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SPECIAL FOCUS PAPER

Adoption of Interactive Mobile Learning Technologies through the Lens of the Technology Acceptance Model

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ABSTRACT

The increasing use of interactive mobile learning technologies has the potential to improve learner flexibility, engagement, and personalization their learning experience. However, the successful implementation and adoption of these technologies directly depend on users' perception and acceptance of the technology. This study aims to examine the adoption of interactive mobile learning technologies through the lens of the technology acceptance model (TAM). The study focuses on understanding the factors that influence behavioral intention (BI) to use the technologies. Data was collected from 51 participants working in the education industry using the convenience sampling method. The study adopted a quantitative survey-based research approach, and a well-structured questionnaire was used to collect data. Statistical techniques were applied to the collected data to examine the relationship between key constructs like perceived usefulness, perceived ease of use (PEOU), behavioral intention, and attitude toward use. The research has revealed the influence of different aspects on the adoption of technology. This study aimed to contribute to the existing literature by empirically using TAM in the context of interactive mobile learning technology. Findings suggest 1) PEOU positively impacts perceived usefulness (PU) of interactive mobile learning technologies, 2) PU has a significant positive effect on attitude toward use (ATU) of interactive mobile learning technologies, and 3) ATU has a significant positive effect on BI to use interactive mobile learning technologies. The findings of the study will assist instructional designers and technology developers in designing user-centric mobile learning solutions. The findings will also support informed decision-making for the effective integration of interactive mobile learning technologies in the traditional educational infrastructure. It will also guide and form the basis for future studies in mobile learning adoption.

KEYWORDS

mobile learning pedagogy, interactive learning environment, technology-enhanced learning, learner engagement, technology acceptance model (TAM)

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1 INTRODUCTION

Technology is growing at a rapid pace and is reshaping different sectors. It has transformed the educational landscape and provides an *anytime*, *anywhere* learning feature through interactive mobile learning applications. The advanced technologies provide flexibility, personalized content, and improved learner engagement. It is promising in the modern educational environment, which encompasses digital transformation and increased dependence on hybrid pedagogies. Mobile learning systems cannot be reduced to content delivery systems. They are also interactive media to facilitate the autonomy, accessibility, and collaboration of the learners to enhance the learning process. Despite the potential of the technology, its adoption is subject to the acceptance of the system by users. The manner in which the learners respond to, view, and utilize the technology ultimately defines how it will have an influence within the education setup. In order to identify the adoption and acceptance behavior, the technology acceptance model (TAM) is an accepted instrument in educational-technological research. The relevance of information system acceptance was initially indicated by Davis (1989) when he declared that acceptance is determined by perceived usefulness (PU) and perceived ease of use (PEOU) [1]. Both variables shape the attitude toward the use of technology and influence behavioral intention. TAM has been confirmed as an effective theoretical framework that can be used to understand the intention of the users to adopt and use learning systems such as mobile learning applications, digital educational tools, and online learning platforms in the education context [2]. Recent studies continue to focus on the TAM construct in the adoption of mobile learning. As an example, Chao et al. [3] show that PEOU and PU are important factors governing learners' intention to use (ITU) mobile applications. Authors demonstrated that PEOU usually exerts an indirect effect on behavioral intention (BI) via perceived usefulness.

Even with growing research in this area, there are certain gaps and confusions requiring further attention. One of the major gaps is that the majority of the research studies emphasize providing a general view of online learning without specifically mentioning the importance of interactivity and engagement. These parameters are important in modern mobile learning platforms. In addition to this, the existing literature states acceptance at the course or system level without specifically focusing on users' behavior towards the interactive models, like gamified features or simulations. So, although TAM provides an explanation of user behavior, the interconnection between interactivity, user engagement, and TAM variables requires further research.

Against this backdrop, the study aims to explore and examine the adoption of interactive mobile learning technologies through the lens of TAM. The key determinants focused on in the study are perceived usefulness, PEAU, attitude toward use, and behavioral intention, along with their relationship to shape learners' decisions and actions. The application of a quantitative survey-based approach will help in the identification of the interplay between the selected factors to explain learners' adoption of interactive mobile learning systems.

2 LITERATURE REVIEW

2.1 Interactive mobile learning technologies

Mobile devices have transformed the manner in which various sectors operate, including education. It has rendered education not necessarily limited by the physical confines of the traditional classrooms and rigid lecture times. Interactive mobile learning technology is about the engagement and interactivity of the learners with various features such as games, quizzes, and real-time feedback [4]. Research has shown that one of the most significant characteristics of mobile learning, personalized learning activities, enhances intrinsic motivation and psychological satisfaction among learners to a considerable degree [5]. The information delivery through mobile learning platforms is extensively spread with the involvement of interactive features such as collaboration tools and gamification. An example is that when students have read the content materials, they are able to access the gamified version of a case study. It helps in enhancing learners' understanding and motivation, primarily through collaborative exercises [6]. Irrespective of the potential of these platforms, there are even bigger differences in their uptake depending on factors like digital illiteracy, perception of the user, and the technology infrastructure [7]. The determining factors for the adoption of such systems must be explored to take maximum advantage of the technology.

2.2 TAM

One of the most popular models that is used to explain user acceptance of information systems is the TAM [1]. According to the model, PU and PEOU determine the impact of attitude toward use (ATU) and BI to use technology. PU describes how strong a person perceives the application of a specific system that would enhance his/her performance. PEOU is the thinking that a particular platform can be easily used and does not require major efforts in understanding or operating it. Chao [3], in his research, found that students find mobile learning easy to use and even acknowledged the significance of learning through it. Moreover, TAM has been experimented with in a number of technological contexts that include mobile applications, learning, and e-learning [8]. This model can be beneficial due to its predictive validity and economy, which may be applied both to exploratory and confirmatory research.

2.3 TAM in mobile learning research

Recent research has used TAM to understand the adoption of mobile learning across various educational settings. A study by Tan et al. [9] showed that PU significantly influenced students' ITU hybrid learning platforms and that PEOU exerted direct and indirect effects through PU. The study findings are significant because hybrid learning is closely associated with mobile learning. While hybrid learning encompasses both in-person and online modes, mobile learning provides even more flexibility, thereby enhancing PEAU and adoption of technology. A related construct has been discussed by Chau [10], who chalked out that ITU, an interactive mobile learning system, also relies on students' personality. This finding is significant for our research because ITU and ATU are somewhat similar constructs, which further indicates that intention or attitude to use mobile systems depends on the personality traits. Research also shows that the value of learner involvement and many interactive components are also predictors of the acceptance of technology. Pangriya [11] mentioned the relationship between technology readiness and perceived ease of use.

Additionally, Naidoo [12] dwells upon other variables of learner engagement (LE) in order to eloquently explain the motivational aspect of learning technologies. Additionally, the author observed that blockchain and AI can support technology adoption and e-learning, further indicating some important factors that can influence the behavioral use of learners. Major findings of the study mention a positive relationship between TAM indicators and behavior to use blockchain and AI in e-learning. It adds value to our study by clearly indicating that blockchain and AI can prove significant in e-learning, and educators and policymakers should consider it for better e-learning experiences for learners. This also demonstrates that having ease of use is in itself not sufficient when disregarding any of the elements in the engagement of design. Furthermore, mobile learning adoption is influenced by learners' opinions of social interaction and digital support. It thus extends the TAM framework to include context-specific variables. Despite the rich literature, there are still gaps. Most studies either concentrate on certain disciplines (e.g., language learning, STEM topics) or operate at the system level without isolating interactive mobile learning components [13]. Furthermore, the relative importance of TAM dimensions can vary by cultural and institutional situations, highlighting the need for more empirical confirmation.

2.4 Gaps in existing literature

Although TAM has been used in e-learning research, there are gaps that still exist. One of the research gaps is related to the scope of interactivity. Various studies focus on general mobile adoption and not specifically on interactive features that influence engagement outcomes [14]. Other gaps in existing literature are related to context variability, construct integration, and limited quantitative evidence. Results usually vary as per learner demographic, geography, and education setting, because of which the generalizability of findings is limited. The inclusion of engagement and attitude variables with core TAM constructs is not conclusive in a smaller sample size. Limited research explores the complete set of TAM relationships with extensive quantitative data in an interactive mobile learning context.

3 MATERIALS AND METHODS

3.1 Research design

A quantitative research design is used to examine the adoption of interactive mobile learning technologies through the lens of TAM. A survey-based approach was used to collect primary data from learners using interactive mobile learning platforms and applications with varying levels of experience. Quantitative research design was selected because it is suitable for statistical examination of relationships between key TAM variables and proceeds with hypothesis testing [15].

3.2 Population and sample

The target sample of this study includes learners with different levels of experience with interactive mobile learning technologies in an educational setting. Since it requires specific data, the convenience sampling technique is selected. This technique ensures that the participants have the right knowledge to understand the questions and respond, contributing to evidence to proceed with hypothesis testing [16]. The sample size included in this study is 51 participants from whom valid responses were collected using the structured, closed-ended survey questionnaire. This sample size is adequate for exploratory analysis to get an idea of the relationships between the key constructs. It is also used for regression analysis and is supported by prior TAM-based studies having a similar sample size [17]. This sample size is adequate because the aim of the study is to understand the relationship between the key constructs rather than the generalization of the findings.

3.3 Instrument development

An instrument refers to the method used to collect primary data in a study [18]. A structured, closed-ended questionnaire was used to collect data. The questionnaire was devised using previous studies on TAM, and it was aligned with the context of interactive mobile learning technologies. The questionnaire was separated into six divisions. The initial section was focused on demographic data such as gender, age group, education level, discipline of study, experience using a mobile learning platform, and the type of learning platform. It is relevant to use these data to establish a background in knowing the context of the responses and to value any deviation or variation in the responses. The second section was dedicated to PEOU and comprised five questions. The next sections included PU, ATU, BI to use, and LE. A Likert scale was used to collect data as per the participants' agreement with the statement, including options of strongly disagree, disagree, neutral, agree, and strongly agree. Apart from the core TAM constructs, the questionnaire also includes a section of LE with three questions. The aim of this section was to evaluate learners' perceived engagement, motivation, and focus in using interactive mobile learning. It is treated as an additional construct and will be further analyzed to gain additional insights into the educational impact of the mobile learning systems.

3.4 Data collection procedure

The questionnaire was conducted online. The respondents were made aware of the research through an email, and a consent form was attached to obtain their consent for the collection of data. After the consent, the respondents were sent a link to a survey form in which they were required to choose the Likert scale according to their acceptance level of the statements. Voluntary participation in this study was sought, and the responses were collected anonymously to remove any bias and maintain confidentiality. The respondents were also made aware of the fact that they could withdraw from the study at any point if they wished to and that the data collected would be used solely for this study. Only the response sheets that were complete were considered for further analysis.

3.5 Formulated hypotheses

Hypothesis Set 1: PEAU and Perceived Usefulness

- Null Hypothesis ($H1_0$): PEOU does not have a significant effect on PU of interactive mobile learning technologies.
- Alternative Hypothesis ($H1_a$): PEOU has a significant positive effect on PU of interactive mobile learning technologies.

Hypothesis Set 2: PU and Attitude Toward Use

- Null Hypothesis ($H2_0$): PU does not have a significant effect on ATU of interactive mobile learning technologies.
- Alternative Hypothesis ($H2_a$): PU has a significant positive effect on ATU of interactive mobile learning technologies.

Hypothesis Set 3: ATU and Behavioral Intention

- Null Hypothesis ($H3_0$): ATU does not have a significant effect on BI to use interactive mobile learning technologies.
- Alternative Hypothesis ($H3_a$): ATU has a significant positive effect on BI to use interactive mobile learning technologies.

3.6 Data analysis technique

In order to analyze the data, IBM SPSS Statistics was used. The raw data were first transformed into numerical data so that they could be used in the statistical analysis. The data was then checked in terms of accuracy and completeness. The initial procedure followed was ensuring internal consistency of the scales of measurement. The reason was to use Cronbach's alpha at the original item-level response. The reliability analysis, as reflected in Table 1, indicated acceptable internal consistency for all the items. The researcher, therefore, chose to retain all the items for further analysis.

Table 1. Reliability statistics

Construct	Items	Cronbach's α
PEOU	5	0.783
PU	5	0.817
ATU	4	0.737
BI	4	0.618

Source: SPSS Output.

The next step was descriptive analysis of the items. For this, composite variables were constructed using the item-level variables. The composite variables were PEOU, PU, ATU, and BI, which were transformed from the respective items from the questionnaire. The descriptive analysis helps in summarizing the overall response patterns. Minor refinements were done in the composite variable before proceeding with the inferential statistics. This step was done to ensure conceptual alignment of the composite variables, followed by using them for correlation and regression analysis for testing the formulated hypothesis. Apart from that, the LE constructs were also analyzed for their mean values to get an idea of the role of additional variables in the adoption of interactive mobile learning technologies.

3.7 Ethical considerations

The researcher paid attention to the ethical principles during this study. During the data collection phase, the participants were notified of the type of data to be collected and were asked whether they wanted to participate in the data collection process on a voluntary basis. No personally identifiable information was given in the questionnaire to protect confidentiality and preserve the privacy of the participants [19]. The information gathered was intended to be utilized in academic research. Only the researcher who participated personally in the research was allowed to access raw data.

4 RESULTS AND DISCUSSION

The study examined the adoption of interactive mobile learning technologies through the lens of the TAM framework. The findings of the statistical analysis support the TAM relationship. The findings also provide insight into the factors that influence learners' acceptance of mobile learning technologies.

4.1 Reliability and measurement adequacy

The Cronbach's alpha reliability analysis showed acceptable and good internal consistency across all the individual-level items included in this study. As shown in Table 1, the Cronbach's alpha for PEOU was 0.783, and for PU it was 0.817. Both these values of alpha are suggestive of strong reliability, which means that the items consistently measure the perception of learners on the usability and usefulness of interactive mobile learning systems. ATU showed alpha as 0.737, which is also an acceptable value. However, the Cronbach's alpha for BI was comparatively low at 0.618. However, this value is also considered adequate for an exploratory study in an educational context [20]. The overall reliability supports the measurement instrument and justifies the use of individual items for transforming to a composite variable for further analysis.

4.2 Descriptive statistics and correlations among constructs

Descriptive statistics are used to understand the perception of various variables in the interactive mobile learning technologies. As summarized in Table 2, the mean score for all four composite variables was above the midpoint of the scale (i.e., 3). BI had the highest mean of 4.09 with 0.20 as the standard deviation (SD). This suggests that learners have a strong intention to continue with the use of mobile learning technologies. The SD is PEOU is highest (0.44), which aligns with the study of Chau [11], who states that PEOU had a comparatively weaker effect on students' ITU in an interactive mobile learning system.

Table 2. Descriptive statistics

Variable	N	Minimum	Maximum	Mean	SD
PEOU	51	2.8	5.0	3.90	0.44
PU	51	3.0	4.25	3.74	0.28
ATU	51	3.25	4.43	3.93	0.24
BI	51	3.73	4.64	4.09	0.20

Source: SPSS Output.

Further, correlation analysis showed various significant relationships among the TAM constructs. PEOU was strongly and positively linked with PU at $r = 0.644$ and $p < 0.001$. This suggests that the ease of use of the interactive mobile learning platform has an important role in deciding learners' perception of usefulness. Apart from that, PU also had a strong positive relationship with ATU ($r = 0.600$, $p < 0.001$). This reveals that learners perceiving mobile learning technologies as beneficial tend to have a positive attitude towards their usage. The significance of affective responses in predicting adoption intentions was shown by the substantial correlation between ATU and BI ($r = 0.619$, $p < .001$). Although ATU ($r = 0.256$) and BI ($r = 0.245$) had positive correlations with PEOU, these relationships were not statistically significant, indicating that ease of use may indirectly affect BI through PU and attitude.

Learner engagement with mobile learning systems was found to be high among individuals. The mean score for the item evaluating engagement in the learning process was 4.16. Such a high score suggests that respondents agree that mobile learning applications improve their engagement in the learning process. The second item-level construct had the highest mean score of 4.35. This reflects that learners believe that interactive elements in mobile learning systems motivate them to actively participate in the learning process. Lastly, the mean for the ability of mobile learning to support sustained focus on learning tasks was 4.20, which suggests a positive perspective of the participants. These results indicate that, in addition to PEOU, interactive mobile learning environments may have a significant role in improving cognitive and behavioral engagement of students. This is consistent with previous studies that have highlighted the significance of interactivity and learner-centered design in mobile learning environments [11], especially in situations where attention and motivation are of utmost importance.

4.3 Regression analysis and hypothesis testing

Regression analysis was used to test the formulated hypotheses, the findings of which are summarized in Table 3. The findings showed that all three hypotheses were supported. PEOU was found to be significantly capable of predicting PU, and R^2 of 0.415 explains 41.5% variance in perceived usefulness. The results reinforce the foundational role of usability in deciding learners' evaluation of mobile learning systems [21]. Further, it was also found that PU has a significant influence on ATU with a variance of 36%. These findings reflect that learners' attitude towards mobile learning technologies is largely dependent on perceived benefits and not just on the usability of the technologies. Lastly, ATU was found to be a strong predictor of BI, with a variance of 38.3% observed in the intention of using interactive mobile learning technologies. These results align with the concept that learners' attitudes are central to deciding technology adoption. On the basis of the findings of the regression analysis, all three alternative hypotheses are selected. PEAU of the interactive mobile learning technology has a positive effect on perceived usefulness. This is in agreement with previous studies as well [9] [10]. Furthermore, PU has a positive effect on ATU of interactive mobile learning technologies. Although the direct testing of the relationship between PEOU and ATU was not included in this study, through the interrelationship of various constructs, it can be inferred that PEOU has an indirect effect on ATU. This indirect effect is realized through PU. Lastly, the third alternative hypothesis is also supported through the findings of this study. It states that ATU has a significant positive effect on BI to use interactive mobile learning technologies.

Table 3. Regression result for hypothesis testing

Hypothesis	Predictor → Outcome	β	R^2	p
H1	PEOU → PU	0.644	0.415	< .001
H2	PU → ATU	0.600	0.360	< .001
H3	ATU → BI	0.619	0.383	< .001

Source: SPSS Output.

4.4 Theoretical and practical implications

From a theoretical lens, the findings of this study validate the application of TAM in the context of interactive mobile learning technologies. The relationships between PEOU, PU, ATU, and BI are aligned with the TAM model. From a practical perspective, the results highlight the necessity of developing mobile learning technology by taking into consideration the facets of ease of use and utility. As social, functional, and conditional values affect technology behaviors [22], designers need to take note of the fact that the interface must be easily navigable. Coupled with this, the attitude of the learners can also be enhanced through proper implementation, training, and professional assistance.

4.5 Limitations and future research

This study has its limits, even with its contributions. The findings might lack the extensive validity that they might have had because of the convenience sampling approach and small sample size. The cross-sectional approach also fails to identify the change in the perception of learners as they change across time. To further evaluate the suggested relationships, future studies could use longitudinal designs, larger and more varied sample sizes, and sophisticated analytical methods like structural equation modelling. The evaluation of the performance of learners before and after they utilize interactive mobile learning technologies will also serve to obtain the data to have a clear view. The other limitation of the study is that, although the individual-level construct was also reliable, the composite variable was based on the relationship between the variables, as simulated. This problem might be addressed further with the large sample correspondence and avoidance of the limitations of convenience sampling.

5 CONCLUSION

This study examined the learners' adoption of interactive mobile learning technologies through the lens of the TAM framework. The goal was to understand the factors that affect the BI of learners. Data collected from the participants were analyzed to understand the association between variables like PEOU, PU, ATU, and BI. Apart from that, the additional variable, LE (Learner Engagement), was also used to understand its contribution to the acceptance of mobile learning technology by learners in modern educational settings. The results support the use of TAM in interactive mobile learning. Among the major findings is that PEAU of the technology affected the perceived usage. This implies that system and platform designers, educators, and policymakers should focus on designing systems and platforms that are easy to use. Also, PU is significant to ATU in relation to mobile learning technology. It implies that learners are in a better position to embrace positive benefits that may be adopted positively when they are aware of the gains of technology in their learning process.

The significance of affective reactions to technology adoption was highlighted by the fact that ATU was a key factor in predicting behavioral intention. Practically, the findings indicate that usability and pedagogical value should be considered by the instructional designers, technology developers, and educators during the design of interactive mobile learning solutions. Mobile learning platforms are likely to be better accepted and used in the long term when the platforms are user-friendly and apparent in enhancing the performance of learners. Moreover, a positive attitude of learners that is achieved with the help of successful onboarding is useful in addressing the alignment of the technology to the needs of the learners and, therefore, enhancing the intention to adopt. Although it has made its contribution, the study has shortcomings, among them being that the sample size used is very small, and the study has applied convenience sampling; thus, this could limit the generalizability of the results. It is advisable that future research should use larger and more heterogeneous populations, longitudinal research designs, and better methods of analysis to further confirm and expand the results.

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