attributable to measurement method effects. Beyond the constructs-level assessment, a multicollinearity test was also conducted at the indicator level. Based on Table 3, the results also show that all indicators had VIF values well below the cutoff, confirming that the model was free from multicollinearity problems.

Table 2. The constructs VIF values

	BE	CE	EE	PLE	PAP
UI	1.417	1.851	1.933	1.911	1.753
BE	—	—	—	1.624	1.668
CE	—	—	—	1.921	1.991
EE	—	—	—	1.990	1.622

The next step in meeting the analytical prerequisites was to evaluate the overall model fit. The analysis results of the fit model indicate that the NFI of the saturated model/estimated model (0.959/0.952) exceeded 0.90, the SRMR (0.069/0.063) was below 0.08, and the RMS Theta (0.084/0.089) was below 0.102. Collectively, these values confirm that the model achieved an acceptable level of fit [22], [32]. Meeting these model fit criteria validates the structural soundness of the model and confirms its appropriateness for further hypothesis testing. The final structural model, including the estimated path coefficients and relationships between indicators, is presented in Figure 3, which illustrates the results of the final analysis.

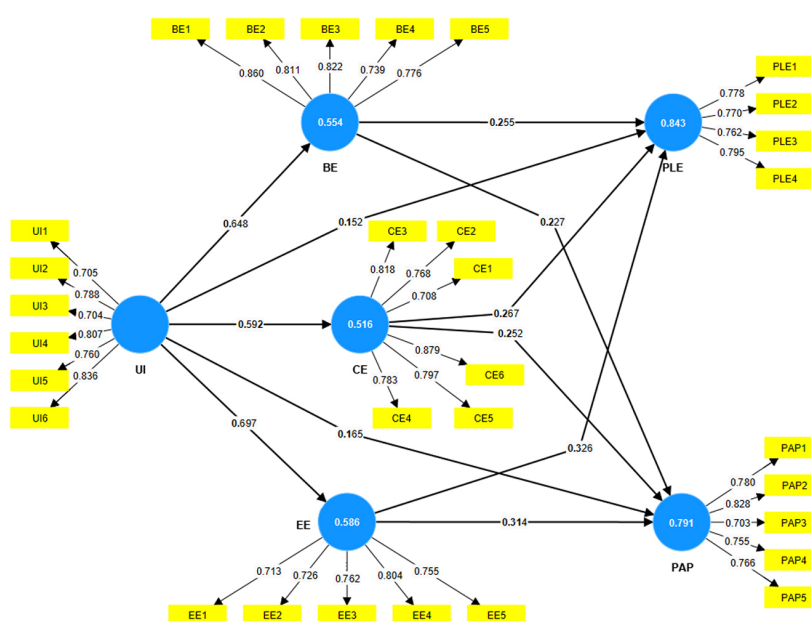


Fig. 3. The visualization of the final research model analysis results

4.1 Indicator analysis

Indicator analysis involves evaluating the measurement model. ICR examines the extent to which indicators consistently measure the intended construct, typically reflected by the CA value. As presented in Table 3, all variables had CA values above 0.70, indicating that the indicators are reliable [22], [32]. The unidimensionality assessment further ensures that no structural issues exist within the measurement model. The results in Table 3 show that all constructs satisfied the unidimensionality criteria, as both CR and CA values exceeded the 0.70 threshold [1], [32]. In addition, CV was assessed to determine whether indicators within a construct are sufficiently correlated. The analysis confirmed that all constructs met the CV criteria, as evidenced by AVE values exceeding 0.50 for each variable [21], [32].

Table 3. The results of the indicator analysis

	VIF	OL	CR	CA	Rho_A	AVE
UI	–	–	0.831	0.751	0.803	0.671
UI.1	1.579	0.705	–	–	–	–
UI.2	1.919	0.788				
UI.3	1.628	0.704				
UI.4	2.015	0.807				
UI.5	2.035	0.760				
UI.6	2.453	0.836				
BE	–	–	0.814	0.732	0.751	0.679
BE.1	2.605	0.860	–	–	–	–
BE.2	2.118	0.811				
BE.3	2.230	0.822				
BE.4	1.823	0.739				
BE.5	1.847	0.776				
CE	–	–	0.824	0.817	0.819	0.746
CE.1	1.702	0.708	–	–	–	–
CE.2	1.894	0.768				
CE.3	2.209	0.818				
CE.4	1.575	0.783				
CE.5	2.537	0.797				
CE.6	2.898	0.879				
EE	–	–	0.848	0.822	0.747	0.695
EE.1	1.822	0.713	–	–	–	–
EE.2	1.570	0.726				
EE.3	1.393	0.762				
EE.4	1.895	0.804				
EE.5	1.797	0.755				

(Continued)

Table 3. The results of the indicator analysis (*Continued*)

	VIF	OL	CR	CA	Rho_A	AVE
PLE	–	–	0.826	0.843	0.777	0.783
PLE.1	1.287	0.778	–	–	–	–
PLE.2	1.220	0.770				
PLE.3	1.596	0.762				
PLE.4	1.703	0.795				
PAP	–	–	0.837	0.811	0.759	0.788
PAP.1	1.407	0.780	–	–	–	–
PAP.2	1.916	0.828				
PAP.3	1.478	0.703				
PAP.4	1.336	0.755				
PAP.5	1.513	0.766				

DV was assessed using the HTMT. As presented in Table 4, the HTMT values for all construct pairs were below the recommended threshold of 0.85, indicating that each construct is empirically distinct and does not exhibit problematic overlap with others. These results confirm that the measurement model in this study demonstrates satisfactory DV.

Table 4. The results of the HTMT analysis

	UI	BE	CE	EE	PLE
BE	0.601	–	–	–	–
CE	0.633	0.744	–	–	–
EE	0.702	0.721	0.732	–	–
PLE	0.566	0.679	0.677	0.753	–
PAP	0.513	0.681	0.641	0.691	0.744

4.2 Construct Analysis

The strength and direction of impact (direct, indirect, and total) are indicated by path coefficients, which range from (–1) to (+1). A coefficient closer to (+1) reflects a strong positive relationship, while a value closer to (–1) indicates a strong negative relationship [24], [32]. The robustness of the structural model was examined through a bootstrapping analysis with 5,000 resamples. A two-tailed significance test and a 95% confidence interval (CI) were applied to determine the significance of the path coefficients [27], [30]. As shown in Table 5, in response to RQ1, Hypotheses 7, 8, and 9 are supported. This indicates that the UI of MobGam showed significant positive relationships with all dimensions of LE. Regarding RQ2, Hypotheses 10 and 11 are supported, complementing the findings of RQ1 by showing that UI not only has significant positive relationships with LE but also exerts a positive and significant association with LO, namely PLE and PAP, although with smaller β values compared to its association with LE. Finally, in response to RQ3, Hypotheses 1, 2, 3, 4, 5, and

6 are supported, confirming that in electrical engineering education, all LE dimensions have a significant positive relationship with LO, as reflected in both PLE and PAP. In addition, the f^2 analysis, interpreted using the thresholds of 0.02 for weak effects, 0.15 (moderate), and 0.35 (large), indicated that UI had moderate to large effects on BE, CE, and EE, but only small on PLE and PAP. Among the engagement dimensions, EE demonstrated the strongest relationship on both PLE and PAP.

Table 5. Direct effects and effect size in the constructs analysis

Direct Effect	β	f^2	P-Value	Hypotheses	Result
BE $\rightarrow$ PLE	0.255	0.166	0.005	H ₁	Supported
CE $\rightarrow$ PLE	0.267	0.187	0.005	H ₂	Supported
EE $\rightarrow$ PLE	0.326	0.211	0.003	H ₃	Supported
BE $\rightarrow$ PAP	0.227	0.142	0.007	H ₄	Supported
CE $\rightarrow$ PAP	0.252	0.113	0.005	H ₅	Supported
EE $\rightarrow$ PAP	0.314	0.231	0.003	H ₆	Supported
UI $\rightarrow$ BE	0.648	0.341	0.001	H ₇	Supported
UI $\rightarrow$ CE	0.592	0.279	0.001	H ₈	Supported
UI $\rightarrow$ EE	0.697	0.363	0.001	H ₉	Supported
UI $\rightarrow$ PLE	0.152	0.104	0.009	H ₁₀	Supported
UI $\rightarrow$ PAP	0.165	0.094	0.009	H ₁₁	Supported

The indirect effect analysis assessed the role of intervening variables in mediating the effects of exogenous variables on endogenous outcomes. As shown in Table 6, the results for RQ4 indicate that all dimensions of LE effectively mediate the association of UI with LO. This is evidenced by the positive and significant indirect effects of UI on LO through each LE dimension. Among the three, EE demonstrates the strongest mediating role, as indicated by larger β values for both PLE and PAP. The mediation results indicate complementary mediation, as both the direct and indirect relationships of UI with PLE and PAP were significant and positive. This suggests that learning engagement (LE) partially mediates the relationship between UI of MobGam and perceived LO, with EE representing the strongest mediating pathway.

Table 6. Indirect effects in the constructs analysis

No.	Indirect Effect	Path Coefficient	P-Value
1	UI $\rightarrow$ BE $\rightarrow$ PLE	0.165	0.009
2	UI $\rightarrow$ CE $\rightarrow$ PLE	0.158	0.009
3	UI $\rightarrow$ EE $\rightarrow$ PLE	0.227	0.007
4	UI $\rightarrow$ BE $\rightarrow$ PAP	0.147	0.010
5	UI $\rightarrow$ CE $\rightarrow$ PAP	0.149	0.009
6	UI $\rightarrow$ EE $\rightarrow$ PAP	0.218	0.007

These findings further reveal that the total effects of UI on PLE ($\beta = 0.702$, $p < 0.05$) and PAP ($\beta = 0.679$, $p < 0.05$) are positive and statistically significant. In addition, the

simultaneous effects were evaluated with thresholds classified as weak ($R^2 = 0.19$), moderate ($R^2 = 0.33$), and substantial ($R^2 = 0.67$) [24], [32]. The analysis results in Table 7 show the R^2 values indicate moderate explanatory power for BE, CE, and EE, and strong explanatory power for PLE and PAP. The blindfolding results in Table 7 show that all Q^2 values exceeded zero, confirming the predictive relevance of the model. BE and CE demonstrated moderate predictive relevance, whereas EE, PLE, and PAP exhibited strong predictive relevance. These findings indicate that the proposed model has satisfactory predictive capability, particularly for EE and perceived learning outcome.

Table 7. The analysis results of simultaneous effect and predictive relevance

Constructs	R^2		Q^2	
	Values	Interpretation	Values	Interpretation
BE	0.554	Moderate	0.231	Moderate
CE	0.516	Moderate	0.296	Moderate
EE	0.586	Moderate	0.355	Strong
PLE	0.843	Strong	0.402	Strong
PAP	0.781	Strong	0.381	Strong

5 DISCUSSION

The results of this study generally indicate that the implementation of MobGam in engineering education learning has a positive and significant relationship with all dimensions of LE, namely BE, CE, and EE. In addition, UI was found to have a positive and significant association with both PLE and PAP. All three dimensions of LE were shown to contribute significantly to students' PLE and PAP. Beyond these direct effects, LE also played a mediating role in bridging the relationship between UI and both PLE and PAP. These findings confirm that students' LE is the primary mechanism linking the UI of MobGam with improved learning outcome.

Consistent with the conceptual framework, the findings align with SDT [16], [17], which emphasizes that fulfilling autonomy, competence, and relatedness enhances intrinsic motivation. Features of MobGam, such as flexible access (autonomy), appropriately challenging tasks (competence), and competitive or collaborative interactions (relatedness), support the development of intense engagement. These results also resonate with CLT [18], [19], which views learning as an active process of exploration, reflection, and interaction. MobGam facilitates this process through challenge-based activities and instant feedback that stimulate CE. Flow Theory further reinforces the findings, highlighting that a balance between challenge and ability creates a state of flow, characterized by deep concentration, enjoyment, and intrinsic motivation [21], [22]. Game elements in MobGam, such as missions, levels, and digital rewards, promote this state, thereby strengthening EE. Within the LE framework [7], [15]. The findings confirm that UI influences all dimensions of LE, which in turn significantly affect learning outcome.

In response to RQ1, UI shows a significant positive relationship with BE, CE, and EE. For RQ2, all three engagement dimensions contributed positively to PLE and PAP, with EE demonstrating the most substantial relationships. Regarding RQ3, UI had an association with PLE and PAP, though its magnitude was smaller than the indirect

effects mediated by LE dimensions. Finally, in addressing RQ4, LE was confirmed as a significant mediator in the relationship between UI and LO (PLE and PAP), with EE emerging as the most dominant mediating pathway. This is consistent with the theoretical framework outlined earlier, which underscores the central role of engagement in linking technology-based learning to outcomes.

These findings reinforce prior research showing that gamification enhances engagement and improves LO (PLE and PAP) [5], [7], [33]. Similarities with previous studies are evident in the evidence that gamification promotes multidimensional LE, particularly by motivating active participation. However, this study places greater emphasis on the EE dimension, which has often been overlooked. Unlike studies that stress behavioral or cognitive aspects, this study identifies EE as the most dominant predictor of PLE and PAP. This result is consistent with studies highlighting the importance of positive emotional experiences in promoting learning satisfaction [7], [34]. It differs, however, from findings that emphasize CE in problem-solving contexts [20], [21]. This divergence may be explained by the context of electrical engineering education, which is highly cognitively demanding and thus requires stronger emotional support for persistence in the learning process. Meta-analyses also support these results by showing that the affective dimension of gamification often has a greater influence than other dimensions [1], [5], [13]. Thus, this study not only confirms existing empirical evidence but also extends it by demonstrating the dominant role of EE in the challenging context of electrical engineering education.

Although all three LE dimensions were significant, EE was found to exert the most decisive association with PLE and PAP compared to BE and CE. This suggests that affective factors such as enthusiasm, interest, satisfaction, and self-confidence are key determinants of the effectiveness of MobGam learning. This finding is in line with Flow Theory, which emphasizes the role of enjoyable experiences in fostering deep engagement [7], [23]. Prior research similarly shows that EE is the strongest predictor of learning satisfaction and PAP [7], [22].

From a theoretical standpoint, this study advances understanding of the TAM by confirming that UI not only contributes to LO but also exerts significant relationship through dimensions of LE, particularly via the EE dimension. Our results provide additional support for extending TAM-based explanations in the context of mobile-based gamification and engineering education. While TAM traditionally focuses on the direct link between 'Use' and 'Outcomes,' our model demonstrates that the primary value of technology (MobGam) lies in its ability to cultivate engagement, notably EE. This positions engagement not as a byproduct, but as the central, mediating mechanism. This adds to the prior literature, which has primarily emphasized behavioral and cognitive mediators. The findings also extend engagement theory by providing empirical evidence of the EE dimension as a powerful predictor in engineering education [7], [22], [23]. Furthermore, they align with gamification theory, which emphasizes the motivational role of game elements in MobGam, such as challenges, rewards, and competition, in enhancing intrinsic motivation and learning effectiveness [1], [7], [22]. Collectively, these results suggest that the success of MobGam in electrical engineering education lies not only in its technological features but also in its capacity to foster emotionally meaningful learning experiences.

From a practical perspective, these findings carry important implications for educators and curriculum designers in engineering. First, instructors should design MobGam strategies that emphasize not only cognitive aspects (e.g., analysis-based questions or challenging levels) but also affective dimensions, such as enjoyable experiences, social interaction, and meaningful rewards. Second, electrical engineering and similar learning contexts may consider integrating MobGam more

extensively as part of their digital learning initiatives, given its potential to enhance LE and PLO. Third, educational technology developers should incorporate features that strengthen emotional motivation, such as engaging progress visualizations, collaborative tools, and positive feedback mechanisms that build students' confidence. Thus, the practical implications of this study primarily relate to the design and implementation of mobile-based gamification in electrical engineering courses, providing insights for enhancing student engagement and perceived LO in digitally supported learning environments.

6 CONCLUSION

This study demonstrates that the implementation of MobGam through Gimkit has a positive and significant association with electrical engineering students' LE across behavioral, cognitive, and emotional dimensions, which in turn enhances PLE and PAP. The findings further confirm that LE plays a critical mediating role in the relationship between UI of MobGam and LO, with EE emerging as the most dominant pathway. This finding highlights the importance of EE in understanding how MobGam is associated with students' PLO in cognitively demanding learning environments. These results provide strong empirical evidence within the context of engineering education, an area that has been relatively underexplored in the gamification literature. The study also consistently addresses all research questions (RQ1–RQ4) while extending the literature by applying the TAM, SDT, Flow Theory, and CLT to electrical engineering education. From a practical perspective, the study highlights that MobGam design should emphasize not only cognitive aspects but also affective dimensions to foster motivation, self-confidence, and enjoyable learning experiences. Thus, this study provides insights for designing MobGam approaches that support student engagement and perceived LO in electrical engineering education. Universities may consider integrating gamified learning platforms such as Gimkit or Kahoot in courses with characteristics like those investigated in this study to support student engagement and perceived LO. Ed-tech developers could further refine these platforms by embedding adaptive features driven by artificial intelligence, enabling personalization of challenges and rewards.

Nevertheless, several limitations should be acknowledged. The cross-sectional design captures conditions at a single point in time, and LO were measured based on student perceptions. Additionally, the research context was limited to a single course within an electrical engineering program. These limitations do not undermine the validity of the findings; instead, they highlight opportunities for further inquiry. Future studies could employ longitudinal designs to capture the dynamics of LE and LO over time, complement perception-based data with objective measures such as exam scores or laboratory performance, and expand the scope to other engineering courses or vocational fields. Moreover, future research could investigate more diverse gamification features, including collaborative or adaptive elements, to deepen understanding of how MobGam design can further strengthen EE and improve LO. Building on this foundation, future studies are expected to develop the theoretical framework further while providing practical solutions for educational innovation in engineering. Future studies could explore cross-country or cross-institutional comparisons to examine whether the role of EE as a mediator is consistent across different cultural, disciplinary, and educational contexts. Moreover, integrating AI-enhanced adaptive gamification may provide deeper insights into how dynamic personalization is associated with engagement and perceived LO in diverse educational settings.

7 CONFLICT OF INTEREST

The authors declare that they have no competing interests.

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