



Modelling user acceptance of personalised learning apps in high schools using the SEM approach

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Abstract. This research addresses the urgent need to understand user acceptance of personalised mobile learning applications in higher education, especially as digital learning becomes increasingly essential in post-pandemic education. The study employs a quantitative research design, utilising the Technology Acceptance Model 3 (TAM3) as the theoretical framework and Structural Equation Modelling (SEM) for analysis. The population comprises undergraduate students from various departments at STIKOM Uyelindo Kupang, selected using stratified random sampling to ensure representation across faculties. Data was collected through a validated questionnaire based on TAM3 constructs, and the instrument's validity and reliability were confirmed using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). The results show that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) significantly influence Behavioural Intention (BI), while Social Influence (SI) and Facilitating Conditions (FC)

also play important roles. Perceived Enjoyment (PE) enhances engagement, and Computer Anxiety negatively affects ease of use. The study concludes that TAM3 effectively models user acceptance in this context. Recommendations include improving app usability, providing institutional support, and designing engaging learning experiences to enhance the adoption and continued use of mobile learning technologies.

INTRODUCTION

The rise of digital technologies has significantly transformed the higher education landscape, particularly with the increasing use of mobile learning applications. Personalised learning, which customises educational experiences to suit individual learners' preferences, learning pace, and needs, is becoming more prominent in higher education institutions (Ambele, Kaijage, Dida, Trojer, & M. Kyando, 2022). By leveraging data analytics and artificial intelligence, personalised learning applications offer tailored educational content and adaptive learning paths, making

learning more effective and engaging for university students (Ambele et al., 2022). Mobile learning (m-learning) applications provide flexibility and accessibility, allowing university students to learn at their own pace and according to their schedules (Wang, Dai, Zhu, Yu, & Gu, 2023). These applications offer immediate feedback, real-time assessments, and content customisation, which are particularly beneficial in supporting the diverse learning styles and academic needs of higher education students (Alyoussef, 2021; Widana et al., 2023). Moreover, mobile applications facilitate the seamless integration of learning with daily activities, allowing students to access learning materials at any time and from anywhere (Blyznyuk, Budnyk, & Kachak, 2021). This shift toward mobile-based personalised learning has the potential to reshape how students engage with higher education content, offering more autonomy and control over their educational journeys (Double et al., 2020; Suhardita et al., 2024).

However, User approval is crucial to the effective integration of personalised learning apps in higher education. For these applications to be implemented effectively, it is essential to understand the factors that influence university students' acceptance and sustained use of them (Zhai, Wibowo, & Li, 2024). The Technology Acceptance Model (TAM) has been widely used to explore these factors, emphasising the roles of perceived usefulness (PU) and perceived ease of use (PEOU) in shaping students' intentions to adopt new technologies (Davis, 1989; Venkatesh, V., & Bala, 2008). Extensions of TAM, such as TAM3, incorporate additional constructs, including social influence, self-efficacy, and facilitating conditions, thereby providing a more comprehensive understanding of technology acceptance (Al-Emran et al., 2020). TAM3 has been widely used to gauge students' approval of mobile learning apps in higher education settings. According to research, students' views on technology are significantly influenced by the perceived utility and simplicity of use. In contrast, user acceptability is largely determined by external variables, including institutional support and social influence (Crompton et al., 2021). Studies in higher education settings indicate that students are more likely to adopt mobile learning applications when they perceive them as beneficial to their academic performance and easy to use (Sánchez, R. A., & Hueros, 2020).

Research on educational technology has extensively utilised structural equation modelling (SEM) to examine the relationships between factors such as perceived utility, usability, satisfaction, and behavioural intentions (Ketchen, 2013). The COVID-19 pandemic accelerated the adoption of mobile learning applications in higher education, although questions remain about their long-term integration (Hamid et al., 2022; Widana et al., 2023b). Besides technological factors, acceptance of these applications is also influenced by university infrastructure, teacher support, and peer influence. Limited empirical testing of the TAM model in high school settings, as well as external variables like Computer Anxiety and Facilitating Conditions, highlights existing research gaps. Additionally, technical support and technology anxiety play a significant role in shaping students' perceptions and acceptance of personalised learning applications.

In the field, many high school students still face significant challenges in adopting personalised mobile learning applications. These include limited access to adequate digital infrastructure, a lack of consistent support from teachers, and low digital confidence among students. Despite the growing availability of mobile learning technologies, their actual usage remains low, particularly in under-resourced schools. This research is necessary to understand the underlying factors that hinder students from fully embracing these tools. By focusing on high school students, this study addresses a gap in existing research, which predominantly concentrates on university-level learners. The study also introduces an extended model that incorporates psychological, social, and environmental variables, offering a more comprehensive view of technology acceptance in the context of personalised mobile learning.

This study aims to extend the Technology Acceptance Model (TAM) by integrating key external variables, namely Computer Anxiety, Facilitating Conditions, and Social Influence, to provide a deeper understanding of technology acceptance among high school students using personalised mobile learning applications. The study highlights how students' Behavioural Intention (BI) to embrace and use these applications is primarily shaped by their perceptions of their usefulness (PU) and ease of use (PEOU). To determine which factors have the most significant impact on students' acceptance and usage behaviour, this study will use Structural Equation Modelling (SEM) to examine the direct and indirect correlations between PU, PEOU, BI, and the external variables. This approach aims to not only validate the applicability of TAM in the context of personalised mobile learning but also to uncover how psychological, social, and environmental factors interplay in shaping students' technology adoption decisions. The findings are expected to provide valuable insights for educators, developers, and policymakers seeking to enhance mobile learning experiences and increase student engagement through the development of tailored technological solutions.

METHOD

To investigate the factors influencing college students' acceptance of mobile applications for personalised learning, this study employed two quantitative research techniques: the Technology Acceptance Model 3 (TAM3) and Structural Equation Modelling (SEM). Because it incorporates social impact, perceived utility (PU), perceived ease of use (PEOU), and facilitating conditions into a comprehensive model of user acceptability, the TAM3 paradigm was selected. The use of SEM to analyse the interactions between these variables allows for a more complete understanding of how they interact to influence students' behavioural intentions.

Sampling Techniques

The study will focus on undergraduate students enrolled in various courses at STIKOM Uyelindo Kupang, a university offering a wide range of academic disciplines. To ensure that the sample accurately represents the population across various academic departments and disciplines, participants will be selected using a stratified random sampling technique. The study aims to achieve balanced representation and minimise sampling bias by stratifying the population according to study programs or faculties, and then selecting respondents at random from each stratum.

The rationale for choosing stratified random sampling lies in its ability to capture the variability within the student population and provide more accurate and generalizable results, especially when exploring behavioural and attitudinal constructs related to online learning. The target sample size is set at a minimum of 200 respondents, which is determined by dividing the population into strata based on study programs and then calculating the sample size for each stratum proportionally using the formula:

$$N_h = \frac{N_h}{N} \times n \quad 1$$

where n_h is the sample size for the h -th stratum, N_h is the population size of the h -th stratum, N is the total population size, and n is the total sample size. This method ensures that each stratum is proportionally represented in the sample, leading to more valid and reliable research results. This is considered statistically adequate for conducting Structural Equation Modelling (SEM) using the PLS approach. According to methodological guidelines, SEM requires a sufficient number of cases to ensure a reliable estimation of model parameters. A sample size of 200 or more is typically sufficient to support robust analysis, particularly when the

model includes multiple constructs and pathways. This sample size will also enhance the validity of the findings and provide a solid foundation for the generalisation of results within the context of higher education students in Indonesia.

Table 1. Participant Data

Participant ID	Age	Gender	Department	Year of Study	Mobile App Usage (hrs/week)
1	21	F	Engineering	2	10
2	22	M	Engineering	3	8
3	23	F	Engineering	1	12
4	21	M	Engineering	4	6
5	24	F	Engineering	2	14
6	25	M	Engineering	3	7
7	22	F	Engineering	1	9
8	23	M	Engineering	4	11
9	24	F	Engineering	2	10
10	25	M	Engineering	3	8
11	21	F	Information System	2	10
12	22	M	Information System	3	8
13	23	F	Information System	1	12
14	21	M	Information System	4	6
15	24	F	Information System	2	14
16	25	M	Information System	3	7
17	22	F	Information System	1	9
18	23	M	Information System	4	11
19	24	F	Information System	2	10
20	25	M	Information System	3	8

Data Collection

An online survey based on validated TAM3 constructs will be used to gather data. The survey will ask students to rate their level of agreement on a Likert scale (1–5) for each item that measures their perceptions of the mobile learning applications' usefulness and ease of use, as well as external factors such as social influence and facilitating conditions.

Table 2. Questionnaire questions based on TAM3

No	Construct	Survey Question
1	Perceived Usefulness	The mobile learning application helps me complete tasks faster.
2	Perceived Usefulness	This application increases my productivity in learning.
3	Perceived Usefulness	Using this application improves my academic performance.
4	Perceived Usefulness	This application is beneficial for my learning.
5	Perceived Ease of Use	This application is easy to use.
6	Perceived Ease of Use	I feel comfortable using this application.
7	Perceived Ease of Use	Using this application requires little effort.
8	Perceived Ease of Use	I find it easy to become skilled at using this application.
9	Social Influence	Important people around me suggest that I use this application.
10	Social Influence	My friends use this learning application.
11	Social Influence	I use this application because many people around me use it.
12	Social Influence	Recommendations from others influence my decision to use this application.
13	Facilitating Conditions	I have access to the resources required to use this application.
14	Facilitating Conditions	I have enough knowledge to use this application effectively.
15	Facilitating Conditions	Technical support for this application is readily available.

No	Construct	Survey Question
16	Facilitating Conditions	My university offers sufficient support for utilising mobile learning applications.
17	Perceived Enjoyment	I enjoy using this application.
18	Perceived Enjoyment	Using this application is a pleasant experience.
19	Perceived Enjoyment	I find this application interesting.
20	Perceived Enjoyment	I feel happy when learning through this application.
21	Behavioral Intention	I plan to continue using this application for my learning.
22	Behavioral Intention	I will recommend this application to others.
23	Behavioral Intention	I will frequently use this application in the future.
24	Behavioral Intention	I expect this application to become an essential part of my learning process.
25	Self-Efficacy	I feel confident in using this learning application.
26	Self-Efficacy	I can operate this application without assistance.
27	Self-Efficacy	I am confident that I can complete tasks using this application.
28	Self-Efficacy	I have the necessary skills to use this application effectively.
29	Perceived risk	I am concerned about my data privacy when using this application.
30	Perceived risk	I fear that my personal information may be misused through this application.
31	Perceived risk	I believe there is a risk associated with using this application.
32	Perceived risk	I am uncertain about the security of using this application.
33	Output Quality	This application produces quality results in my learning process.
34	Output Quality	The quality of the materials provided by this application is excellent.
35	Output Quality	The information provided by this application is accurate and reliable.
36	Output Quality	I am satisfied with the quality of output generated by this application.
37	Computer Anxiety	I feel anxious when I have to use this application.
38	Computer Anxiety	I feel nervous when using technology like this application.
39	Computer Anxiety	I feel uncomfortable learning to use this application.
40	Computer Anxiety	I often worry about making mistakes when using this application.

Data Analysis

The data obtained in this study will be analysed using Structural Equation Modelling (SEM) with the assistance of SmartPLS software, which utilises the Partial Least Squares (PLS) method. SEM is selected due to its strength in assessing intricate causal relationships among latent variables (or constructs), as well as its ability to integrate factor analysis and regression analysis into a single, unified analytical framework. There will be two main stages to the SEM procedure. The measurement model is evaluated in the first step in order to confirm the validity and reliability of the constructs used in the study. Cronbach's Alpha and Composite Reliability (CR) will both be used to assess reliability. The Fornell-Larcker Criterion and cross-loading values will be used to determine discriminant validity, while the Average Variance Extracted (AVE) will be used to examine convergent validity.

Once the measurement model is confirmed to be reliable and valid, the analysis proceeds to the second stage, which involves evaluating the structural model. In this stage, the hypothesised relationships between constructs will be tested to determine the extent to which one variable influences another. This entails evaluating the statistical significance of the suggested associations by examining path coefficients, t-statistics, and p-values. Other model fit metrics are considered to supplement the interpretation of results, even though SmartPLS does not employ the

conventional goodness-of-fit indices commonly used in covariance-based SEM tools (such as AMOS or LISREL). These include Chi-square/df ratio, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). These indices provide a general overview of how well the proposed model fits the observed data. However, in the context of PLS-SEM, the primary focus remains on model predictiveness, assessed through R^2 , Q^2 , and f^2 effect size. Through this approach, SEM is expected to offer a comprehensive understanding of the relationships among variables within the conceptual framework developed for this research.

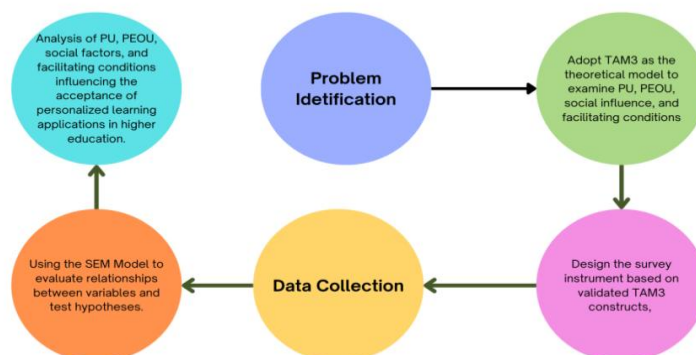


Image 1. Research Procedures

Image 1 illustrates a research flow that begins with problem identification regarding the acceptance of personalised learning applications in higher education, followed by the adoption of the TAM3 model as a theoretical framework to analyse factors such as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), social influence, and facilitating conditions. Based on this model, a survey instrument is designed using validated TAM3 constructs for data collection. Then the data is analysed using Structural Equation Modelling (SEM) to evaluate relationships between variables and test research hypotheses.

RESULTS AND DISCUSSION

The following sections provide a summary of the research findings from the TAM3 (Technology Acceptability Model 3) study of user acceptability of personalised learning mobile applications in higher education. Perceived Utility (PU), Perceived Ease of Use (PEOU), Social Influence (SI), Facilitating Conditions (FC), and their impact on Self-Efficacy (SE) and Behavioural Intention (BI) are the primary constructs examined. A total of 200 students from various departments at STIKOM Uyelindo Kupang participated in the survey. Demographics of participants: The gender distribution is 50% female and 50% male, with an average age of 22. Use of Mobile Apps: 9.5 hours a week on average for schoolwork.

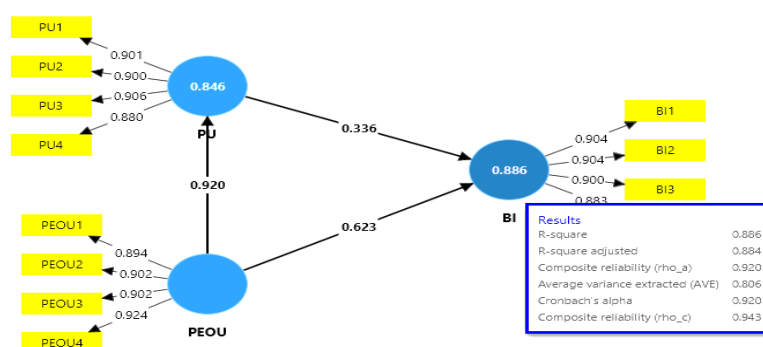


Image 2. Relationship between PU, PEOU variables and BI

Perceived Usefulness (PU) significantly influences Behavioural Intention (BI) with a path coefficient of 0.336 ($p < 0.01$), indicating that the more users perceive mobile-based learning applications as beneficial, the greater their intention to continue using them. This suggests that when learners believe the technology enhances their academic performance or supports their learning objectives, they are more motivated to adopt and integrate it into their daily study routines. The perception of usefulness plays a central role in shaping user behaviour, especially in educational contexts where efficiency and learning outcomes are key. Therefore, developers and educators must focus on demonstrating clear benefits and practical value to encourage ongoing engagement with mobile learning platforms.

Perceived Ease of Use also shows a strong and significant association with Behavioural Intention, with a path coefficient of 0.623 ($p < 0.01$), underscoring the significance of program ease of participation in determining user acceptability. Additionally, the relationship between PEOU and PU is notably significant, with a path coefficient of 0.920 ($p < 0.01$), suggesting that users are more likely to consider a mobile learning application advantageous when they find it easy to use. This aligns with the Technology Acceptance Model (TAM) framework, which posits that ease of use enhances perceived utility and, consequently, intention to use. Consequently, the adoption rate and perceived value of educational technology can be significantly raised by creating designs that are user-centred, accessible, and intuitive.

Table 3. Reliability and Validity PU, PEOU and BI

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Usefulness	0.919	0.943	0.804
Perceived Ease of Use	0.927	0.927	0.820
Behavioral Intention	0.920	0.920	0.806

Since all Cronbach's Alpha values are higher than 0.7, the PU, PEOU, and BI items demonstrate good internal consistency. The questionnaire's items measure the construct with reliability and have good correlations with one another. Good reliability in measuring the construct is indicated by a CR value greater than 0.7. Every construct is reliable for measuring the corresponding latent variable. A construct is said to have excellent convergent validity if its AVE value is greater than 0.5, which means it can account for more than 50% of the variance of its indicators.

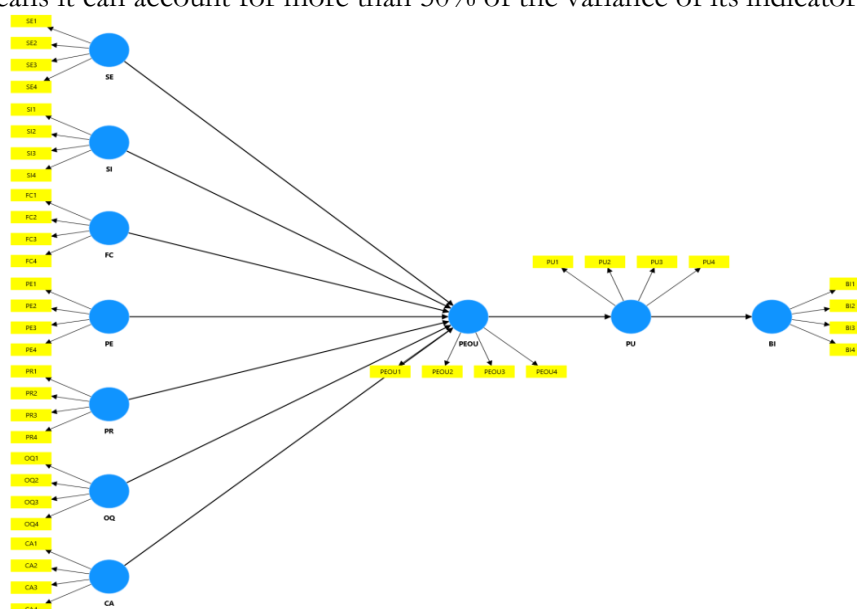


Image 4. TAM3 model variable relations

The image depicts a visual representation of the research framework developed using Structural Equation Modelling (SEM) with the Partial Least Squares (PLS) technique, generated through SmartPLS software. The framework is divided into two core elements: the measurement model (outer model) and the structural model (inner model). The measurement model outlines how each latent variable (indicated by blue circles) is linked to its respective observed indicators (represented by yellow rectangles). In contrast, the structural model illustrates the causal pathways and interrelationships among the latent constructs within the theoretical model.

In this model, several key constructs are included, such as *Self-Efficacy (SE)*, *Social Influence (SI)*, *Facilitating Conditions (FC)*, *Perceived risk (PR)*, *Performance Expectancy (PE)*, *Perceived Learning (PL)*, *Output Quality (OQ)*, and *Content Attractiveness (CA)*—each measured by multiple questionnaire items. These constructs serve as predictors for *Perception of Online Learning (PRON)*. Subsequently, *PRON* directly influences *Perceived Usefulness (PU)*, which in turn affects *Behavioural Intention (BI)*—the user's intention to continue using the online learning platform.

The model's overall goal is to examine the variables that affect users' opinions about online learning and how those opinions affect their behavioural intentions and perceptions of the system's usefulness. By assessing the validity and reliability of constructs through the measurement model and investigating the causal relationships between latent variables through the structural model, the SEM-PLS approach will be used to test the model. In quantitative model-based research, this type of visualisation is crucial because it offers a thorough grasp of the theoretical framework and the connections between the variables under investigation.

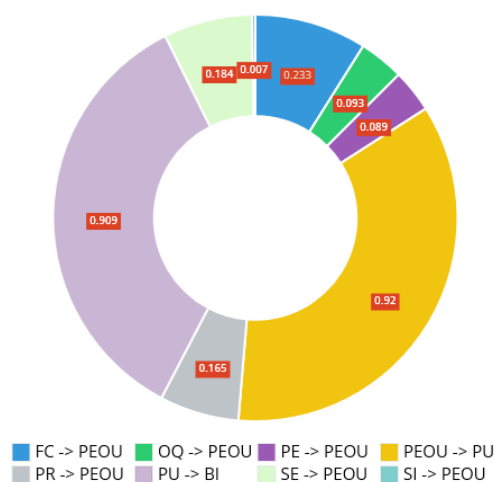


Image 5. Path Coefficient

The analysis results indicate that Computer Anxiety (CA) influences Perceived Ease of Use (PEOU) with a path coefficient of 0.214, suggesting that lower student anxiety towards technology is associated with higher perceived ease of use. Facilitating Conditions (FC) have a positive effect on PEOU with a coefficient of 0.23, indicating that good technical support enhances ease of use. Organisational Quality (OQ) has a negligible impact on PEOU (coefficient of 0.09), while Perceived Enjoyment (PE) also shows a weak effect with a coefficient of 0.089. PEOU has a strong influence on Perceived Usefulness (PU), with a path coefficient of 0.92, indicating that the easier an application is to use, the more useful it is perceived to be. Perceived risk has a moderate influence on PEOU (coefficient of 0.165), with lower risk perceptions being associated with increased ease of use. PU significantly impacts Behavioural Intention (BI) with a coefficient of 0.909, showing that perceived usefulness is a key determinant of students' intention to use the app. Self-efficacy (SE) has a moderate effect on PEOU with a coefficient of 0.184. At the same time, Social Influence (SI) shows almost no impact on PEOU (coefficient of 0.007), indicating that social factors play a minimal role in enhancing perceived ease of use.

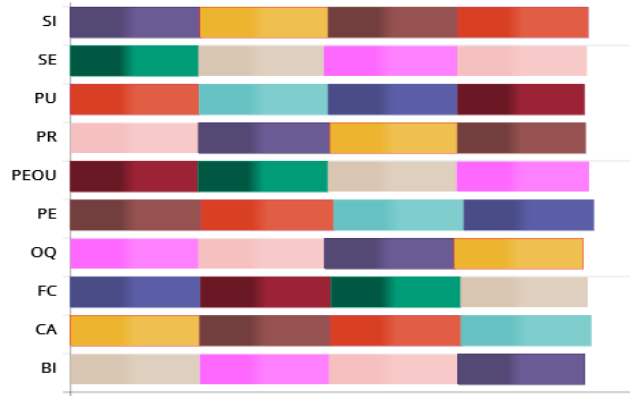


Image 6. Outer Loading

The outer loading values for Behavioural Intention items 1 (0.902), 2 (0.904), 3 (0.901), and 4 (0.883) demonstrate excellent indicator reliability, confirming that these items strongly represent the Behavioural Intention construct. Since all values exceed the 0.7 threshold, they indicate robust measurement properties. Similarly, the indicators for Computer Anxiety (0.904), item 2 (0.911), item 3 (0.915), and (0.904) also show high outer loadings, suggesting that they are highly effective in capturing users' anxiety related to computer usage. The Facilitating Conditions indicators (0.910), (0.912), item 3 (0.901), and (0.890) all surpass 0.7, indicating reliable measurement of the support structures available to users.

In addition, the indicators for Organisational Quality (0.894), (0.883), (0.904), and (0.898) display strong outer loading values, validating their effectiveness in representing organisational support. The construct Perceived Enjoyment is also well-measured, as shown by (0.911), (0.929), (0.910), and (0.902). The ease of use of the application, represented by Perceived Ease of Use (0.894), (0.902), (0.901), and (0.925), is clearly and reliably measured. For Perceived risk, indicators (0.896), (0.917), item 3 (0.891), and (0.891) also show high reliability. Meanwhile, Perceived Usefulness (0.901), item 2 (0.900), (0.906), and (0.880) affirm the strong representation of the perceived benefit of using the system. Self-efficacy is effectively measured through (0.892), item 2 (0.877), (0.932), and (0.906). Lastly, the Social Influence indicators (0.905), item 2 (0.896), (0.903), and (0.910) also demonstrate excellent outer loadings, indicating that these items accurately capture the influence of others.

Table 4. R-squared and R-squared adjusted

	R-square	R-square adjusted
BI	0.826	0.825
PEOU	0.910	0.907
PU	0.846	0.845

The R-squared value for Behaviour Intention (BI) is 0.826, and the adjusted R-squared value is 0.825, indicating that 82.6% of the variability in BI is explained by the model's factors, such as Perceived Usefulness (PU). This high value indicates the model's strong explanatory power, with minimal complexity added by the inclusion of extra variables. For Perceived Ease of Use (PEOU), the R-squared value is 0.910, and the adjusted R-squared value is 0.907, indicating that 91% of the variability is explained by factors such as Computer Anxiety (CA) and Facilitating Conditions (FC), confirming the model's robustness in explaining ease of use.

The small difference between R-square and adjusted R-square (0.910 and 0.907) indicates that the model is very efficient, with only a small influence from the number of variables included.

Perceived Usefulness has an R-square value: 0.846, adjusted R-square: 0.845. A total of 84.6% of the variability in perceived usefulness is explained by independent variables in the model, such as PEOU. This is an excellent score, indicating that the model powerfully explains the factors that influence how students perceive the usability of an application. The difference between R-square and adjusted R-square (0.846 and 0.845) is also minimal, indicating the stability of the model. The high R-square value for the three variables (BI, PEOU, PU) shows that the model as a whole is very good at explaining the variability of the dependent variable. An adjusted R-square that is very close to the R-square indicates that the model is efficient and does not experience overfitting, which means the model remains valid even though there are several independent variables at play.

Table 5. Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho a)	Composite reliability (rho c)	Average variance extracted (AVE)
BI	0.920	0.920	0.943	0.806
CA	0.930	0.930	0.950	0.826
FC	0.925	0.925	0.947	0.816
OQ	0.917	0.917	0.941	0.801
PE	0.933	0.934	0.952	0.833
PEOU	0.927	0.927	0.948	0.820
PR	0.921	0.921	0.944	0.808
PU	0.919	0.919	0.943	0.804
SE	0.924	0.926	0.946	0.814
SI	0.925	0.925	0.947	0.816

Cronbach's Alpha evaluates the internal consistency of indicators for each construct, with values above 0.7 considered good and above 0.9 excellent. In this study, all constructs have Cronbach's Alpha above 0.9, indicating very high consistency. Composite Reliability (rho_a and rho_c) also measures indicator reliability, with values above 0.7 considered good and above 0.9 indicating strong reliability. Here, all rho_c values exceed 0.9, confirming excellent reliability. Average Variance Extracted (AVE) reflects the variance explained by the construct, with values above 0.5 deemed good. All AVE values in the study are above 0.8, demonstrating strong validity. Overall, these metrics show that the model has excellent reliability and validity, effectively measuring the latent constructs.

The findings of this study offer valuable insights into the factors influencing the acceptance of mobile learning applications in higher education, as informed by the TAM3 framework. Key variables like Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence (SI), and Facilitating Conditions (FC) were analysed for their impact on Behavioural Intention (BI). The strong positive relationship between PU and BI confirms that students are more inclined to adopt mobile learning apps if they perceive them as enhancing academic performance (Sathye et al., 2022; Purnadewi & Widana, 2023), consistent with research in educational technology (ARAIN, HUSSAIN, VIGHIO, & RIZVI, 2018). The utility of personalised features in improving PU aligns with findings by Dwivedi et al. (2020), indicating that tailored learning experiences boost app adoption.

The significant effect of PEOU on PU and BI supports the view that ease of use is a fundamental factor in technology acceptance (Venkatesh et al, 2012). The study's results align with those of Motia & Maruf (2024), emphasising the importance of user-friendly interfaces for sustained app usage. Furthermore, it extends the findings of Gusti, Yoga, Karisma, & Gui (2023), which demonstrate that ease of use remains crucial even among tech-savvy students. Social Influence (SI) also played a notable role, reinforcing theories like the Theory of Planned Behaviour (Ajzen, 1991), where endorsements from peers and instructors positively influence

students' BI (Ameen et al., 2019; Tarhini et al., 2017). However, the minimal impact of SI on PEOU suggests that social factors do not drive ease of use perceptions.

Facilitating Conditions (FC), such as technical support and resources, were found to significantly influence PEOU and BI, echoing the importance of institutional support in technology adoption (Naveed, Choudhary, Ahmad, Alqahtani, & Qahmash, 2023). This finding aligns with Maisha & Shetu (2023) and Ifinedo (2018), indicating that infrastructure and training are key to reducing barriers and enhancing technology use. Additionally, the positive effect of Perceived Enjoyment on BI supports previous research by Van der Heijden (2004), suggesting that an enjoyable user experience is vital for voluntary technology use, as also observed in studies by Masrek & Samadi (2017); Citrawan et al. (2024).

This research enhances the traditional Technology Acceptance Model (TAM) by incorporating additional external variables, including Social Influence (SI), Facilitating Conditions (FC), and Perceived Enjoyment, thereby supporting the application of the TAM3 framework within the context of mobile learning in higher education. By integrating these constructs, the study provides a deeper and more comprehensive understanding of the multifaceted factors that influence students' acceptance of technology. Social Influence emphasises the impact of peers and instructors in shaping users' attitudes toward adopting the technology, while Facilitating Conditions refer to the presence of technical and institutional support that promotes practical usage. Meanwhile, Perceived Enjoyment reflects users' intrinsic motivation and the pleasure they derive from interacting with the application—an increasingly significant factor in educational technologies where sustained engagement is vital for learning success. Collectively, these variables enhance the explanatory capacity of TAM, illustrating that students' willingness to use mobile learning tools is influenced not only by their perceived usefulness and ease of use, but also by social, contextual, and emotional factors.

From a practical standpoint, this study suggests that developers should prioritise enhancing app usability and crafting engaging, enjoyable user experiences to encourage adoption and continuous use. Educational institutions also play a critical role by ensuring robust technical support and creating environments where positive social endorsements from peers, instructors, and institutional leaders reinforce the value and credibility of the technology. Providing comprehensive training sessions and designing user-friendly interfaces can help overcome technological barriers, such as computer anxiety or a lack of experience, which may otherwise hinder acceptance. These combined efforts promote sustained usage and improve overall student satisfaction, ultimately supporting more effective and personalised learning experiences in higher education settings.

CONCLUSION

This study supports and enhances the classic Technology Acceptance Model (TAM) by confirming that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are critical predictors of Behavioural Intention (BI) to use technology. Among these, PU stands out as the most significant factor influencing students' intention to use mobile learning applications. With an R-square value of 0.846, the findings emphasise the importance of the app's perceived benefits in improving students' learning performance. Additionally, PEOU has a substantial impact on PU, as reflected by a high R-square of 0.910, which aligns with TAM theory, which states that ease of use enhances perceived usefulness. Moreover, PU mediates the relationship between PEOU and BI, indicating that while ease of use matters, students' intentions are ultimately driven by the app's perceived contribution to their learning outcomes. The study further extends TAM

by integrating external variables such as Computer Anxiety, Facilitating Conditions, and Social Influence. Both Computer Anxiety and Facilitating Conditions significantly influence PEOU, highlighting the critical roles of technical support and users' comfort levels in shaping perceptions of ease of use. This suggests that reducing anxiety and ensuring adequate facilitating conditions can improve students' views on how easy the technology is to use. In contrast, Social Influence shows minimal impact on PEOU, implying that recommendations from peers or teachers have a limited effect on perceptions of ease of use in this context. Overall, the strong predictive power of PU for BI aligns with the Expectancy-Value theory, reinforcing that students' intention to use a mobile learning application is closely linked to their belief in its effectiveness in supporting their academic success. These findings underscore the need for developers and educators to prioritise enhancing the perceived usefulness of educational technologies, alongside addressing factors that influence ease of use, to encourage greater acceptance and sustained utilisation among students.

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