

## PAPER

# Exploring Influential Factors in Engineering Students' Adoption of Mobile-Based Gamified Learning

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## ABSTRACT

Gamification in education has gained increasing popularity as a means to promote quality education, particularly when integrated with mobile technology to create engaging and accessible learning environments that align with technological advancements. However, a more comprehensive understanding is needed regarding students' acceptance of such technology, especially in the context of the electrical machinery course. This study investigates students' acceptance of mobile-based gamified learning (MoGaLearn) in the instruction of electrical machinery. Student acceptance is assessed through the actual use (AU) variable, based on the technology acceptance model (TAM) framework. The theoretical model employed includes key determinants such as perceived ease of use (PEU), perceived usefulness (PU), attitude toward use (A), and behavioral intention (BI). A quantitative, survey-based approach was adopted, involving 136 engineering students who completed a structured questionnaire. Data were analyzed using variance-based structural equation modeling (VB-SEM). The findings reveal that students of the Industrial Electrical Engineering program demonstrate a high level of acceptance toward MoGaLearn in the electrical machinery course. The constructs PEU, PU, A, and BI were empirically found to have a positive and significant influence on students' acceptance of MoGaLearn. These results highlight the importance of considering these factors in the design, development, selection, and implementation of gamification learning tools in engineering education.

## KEYWORDS

quality education, students' acceptance, mobile-based gamification learning, technology acceptance model (TAM), empirical analysis

## 1 INTRODUCTION

The advancement of digital technology has brought about a significant transformation in the field of education, particularly in how learning is designed and delivered. One innovative approach that has gained increasing attention in higher

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education is gamified learning, the integration of game elements into educational contexts to enhance student engagement, motivation, and learning outcomes [1], [2], [3]. When combined with mobile technology, gamification learning has the potential to create a more flexible, personalized, and interactive learning experience [3], [4]. This type of learning is becoming increasingly relevant to promote quality education, especially in the digital era [5], [6].

The electrical machinery course, a core subject in the industrial electrical engineering program, presents unique learning challenges that require mastery of complex technical concepts and the development of adequate practical skills [7], [8]. Students often find the course difficult due to its abstract content and the need for extensive hands-on practice [8], [9]. Consequently, an effective learning strategy is needed, one that not only conveys theoretical knowledge but also fosters active student participation and enjoyment. In this context, MoGaLearn emerges as a promising solution by offering a mobile-based learning platform that is accessible anytime and anywhere while incorporating gamification elements to boost student engagement and motivation [10], [11].

Previous studies have demonstrated that gamification can enhance learning motivation, student engagement, and academic performance across various educational disciplines, including computer science, mathematics, and the natural sciences [1], [5], [10]. However, most of these studies have not specifically investigated the application of MoGaLearn within the field of electrical engineering, particularly in courses that integrate both theoretical and practical components, such as electrical machinery. Given the inherently technical and complex nature of this subject, which demands both conceptual understanding and procedural competence, it presents a compelling context for evaluating the effectiveness and acceptance of MoGaLearn approaches.

Despite the growing interest in gamification learning, research on student acceptance of MoGaLearn technology remains relatively limited, particularly studies employing quantitative approaches grounded in theoretical models such as the TAM. While several studies have validated the use of TAM in the context of online learning and learning management systems [12], [13], [14], the application of mobile gamification in electrical engineering education has not been extensively examined from an empirical perspective. This study seeks to address this gap by empirically investigating the factors that influence student acceptance of MoGaLearn in the context of the electrical machinery course. The theoretical framework is based on TAM, which includes four core constructs: perceived ease of use (PEU), perceived usefulness (PU), attitude toward use (A), and behavioral intention (BI) [15], [16], [17]. These constructs are hypothesized to structurally influence students' decisions to adopt the technology in their learning process. To guide this investigation, the following research questions were formulated:

RQ1: How do engineering students perceive and accept the use of MoGaLearn in the electrical machinery course?

RQ2: How do the factors of PEU, PU, A, and BI influence students' acceptance of MoGaLearn in the Electrical Machinery course?

This study offers novelty through its specific focus on the application of MoGaLearn in electrical engineering education, as well as its integration of the

TAM with the VB-SEM approach to examine the relationships among key acceptance variables empirically. Furthermore, the study introduces and evaluates MoGaLearn, a mobile-based learning platform specifically developed to facilitate an interactive and engaging learning process in the electrical machinery course. The contributions of this research are to enrich the existing body of literature on technology acceptance within engineering education and to provide valuable insights for learning system developers and educators in designing instructional strategies that align more closely with the needs and preferences of engineering students in the digital era. Overall, this study is expected to make a significant contribution to the advancement of innovative, technology-enhanced learning in engineering and vocational education while also reinforcing the empirical foundation for educational technology acceptance models in the context of gamification learning environments.

## 2 RELEVANT LITERATURE

### 2.1 Mobile-based gamification learning

MoGaLearn represents an innovative instructional approach that integrates gamification elements into mobile applications to support interactive and enjoyable learning experiences [18], [19], [20]. This approach combines the advantages of mobile technology, such as flexibility, accessibility, and high connectivity, with the motivational power of game elements that can enhance students' cognitive and affective engagement [3], [4], [21]. In the context of engineering education, particularly in the study of electrical machinery, MoGaLearn serves as a supportive tool that enables students to access questions, challenges, and real-time feedback via mobile devices. In this study, MoGaLearn was implemented using the Kahoot! platform, an interactive, quiz-based application that facilitates both synchronous and asynchronous gamified learning [5], [22]. Kahoot! was selected due to its capacity to present questions with visually appealing formats, its scoring system based on speed and accuracy, and its leaderboard feature, which fosters healthy competition among students. Additionally, the platform's mobile compatibility ensures ease of access both inside and outside the classroom.

Unlike conventional implementations of Kahoot! that primarily focus on quizzes and student engagement, MoGaLearn was designed as a learning framework specifically developed for engineering education. All quiz items are aligned with the electrical machinery syllabus and learning outcomes, supported by a competency-based feedback system that provides conceptual explanations for each response, and organized through a progressive challenge structure based on Bloom's taxonomy. Furthermore, MoGaLearn integrates game sessions that combine theoretical quizzes and problem-solving tasks, enabling students to simulate decision-making processes relevant to electrical machinery operations. This implementation extends beyond typical Kahoot! usage by emphasizing pedagogical alignment, contextual relevance, mobile accessibility for synchronous and asynchronous learning, and deeper cognitive engagement within the engineering education context. The MoGaLearn interface is illustrated in Figure 1.

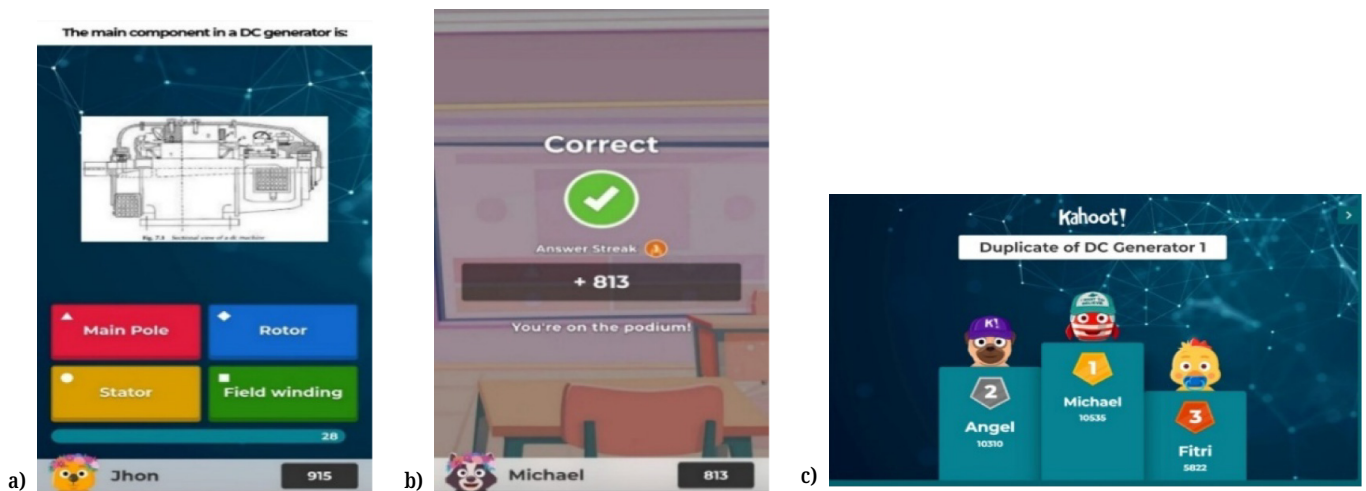


Fig. 1. The MoGaLearn Interface: (a) Quizzes; (b) Immediate feedback on correct/incorrect answers and achieved scores; (c) Final score

## 2.2 Technology acceptance model

The TAM is one of the most widely adopted theoretical frameworks for explaining and predicting user behavior toward new technologies, particularly in the domains of information systems and digital learning [12], [23]. TAM posits that two primary constructs, PEU and PU, are key determinants of users' attitudes and BI regarding the adoption of technology. PEU refers to the degree to which an individual believes that using a particular technology will be free of excessive physical or mental effort, while PU reflects the extent to which the technology is perceived to enhance the user's performance or productivity [23], [24], [25].

In the educational context, TAM provides a valuable lens for understanding how students accept and adopt digital learning technologies, including mobile-based gamification platforms such as MoGaLearn [3], [14]. In this study, TAM is employed as the core theoretical framework to investigate the factors influencing student acceptance of MoGaLearn within the electrical machinery course. In addition to the two core constructs (PEU and PU), the model incorporates A and BI as mediating variables that bridge the relationship between students' PEU and PU with their AU of the technology. Prior studies utilizing TAM in digital learning contexts have demonstrated the model's effectiveness in explaining technology acceptance and its utility as a foundation for developing strategies to support the successful implementation of educational technologies [24], [26], [27].

- $H_1$ : PEU has a significant effect on PU.
- $H_2$ : PEU has a significant effect on A.
- $H_3$ : PU has a significant effect on A.
- $H_4$ : PU has a significant effect on BI.
- $H_5$ : A has a significant effect on BI.
- $H_6$ : BI has a significant effect on AU.

### 3 METHODS

#### 3.1 Research design

This research adopts a quantitative design through the implementation of a survey-based method [9], [25], [28]. The survey approach was chosen as a structured mechanism for systematically gathering pertinent data and identifying viable solutions to the research problems, utilizing both descriptive techniques and analysis of inter-variable associations [29], [30]. Additionally, this approach facilitates the assessment of the consistency and accuracy of the collected data through reliability and validity testing [30], [31]. The analytical framework focuses on evaluating the direct, mediated, overall, and combined impacts of key constructs, PEU, PU, A, BI, and AU, to interpret the extent of student acceptance of the MoGaLearn platform, along with the determinants that influence it within the instructional setting of the electrical machinery course. An illustration of the proposed conceptual model is provided in Figure 2.

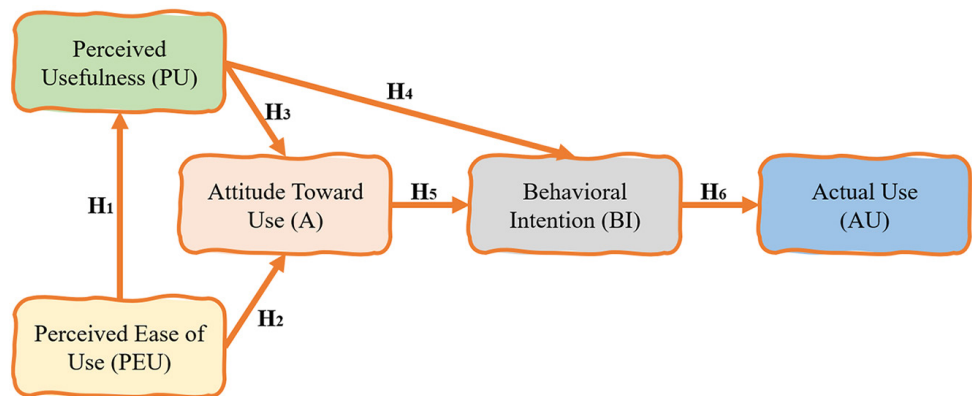


Fig. 2. The research framework

Data were collected through an online survey administered via an online form at the end of the semester, after students had completed the MoGaLearn-based learning process in the electrical machinery course. Each participant received a brief explanation of the research objectives and was assured that participation was voluntary and anonymous. To prevent data duplication, each respondent was permitted to complete the questionnaire only once. To minimize potential response bias, clear instructions were provided, and the order of survey items was randomized to avoid repetitive response patterns. All responses were automatically stored in an institutional database accessible exclusively to the research team.

#### 3.2 Research instruments

This study employed a five-point Likert scale questionnaire (ranging from 1 to 5) as the primary instrument for data collection [25], [31]. The indicators used in the instrument, as presented in Table 1, were developed through adaptations from multiple literature sources identified during an extensive review of relevant studies. The use of a Likert scale provides a standardized method for capturing respondents' perceptions, which is particularly appropriate in survey-based research that relies on empirical data [28], [32]. The data gathered through this questionnaire are expected to offer valuable insights and contribute meaningfully to a deeper understanding of the core variables investigated in this study.

**Table 1.** Questionnaire indicators

Variables	Indicators
PEU	PEU.1. Ease of learning to operate MoGaLearn. PEU.2. Level of effort required to use MoGaLearn. PEU.3. Clarity and readability of MoGaLearn's navigation. PEU.4. Speed of understanding how to operate MoGaLearn. PEU.5. Level of comfort when using MoGaLearn. Sources: [25], [30], [33], [34]
PU	PU.1. Effectiveness of MoGaLearn in facilitating the understanding of electrical machinery concepts. PU.2. Enhancement of the learning process effectiveness through the use of MoGaLearn. PU.3. Impact of MoGaLearn on students' academic achievement. PU.4. Acceleration of assignment completion using MoGaLearn. PU.5. Improvement in the quality of learning outcomes due to MoGaLearn. PU.6. Ability to master electrical machinery concepts with the support of MoGaLearn. Sources: [14], [25], [30], [34]
A	A.1. Positive attitude toward using MoGaLearn in the learning process. A.2. Perception that using MoGaLearn is a good idea. A.3. Perception of enjoyment when using MoGaLearn. A.4. Willingness to recommend the use of MoGaLearn to fellow students. A.5. Perception that MoGaLearn is an interesting learning medium. Sources: [14], [25], [33], [34]
BI	BI.1. Intention to continue using MoGaLearn in learning Electrical Machines. BI.2. Plan to use MoGaLearn in future learning activities. BI.3. Motivation to maximize the use of MoGaLearn. BI.4. Commitment to using MoGaLearn regularly. BI.5. Desire to engage in further learning using MoGaLearn. Sources: [14], [25], [28], [34]
AU	AU.1. Frequency of using MoGaLearn in the Electrical Machinery learning process. AU.2. Routine use of MoGaLearn as part of independent learning activities. AU.3. Utilization of interactive features in MoGaLearn. AU.4. Use of MoGaLearn for regularly completing practice questions or material evaluations. AU.5. Frequency of accessing MoGaLearn via mobile devices inside and outside the classroom. AU.6. Participation in competitive activities in MoGaLearn, such as quiz challenges or learning games. Sources: [14], [25], [28], [34]

In addition to self-reported indicators, this study also utilized basic system-generated data from the MoGaLearn platform, including the number of quiz sessions, total attempts, and cumulative time spent on the application. These objective usage records were collected to complement the self-reported measures of the AU construct and to enhance the validity of the behavioral engagement assessment. Before the full-scale data collection, the research instrument underwent a preliminary trial involving 30 students who were not part of the primary study sample. This pretesting phase aimed to verify both the instrument's validity and reliability. The construct validity was examined using Pearson's correlation coefficient [9], [15], whereas reliability was determined using Cronbach's alpha coefficient [14], [30]. Before these statistical analyses, the content validity was evaluated through expert judgment. Eight subject matter experts assessed each questionnaire item for its relevance, clarity, and comprehensiveness, offering critical feedback that guided item refinement. The expert review process confirmed that the instrument satisfied content validity standards.

Following the pilot test, the correlation analysis revealed that all item scores (r-calculated) were higher than the critical value ( $0.597 > 0.3610$ ) and statistically significant ( $p < 0.05$ ), suggesting that each item demonstrated strong validity [16], [30]. Furthermore, the instrument's internal consistency was supported by a Cronbach's alpha value of 0.759, which exceeded the minimum acceptable criterion of 0.60 [14], [25]. These results provide strong evidence that the instrument is both valid and reliable, affirming its appropriateness for application in the main study.

### 3.3 Research participant

In this study, the entire population of second-year students ( $n = 136$ ) enrolled in the Electrical Machinery course within the Industrial Electrical Engineering Study Program, Faculty of Engineering, Universitas Negeri Padang, Indonesia, was selected as the respondent group. All participants had previously engaged in learning activities within the Electrical Machinery course and had utilized the MoGaLearn platform comprehensively throughout the instructional process. The number of respondents met the methodological requirements for PLS-SEM analysis. According to the "10-times rule," the minimum sample size should be at least ten times the maximum number of structural paths directed toward a single construct in the model [25], [35]. Therefore, the valid responses obtained from a total of 136 participants, exceeding ten times the number of structural paths (60) in this study, are considered statistically adequate to ensure the reliability and stability of the model estimation.

### 3.4 Data analysis technique

The data collected in this study were analyzed using the VB-SEM approach, also known as partial least squares-structural equation modeling (PLS-SEM) [30], [33]. The analysis was conducted using SmartPLS 3 software, which enables an empirical assessment of students' acceptance of MoGaLearn in the learning process, as well as the identification of factors influencing this acceptance. The technique was applied to verify the measurement model's reliability and validity, as well as to examine the direct and indirect causal pathways connecting independent and dependent constructs. The study was conducted in accordance with institutional ethical standards and approved by the Research and Community Service Institutions (LPPM) of Universitas Negeri Padang (No. 2047/UN35.15/LT/2025). All participants were informed about the study's objectives and provided electronic consent before participation. No incentives were offered, and anonymity and confidentiality were strictly maintained. All data were anonymized, securely stored, and used solely for research purposes. The anonymized dataset is available from the corresponding author upon reasonable request.

## 4 RESULTS

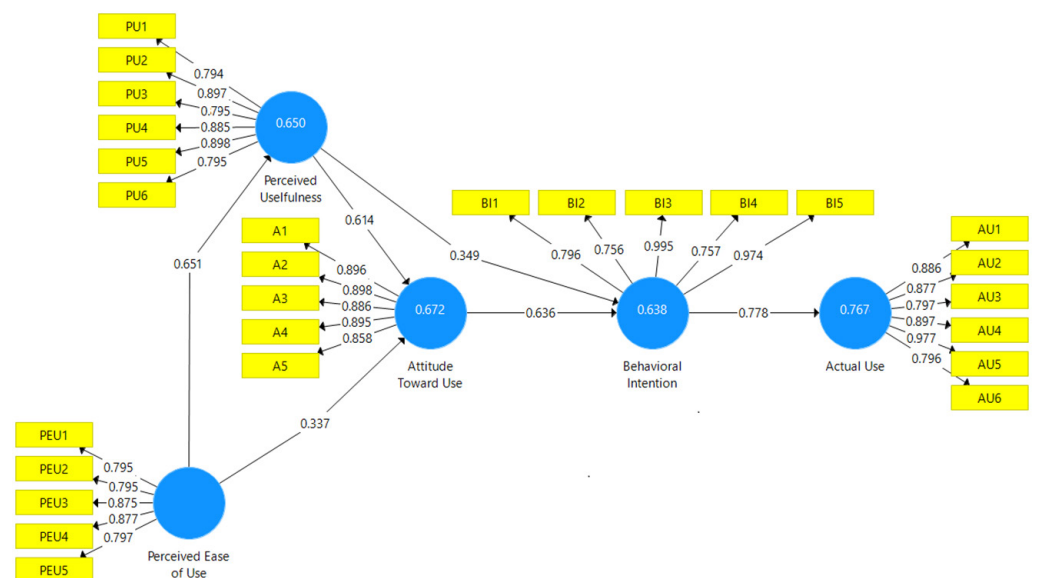
The preliminary model based on the research framework in Figure 1 was examined to verify its conformity with the assumptions and standards required for VB-SEM. This evaluation encompassed the assessment of both the inner (structural) model constructs and the outer (measurement) model indicators. The objective was to ensure that the model did not exhibit multicollinearity and satisfied the necessary criteria for structural model fit [31], [35], [36]. One essential measure used to detect

multicollinearity is the variance inflation factor (VIF), which should remain below the cutoff value of 5 ( $VIF < 5$ ) [31], [36]. As presented in Table 2, all indicators in the outer model demonstrated VIF scores below this threshold, indicating that multicollinearity is not present. These findings confirm that the initial model utilized in this study adheres to the required diagnostic criteria and is statistically appropriate for further VB-SEM analysis.

**Table 2.** Outer VIF values of the research model

PEU	VIF	PU	VIF	A	VIF	BI	VIF	AU	VIF
PEU.1	1.173	PU.1	1.110	A.1	1.726	BI.1	1.421	AU.1	1.502
PEU.2	1.301	PU.2	1.622	A.2	1.366	BI.2	1.373	AU.2	1.533
PEU.3	1.161	PU.3	1.211	A.3	1.912	BI.3	1.523	AU.3	1.224
PEU.4	1.251	PU.4	1.324	A.4	1.221	BI.4	1.733	AU.4	1.338
PEU.5	1.613	PU.5	1.121	A.5	1.934	BI.5	1.654	AU.5	1.834
–	–	PU.6	1.565	–	–	–	–	AU.6	1.532

Multicollinearity testing was also conducted for the relationships among variables within the inner model. Similar to the indicator-level analysis, this step is essential to ensure that multicollinearity is not present among the constructs being examined [33], [36]. The results of the VIF analysis for the inner model show that all VIF values are below the commonly accepted threshold of 5. PEU-PU: 2.290, PEU-A: 2.902, PU-A: 2.911, PU-BI: 2.223, A-BI: 1.914, and BI-AU: 2.119. This indicates that the research model does not suffer from multicollinearity issues among its constructs. Thus, the final model analysis can be conducted as presented in Figure 3. 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 (1.129/1.122) exceeded 0.90, the SRMR (0.072/0.067) was below 0.08, and the RMS Theta (0.086/0.091) was below 0.102. Collectively, these values confirm that the model achieved an acceptable level of fit.



**Fig. 3.** The final results of the VB-SEM analysis using SmartPLS 3

#### 4.1 Outer model analysis

The outer model analysis in this study was conducted to assess convergent validity (CV), unidimensionality of the model (UM), and internal consistency reliability (ICR) [24], [35]. ICR evaluates the internal consistency of the indicators in representing their respective constructs, as reflected by Cronbach's alpha (CA) values [35], [36]. As shown in Table 3, all constructs demonstrate CA values exceeding the threshold of 0.70, indicating a satisfactory level of reliability for the indicators within each variable [29], [35], [36]. The UM test was performed to ensure that the measurement instrument did not suffer from dimensional inconsistency. The results presented in Table 3 also reveal that all constructs satisfy the unidimensionality criteria, with both composite reliability (CR) and CA values surpassing the recommended threshold of 0.70, as listed in Table 3. CV was assessed to determine the degree to which indicators consistently measure the same underlying construct [29], [35]. The findings indicate that all variables meet the criteria for CV, as evidenced by outer loading values greater than 0.70 for each construct, as shown in Figure 3 [16], [35].

**Table 3.** Outer model analysis

	CR	AVE	CA	Rho_A
<b>PEU</b>	0.793	0.681	0.916	0.778
<b>PU</b>	0.921	0.696	0.892	0.815
<b>A</b>	0.877	0.749	0.971	0.833
<b>BI</b>	0.891	0.712	0.828	0.709
<b>AU</b>	0.919	0.696	0.936	0.751

Discriminant validity (DV) was assessed using the HTMT, which evaluates the ratio of correlations between indicators of different constructs to those within the same construct. This method is recognized as a more robust and reliable criterion for detecting DV issues compared to other techniques. Table 4 shows that the HTMT values for all construct pairs were below the recommended threshold of 0.85, indicating that the measurement model demonstrates satisfactory DV.

**Table 4.** The results of the HTMT analysis

	PEU	PU	A	BI
<b>PU</b>	0.611	–	–	–
<b>A</b>	0.622	0.644	–	–
<b>BI</b>	0.491	0.621	0.652	–
<b>AU</b>	0.466	0.479	0.424	0.653

#### 4.2 Inner model analysis

This analysis aims to evaluate the relationships among variables within the structural model and to identify the effects exerted by exogenous variables on

endogenous variables. These effects are examined in the form of direct effects, indirect effects through mediating variables, total effects, and simultaneous effects. The direct effects between exogenous and endogenous variables in the research model are indicated by path coefficient values, which range from  $-1$  to  $+1$ . A coefficient approaching  $+1$  signifies a strong positive effect of the exogenous variable on the endogenous variable, whereas a value approaching  $-1$  indicates a strong negative effect [16], [24], [35]. To ensure the robustness of the structural model, a bootstrapping procedure with 5,000 resamples and a two-tailed significance test was conducted, using a 95% confidence interval (CI) to assess the significance of each path coefficient. In addition, the  $f$ -square ( $f^2$ ) value is used to assess the magnitude of the effect between variables. An  $f^2$  value of 0.02 indicates a small effect, 0.15 a medium effect, and 0.35 a large effect. Values below 0.02 can be disregarded or interpreted as having no meaningful effect [16], [24], [35]. As outlined in Table 5, the findings reveal the following results: (1) The effect of PEU on PU was found to be positive and statistically significant ( $\beta = 0.651$ ,  $p < 0.05$ ). In addition, the  $f^2$  value of 0.401 indicates that the influence is at a large level. (2) The path from PEU to A was found to be positive and statistically significant with a small effect; (3) The effect of PU on A was found to be positive and statistically significant with a large effect; (4) The effect of PU on BI was found to be positive and statistically significant with a medium effect (5). The effect of A on BI was found to be positive and statistically significant with a large effect. Finally, (6) The effect of BI on AU was found to be positive and statistically significant with a strong effect. The results show that the majority of paths exhibit medium-to-large effect sizes, confirming that the relationships among constructs are not only statistically significant but also practically meaningful.

**Table 5.** The direct effect and  $f^2$  analysis of the research model

No.	Path	Path coefficient ( $\beta$ )	$f^2$	P-value (p)
1	PEU $\rightarrow$ PU	0.651	0.401	0.001
2	PEU $\rightarrow$ A	0.337	0.145	0.029
3	PU $\rightarrow$ A	0.614	0.373	0.001
4	PU $\rightarrow$ BI	0.349	0.152	0.022
5	A $\rightarrow$ BI	0.636	0.389	0.001
6	BI $\rightarrow$ AU	0.778	0.433	0.001

Evaluating indirect effects aims to investigate how exogenous variables affect endogenous constructs through one or more intervening variables. The purpose is to uncover the extent and significance of these mediated pathways in shaping the overall relationships within the structural model. Referring to the results summarized in Table 6, the following key findings were identified: (1) The indirect effect of PEU on A through PU was found to be positive and statistically significant ( $\beta = 0.400$ ,  $p < 0.05$ ); (2) The path from PEU to BI through A was found to be positive and statistically significant; (3) The effect of PEU on BI through PU was found to be positive and statistically significant. (4) The effect of PU on BI through A was found to be positive and statistically significant; (5) The effect of PU on AU through BI was found to be positive and statistically significant; Finally, (6) The path of A to AU through BI was found to be positive and statistically significant.

**Table 6.** The indirect effect analysis of the research model

No.	Path	$\beta$	p
1	PEU $\rightarrow$ PU $\rightarrow$ A	0.400	0.009
2	PEU $\rightarrow$ A $\rightarrow$ BI	0.240	0.009
3	PEU $\rightarrow$ PU $\rightarrow$ BI	0.227	0.006
4	PU $\rightarrow$ A $\rightarrow$ BI	0.391	0.009
5	PU $\rightarrow$ BI $\rightarrow$ AU	0.272	0.006
6	A $\rightarrow$ BI $\rightarrow$ AU	0.495	0.009

The total effect provides a comprehensive understanding of the influence exerted by exogenous variables on endogenous variables, encompassing both direct and indirect contributions. In the context of this research model, key exogenous variables with cumulative effects include PEU on A and PU on BI. The results of the total effect calculations reveal that PEU has a total effect of 0.737 on A ( $p = 0.001$ ). Similarly, PU exerts a total influence of 0.700 on BI ( $p = 0.001$ ). All total effect values were found to be statistically significant, as indicated by p-values below the 0.05 significance threshold.

In the VB-SEM approach, the simultaneous influence of exogenous variables on each endogenous construct is assessed using R-squared ( $R^2$ ) and adjusted R-squared (Adj.  $R^2$ ) values. The evaluation of  $R^2$  values follows commonly accepted criteria:  $R^2 \geq 0.67$  indicates a strong effect, values between 0.33 and 0.67 reflect a moderate effect, and  $R^2 \geq 0.19$  is considered a weak effect [35], [37]. Based on the analysis results, the PU variable exhibits a moderate simultaneous effect, with an adjusted  $R^2$  of 0.646. The A variable shows a strong effect with an  $R^2$  of 0.668, while the BI variable demonstrates a moderate effect with an  $R^2$  of 0.634. The AU variable displays a strong simultaneous effect with an  $R^2$  of 0.763.

### 4.3 Student acceptance of MoGaLearn in electrical machinery course

In this study, students participated in the electrical machinery course, which incorporated MoGaLearn as part of the instructional process. The result indicates that students in the industrial electrical engineering study program exhibit a very high level of acceptance toward the use of MoGaLearn. This strong acceptance is reflected in the high level of AU Variable, which measures the extent to which students actively engage with MoGaLearn as part of their learning activities. The six indicators used to assess AU yielded consistently high average scores, demonstrating intensive and sustained utilization of the platform.

Specifically, the AU.1 indicator reveals a very high frequency of MoGaLearn usage during the learning process, with a mean score of 4.89. The AU.2 indicator indicates that students regularly incorporate MoGaLearn into their self-directed learning routines, as reflected by an average score of 4.91. The AU.3 indicator shows active student engagement with the interactive features of MoGaLearn, yielding a mean score of 4.82. For AU.4, the findings indicate that students use the application consistently to complete practice questions and periodically review course content, with an average score of 4.84. The AU.5 indicator, which records a mean score of 4.92, reflects the frequent use of MoGaLearn via mobile devices both in and outside

of classroom settings, supporting flexible and optimized learning experiences. Finally, AU.6 demonstrates that students actively participate in competitive activities within the platform, such as quizzes and educational games, with an average score of 4.81. Collectively, these findings confirm that students in the Industrial Electrical Engineering program demonstrate a high degree of acceptance and active utilization of MoGaLearn, supporting its effectiveness as a technology-based pedagogical intervention in engineering education.

## 5 DISCUSSION

The findings of this study indicate that engineering students demonstrate a high level of acceptance toward MoGaLearn, as evidenced by their consistent and structured patterns of AU. Students not only utilized MoGaLearn frequently during class sessions but also integrated it into their independent learning activities outside the classroom. This consistent behavior suggests that MoGaLearn has become an integral component of their learning strategy, reinforcing both conceptual understanding and practical application of course materials.

Moreover, students actively and regularly engaged with MoGaLearn's interactive features, such as competitive quizzes, leaderboards, and automated feedback, which have been shown to enhance both cognitive engagement and affective motivation. These findings are consistent with prior research emphasizing that well-designed gamification elements can strengthen learning engagement and improve affective involvement in engineering and STEM education [25], [38]. The mobile accessibility of MoGaLearn further supports flexible learning anytime and anywhere, aligning with previous studies that highlight the critical role of digital learning flexibility in sustaining student engagement [5], [38], [39].

From the perspective of the TAM framework, the analysis results confirm that PEU plays a crucial role in shaping both PU and A. When students perceive MoGaLearn as easy to use, they are more likely to regard it as useful in supporting their learning processes. The positive relationship observed between PEU and PU suggests that the platform's interface design and overall user experience contribute meaningfully to students' comfort and ease in engaging with the technology. Furthermore, PU emerges as a significant determinant of students' positive attitudes toward the use of MoGaLearn. Students who perceive the platform as beneficial, particularly in enhancing their understanding of complex subject matter, tend to develop a more favorable attitude toward its continued use. This positive attitude subsequently influences BI, which in turn directly drives the AU of the technology in the learning environment.

The findings, which highlight PEU and PU as critical factors influencing students' attitudes and intentions to use MoGaLearn, are consistent with several previous studies that have likewise identified PEU and PU as key predictors of user attitudes and behavioral intentions in the adoption of educational technologies [13], [14], [25], [30]. Moreover, in the specific context of gamification learning, prior research has demonstrated that students are more likely to adopt educational technologies when they perceive such tools as easy to use and beneficial to their learning processes [25], [28], [40]. This alignment with earlier findings reinforces the external validity of the TAM in explaining user behavior, particularly about mobile gamification learning technologies within engineering education settings.

Another key finding reveals that BI exerts a strong influence on AU. This suggests that students' intentions to use MoGaLearn are a significant determinant of their

actual engagement with the platform in their learning activities. Such a result underscores the notion that the successful implementation of educational technologies is influenced not only by the quality of system design but also by students' cognitive and affective readiness to accept and integrate the technology into their learning routines. The strong relationship observed between BI and AU aligns with findings from prior studies on gamification learning systems in higher education, where BI has consistently been identified as a powerful mediating variable linking user perceptions of technology with AU behavior [14], [25], [30]. This study extends these insights to the context of engineering education by demonstrating that students who develop a positive attitude toward MoGaLearn are more likely to express a strong intention to use it, which, in turn, translates into active and consistent use, particularly in mastering complex concepts in electrical machinery.

The analysis of indirect effects within the model reveals several important dynamics. PEU influences BI not only directly but also indirectly through PU and A as mediating variables. Similarly, PU and A impact AU through the mediating role of BI. These findings reinforce the understanding that the acceptance of educational technology is a complex, multi-layered process that involves the interaction of cognitive perceptions, emotional attitudes, and behavioral intentions. As such, the adoption of technology-based learning approaches cannot be viewed independently of the psychological and perceptual dimensions of learners [25], [27], [28]. The robustness of the model is further evidenced by the strong predictive power of the exogenous variables on the endogenous constructs, which collectively explain a substantial portion of the variance in AU. This supports the argument that MoGaLearn has not only been positively received by students but has also been effectively adopted as a part of their learning behavior in the electrical machinery course.

These findings are consistent with prior studies, which have similarly demonstrated that in the context of technology-enhanced learning, indirect pathways, particularly through PU and A, serve as critical mediators in shaping students' intention to use educational technologies [14], [24], [41]. Therefore, this study not only validates the causal structure proposed in the TAM but also highlights the importance of understanding mediation mechanisms when designing strategies for the successful adoption of gamification learning technologies in engineering education.

However, this study offers novel contributions compared to previous research, particularly within the context of engineering and vocational education. While much of the existing literature has primarily focused on general learning domains, such as language education or educational management, many of these studies have emphasized the motivational benefits of gamification without specifically examining the relationships among psychological constructs within the acceptance model framework in technical fields [14], [25], [28], [30]. By centering the investigation on an electrical engineering course, this study provides more targeted and empirically grounded insights that are directly applicable to the development of digital-based learning strategies in engineering education. Specifically, it advances the understanding of how mobile gamification technologies, such as MoGaLearn, are perceived and adopted by students in a learning environment that requires mastery of complex conceptual and procedural knowledge. This contribution helps bridge the gap between gamification research and its implementation in practice-based, technical education settings.

The application of the TAM in this study has successfully revealed students' acceptance of MoGaLearn in the learning process of electrical engineering courses and identified the key factors influencing that acceptance. All hypothesized relationships in the model were found to be statistically significant and consistent with

prior research, while simultaneously enriching the existing literature by uncovering complex mediation mechanisms among the variables. This study affirms that the successful integration of gamification learning technologies is not solely dependent on technical features but is also significantly influenced by users' PEU and PU, and their overall attitudes toward the technology. The contribution of this research is particularly important as it extends the application of TAM into the engineering education domain, an area that has received comparatively limited attention in previous studies. Furthermore, it provides an empirical foundation for the development of more effective, engaging, and learner-centered digital learning strategies that are better aligned with the characteristics and expectations of today's generation of learners.

## 6 CONCLUSION

This study empirically investigated students' acceptance of MoGaLearn in the context of electrical engineering courses, employing the TAM as its theoretical framework. The findings revealed that all core constructs of TAM (PEU, PU, A, and BI) exerted a significant influence on students' AU of MoGaLearn. Both direct and indirect paths among these variables demonstrated statistically significant relationships. The high level of AU reflects students' positive behavioral responses to the integration of MoGaLearn within an engineering education environment. This interpretation was further supported by the inclusion of objective usage statistics, which provided additional evidence of students' active engagement beyond self-reported responses. These results suggest that digital learning platforms incorporating gamification elements, when designed with intuitive, user-friendly interfaces and aligned with sound pedagogical principles, can be effectively adopted by students for meaningful engagement in their learning processes. Accordingly, MoGaLearn is not only perceived positively but is also actively and consistently utilized by students as part of their learning routines, particularly in mastering complex subject matter such as electrical machinery.

Theoretically, this study extends the application of the TAM to a relatively underexplored context, MoGaLearn in engineering education. It demonstrates the model's robustness in explaining technology acceptance within technical and practice-oriented learning environments. Practically, the findings offer valuable implications for educational institutions, instructional designers, and developers of educational technology. The results highlight the importance of prioritizing perceived ease of use and perceived usefulness from the users' perspective when designing and implementing learning technologies. Moreover, students' psychological and affective factors are shown to be key determinants in the successful adoption and long-term sustainability of gamification learning solutions. Therefore, aligning technological design with user-centered principles is essential for maximizing student engagement and learning outcomes in digital education environments.

## 7 LIMITATIONS AND FUTURE WORK

Although this study offers meaningful contributions through its findings, several limitations must be acknowledged. First, the research was conducted within a specific context, namely, the electrical machinery course in the industrial electrical engineering program at a single higher education institution. As such, caution

should be exercised when generalizing the results to other courses, disciplines, or institutional contexts. Second, the research model employed in this study was limited to the core constructs of the TAM. While these constructs were found to explain a substantial proportion of the variance in technology usage behavior, it is likely that other external factors, such as perceived enjoyment, technological self-efficacy, or institutional and instructor support, also play a critical role in shaping students' acceptance of learning technologies. Future studies are therefore encouraged to expand the model by incorporating these and other relevant variables to provide a more comprehensive understanding of user acceptance. Finally, the cross-sectional nature of this study limits the ability to assess long-term effects. Longitudinal studies or extended experimental designs are recommended to evaluate the sustained impact of MoGaLearn on learning outcomes, continuous motivation, and the development of professional competencies in engineering. Additionally, cross-institutional and cross-cultural investigations may offer deeper insights into the broader dynamics of gamification learning technology acceptance across diverse educational settings.

## 8 CONFLICT OF INTEREST

The authors declare that they have no competing interests.

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