

PAPER

Formative Assessment of Student's Academic Achievements in Mobile Learning Environments

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ABSTRACT

This study investigates the formative assessment of student academic achievements within the context of mobile learning (m-learning) environments. As mobile technologies continue to reshape educational practices, understanding how to effectively implement formative assessment strategies in these dynamic digital spaces is essential. The study explores various approaches and methodologies for conducting formative assessments tailored specifically for m-learning environments. These include the integration of mobile applications to deliver interactive quizzes, exercises, and simulations that engage learners actively and provide immediate feedback. Additionally, the research examines the use of adaptive formative assessments, which utilize mobile technology to personalize assessment content and pacing according to individual learner needs and progress. The study also examines the role of m-learning analytics in formative assessment, allowing educators to gather real-time data on student interactions and performance to guide instructional decisions. Furthermore, the study explores innovative practices such as gamified formative assessments, which incorporate elements like badges or leaderboards to enhance motivation and engagement among learners. By synthesizing existing literature and empirical studies, this study contributes to advancing the understanding of effective formative assessment practices in m-learning environments. It offers valuable insights for educators, curriculum designers, and policymakers who aim to enhance student learning and achievement in digital-age education.

KEYWORDS

mobile learning (m-learning), student academic achievements, formative assessment, learning analytics, mobile applications, gamified assessments, Technology Acceptance Model (TAM)

1 INTRODUCTION

Numerous research studies conducted in the last ten years have shown the advantages of web-based learning. To enhance the effectiveness of web-based learning, various learning approaches and tools have been developed. These include self-explanatory prompts, learning material recommendation methods, assessment and

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feedback mechanisms, and instructional assessment criteria. In the interim, educators have emphasized the value and importance of “authentic learning operations” in which students can engage with challenges from the real world [1]. Therefore, it has become a significant and demanding issue to place students in a series of customized lessons that integrate practical and digital-world learning materials through the utilization of portable and wireless connectivity technology.

In recent years, many academics have utilized cloud-based and mobile technologies as learning aids.

Mobile technology refers to a device's capability to handle interactions, access data, and conduct commercial activities while in motion. Cloud-based and mobile technologies can assist students in studying and provide teachers with the opportunity to create educational activities. Furthermore, employing cloud- and mobile-based technologies can enhance learning outcomes and motivate students to engage at a higher level.

Additionally, some academics have put forth evidence that using assistive technology in the classroom can lead to improved learning outcomes [2]. Examples of this include the use of mobile learning (m-learning) and web-based learning systems. Assessing happiness, surroundings, learner, and teacher are the fundamental components of m-learning. A successful m-learning strategy's fundamental components are depicted in Figure 1.

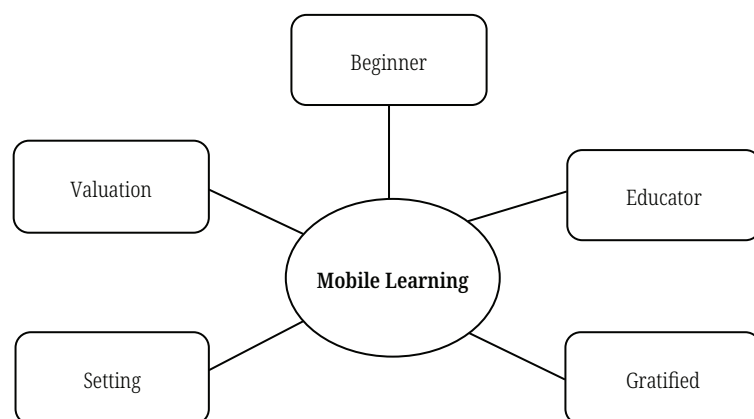


Fig. 1. Fundamentals of mobile learning

According to contemporary educational techniques, learners are at the center of all learning and instructional activities. Every other component benefits the student. As the name suggests, m-learning places the learner at the center of the process through a pedagogical approach that leverages their interests, experiences, and needs. In conventional learning contexts, teachers transmit knowledge to students through books and other visual aids. Conversely, students now have greater access to information due to the recent utilization of technology for information storage. All parties involved, including parents, teachers, and students, should be consulted when choosing the content. Teachers cannot achieve the intended outcomes otherwise. A user must be able to quickly focus on the information they need from learning content. Quizzes and interactive games can also be used to present content. Contents should be integrated with graphics, audio, and other multimedia components.

Proper design of the environment is necessary to achieve successful learning outcomes. The environment is where students access information. Accessibility to

all unit content, including learning objectives, assignment specifications, and relevant resources, is mandatory for all students enrolled in fully online courses. Using mobile devices, students attending in-person classes can access both in-class and online resources. One essential element of the entire m-learning process is assessment. Instructors can receive reports and assessments on student performance through mobile devices. Hence, online tests, chat rooms, discussion boards, software programs, database logs, online quizzes, and project evaluations should all be utilized for assessing students. Students should assess themselves and others. It provides the components necessary for accurately assessing a student's aptitude, creativity, and other attributes. Furthermore, earlier studies have indicated that to enhance the efficiency of the peer review process, academics should consider using mobile devices in combination with cloud databases. Additionally, research has demonstrated that employing game-based learning techniques effectively enhances learning outcomes for students. As a result, enhancing the entertainment value of apps by improving interface attractiveness to make the user experience more engaging could boost students' satisfaction with the software.

Nevertheless, there is a knowledge gap that needs to be filled. To that end, this paper develops a mobile application for a point-of-care learning system called My-Fitness that helps students enhance their HRPF achievements. The system is phone-based and has a user-friendly interface that allows students to upload information to the cloud. Teachers can use Firebase on the web to assess students' learning achievement and promptly provide guidance and encouragement to learners [3]. The best way to spread information was through mobile devices, enabling students to access course materials at any time and from any location. Teachers could also use them to create engaging lesson plans. Furthermore, according to some researchers, mobile technologies enable a wide range of applications in the field of education. These include creating customized learning plans and objectives, understanding the unique characteristics of different communication channels, and providing wireless learning support.

This paper's remaining sections are organized as follows: In Section 2, we will first discuss the related works. Section 3 introduces the main design concept and structure of the mobile platform. We describe the platform's implementation in Section 4, along with the simulations that were run to assess the performance of our proposed algorithm. We conclude this paper in Section 5.

2 LITERATURE REVIEW

[4] To investigate students' learning strategies, the learning pattern framework's cognitive processing and metacognitive control strategies were selected and also they encompass dimensions—such as memorization, lack of oversight, and motivation—that highlight issues within these areas. This was considered an added value since the current study focused on first-year students and their persistence or dropout rates. Furthermore, the learning patterns model incorporates an application-oriented approach (specifically in building materials processing) into its learning strategy components, making it particularly suitable for study within the framework of a vocational bachelor course that is more career-focused.

[5] The concept of evaluation must always be brought up when discussing the learning process because it is essential for teachers' professional development and

students' learning processes. The exam yields valuable information that helps learners advance to the next level, enables them to make informed decisions, and tracks progress and accomplishments. It is essential to all teaching and learning activities. The format and subject matter of assessments have a variety of effects on the learning process. Since assessment is a crucial part of the learning process, an adaptive learning system must include an adaptive assessment that considers the characteristics and needs of the learners.

[6] The robotics researchers are studying how to avoid obstacles during robot navigation, whether they are local or global. Global navigation refers to the mobile robot's complete awareness of its surroundings. Various methods have been utilized in the pursuit of resolving global navigation challenges, including the artificial potential field, lines, visible graphs, cell decomposition, and voronoi graphs. During local navigation, the mobile robot utilizes various attached sensors to control its movements in an area that is either entirely unfamiliar or somewhat unfamiliar.

[7] Furthermore, the widespread notion of a standardized curriculum that must be completed within a fixed timeframe has been partially challenged, particularly in Europe, due to the adoption of the European Credit Transfer System (ECTS), which promotes increased flexibility. More and more evidence points to the fact that not every student enrolls in a full program, completes the same course modules in the same school year, or studies at the same speed. Given that earning credits is increasingly crucial for students in this context, it is uncertain whether GPA should remain the primary metric for evaluating students' performance or if it should only serve as a reference point.

[8] To determine curb candidates, the curb features are obtained from the geometric aspects of the road. Principal component analysis (PCA) is used to create a validation criterion that helps in selecting the correct curb from various curb alternatives. In a road setting, the curb extraction is completed effectively. On the other hand, PCA has a fundamental drawback. The curb and non-core data classifications are not considered by the validation gate. False detections may also occur when non-curb data is mistakenly identified as curbs. When incorrect detection information is utilized for translation, the accuracy of the computed pose decreases.

[9] Try to reduce brute-force attacks on encrypted data by addressing this issue. This method generates the encryption keys on a separate key server. The key server has its own private key and creates keys for users using an oblivious protocol for each request. It utilizes the private key and a blinding hash calculated from the data to generate an encryption key, which is then sent back to the user. By doing this, the encryption keys become more randomized through the secret key of the key server, making brute-force attacks impossible and safeguarding the secret key from attackers.

[10] Coronary heart disease claims millions of lives every year, and the elderly are particularly vulnerable to it. Systems that can wirelessly and continuously monitor the electrocardiograms (ECGs) of residents are being installed in many senior communities. AlarmNet is an example of an assisted living and home monitoring network that creates new opportunities for continuous monitoring of the elderly and individuals requiring medical care. Medical personnel can be informed of any changes in a patient's status through wearable ECG devices. These devices can wirelessly monitor a patient's heartbeat and transmit information to a back-end archive platform for longer-term storage.

3 METHODS AND MATERIALS

3.1 Procedure for getting ready to learn facilitated by mobile technologies

Before implementing mobile technology in schools, the following preparatory work was identified in this study as necessary [11], except for creating blended mobile education and the 10 m-learning methods:

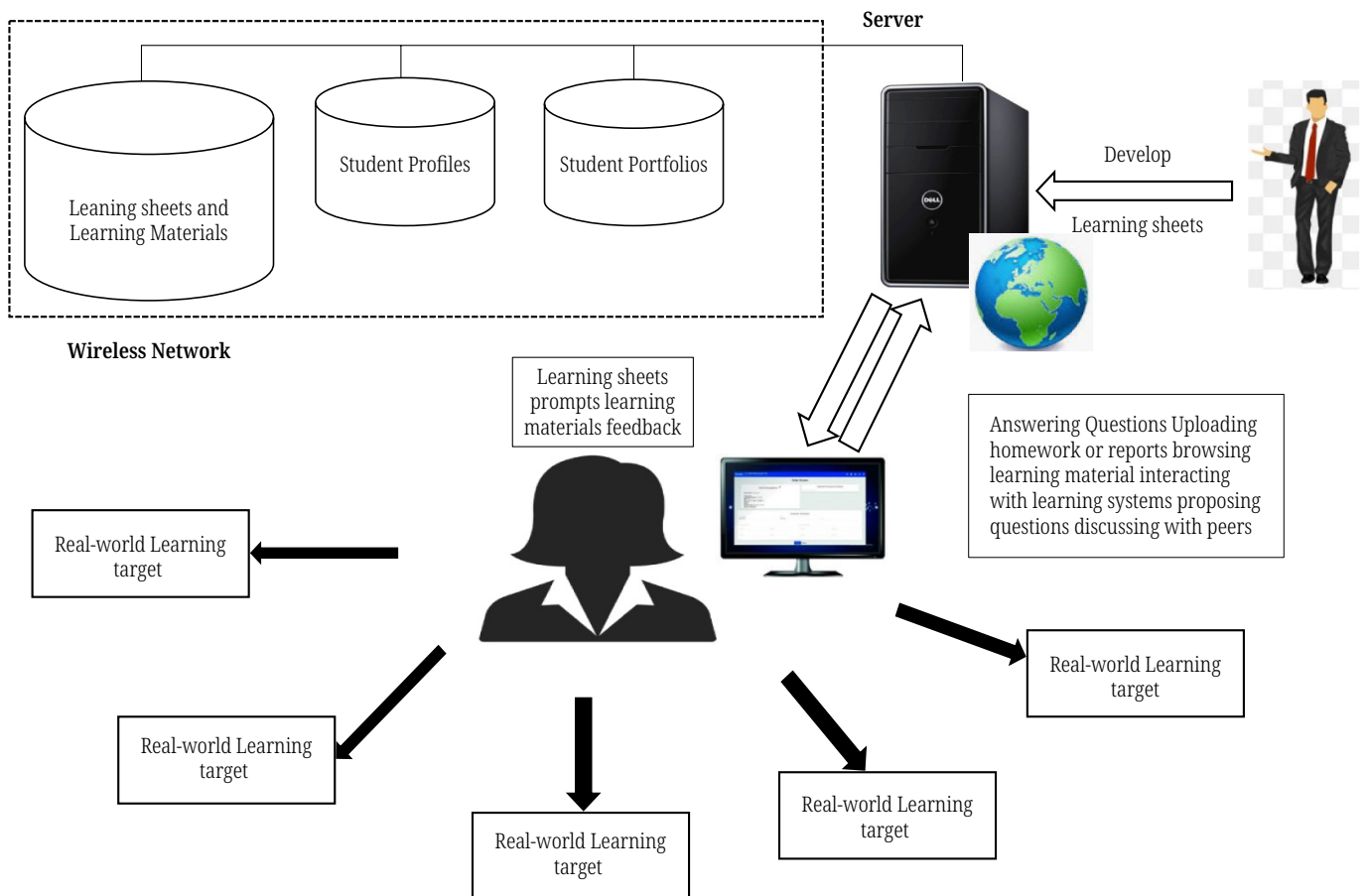


Fig. 2. An example of an instructive mobile learning environment

Configuring the server and wireless network in the learning environment, as illustrated in Figure 2. Some web-based research tasks can be replaced with real-world information-seeking activities if schools are unable to provide students with Internet access. Examples of these tasks include locating relevant books in the library, conducting interviews, collecting information through questionnaires, or preparing reports in specific areas.

3.2 Structures within the TAM perfect

The technology acceptance model (TAM) was expanded for this study to create the model illustrated in Figure 2. This model aids in comprehending and elucidating the significant factors that influence students’ utilization of the JORDAN m-learning platform. The most recent and widely utilized model is the TAM, as mentioned earlier. The study used five distinct variables to predict the adoption and utilization of

technology: perceived value, ease of use, attitude towards use, intention to use, and actual usage. The TAM depicted in Figure 3 posits that an individual's perceptions of a new technology's usability and simplicity of use are the two primary factors influencing their decision to adopt it.

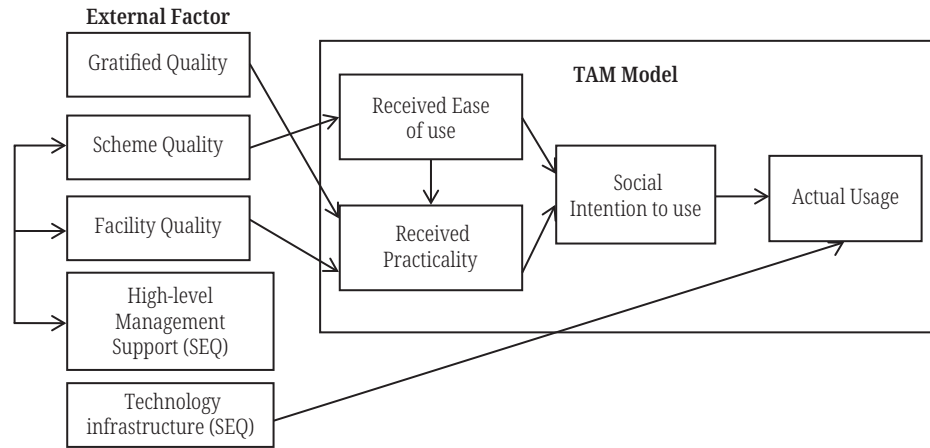


Fig. 3. Theoretical frameworks for analyzing mobile learning platform consumption

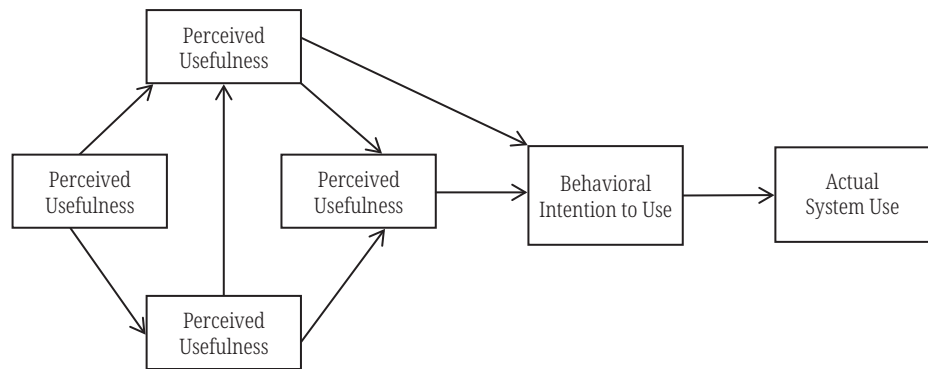


Fig. 4. Model of technology acceptance

One of the important constructs to be included in the proposed model in the context of the present investigation is the perceived ease of use. Perceived ease of use in Figure 4, according to Davis, refers to the extent to which an individual believes that using technology (such as a m-learning platform) would be effortless. Another construct we will employ in our study is perceived usefulness (PU), which measures how much a person believes that using a particular data system or technology improves their performance at work. According to the TAM paradigm, PEU directly affects PU, and PU directly affects ATU and BI's ability to use technology. The m-learning platform is the technology being discussed in the broader context of this study. Based on the TAM described above, the theories developed are discussed in the subsections.

3.3 Outside factors

In the model proposed for this study [12], we integrated five external factors with the characteristics of the TAM model to identify the critical components that impact students' adoption of m-learning platforms. The literature on technology usage and adoption identifies three critical components that influence the use of electronic

devices in education: content quality (CQ), system quality (SYQ), and service quality (SEQ). Numerous scholars have validated the significance of these dimensions regarding their impact on the adoption of new technology through their studies. The underlying premise is that high-quality systems, content, and services will inevitably lead to high-quality services and functionality from those systems. In this instance, learning activities and content provided by a m-learning platform will be of higher quality if the platform has a high-quality system, user satisfaction, and service. This will have a positive impact on students' learning outcomes, as shown in Figure 5.

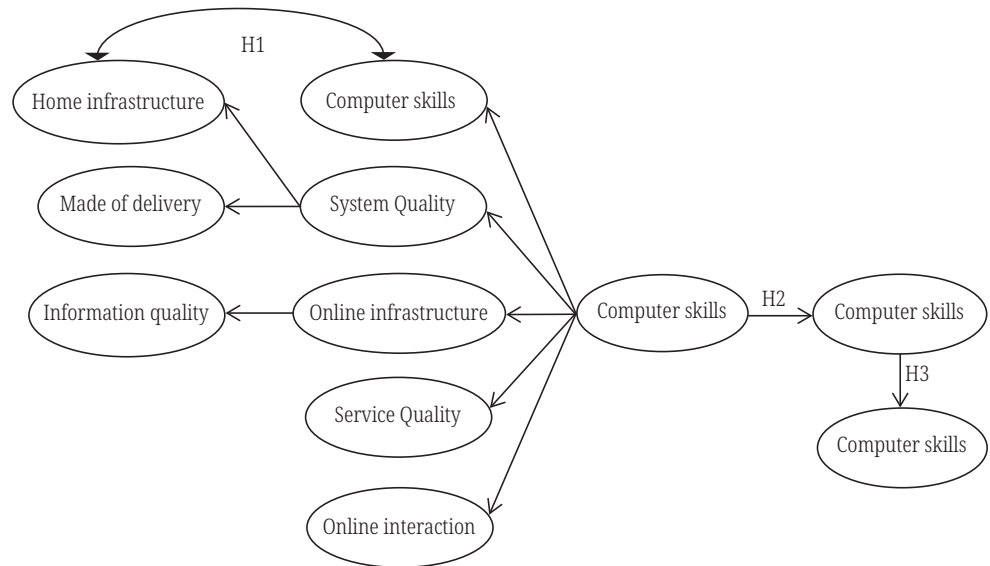


Fig. 5. Conceptual representation of the COVID-19 pandemic's perceived performance among learners in online learning

4 IMPLEMENTATION AND EXPERIMENTAL RESULTS

4.1 Dependability and validity evaluation

Cronbach's alpha reliability coefficient was used to assess the variables in the proposed model for consistency and dependability. Table 1 presents the results of the study. All components in the proposed research model have sufficient reliability, as all Cronbach's alpha values exceed the acceptable threshold of 0.60.

Table 1. Finding from the convergent validity and reliability examination

Constructs	Cronbach's Alpha	Average Variance Extracted (AVE > 0.5)
PEU	0.902	0.753
PU	0.774	0.780
BI	0.888	0.830
AU	0.866	0.802
CQ	0.913	0.751
SYO	0.898	0.883
SEQ	0.833	0.913
HLM	0.793	0.938
TF	0.874	0.919

Both discriminant and convergent validity were examined in the validity investigation. Using the average variance extracted (AVE) criteria, convergent validity was assessed. As indicated by Table 1, the AVE values above meet the minimum cut-off requirement of 0.5. An AVE larger than 0.5 is considered appropriate, as stated in reference [13]; therefore, the convergent validity values of the research constructs are considered satisfactory.

To demonstrate discriminant reliability, the square root of each construct's AVE must exceed the correlation values between two constructs, as illustrated in Table 2.

Table 2. Discriminant validity analysis outcomes

	PEU	PU	BI	AU	CQ	SYQ	SEQ	HLM	TF
PEU	0.937								
PU	0.798	0.959							
BI	0.631	0.759	0.965						
AU	0.647	0.685	0.546	0.979					
CQ	0.760	0.770	0.564	0.690	0.964				
SYQ	0.770	0.793	0.644	0.708	0.791	0.944			
SEQ	0.531	0.624	0.507	0.644	0.528	0.615	0.989		
HLM	0.739	0.658	0.515	0.585	0.622	0.718	0.526	0.961	
TF	0.646	0.689	0.528	0.666	0.608	0.640	0.737	0.576	0.967

4.2 Analysis of modeling structural equations

As shown in Table 3, the service quality factor (SEM) analysis findings indicated that each hypothesis in the proposed model was validated. The findings supported hypothesis H5, showing that the content quality factor (CQ) significantly increases perceived usefulness (PU) (β -value = 0.427, $p < 0.004$). Additionally, the results showed that perceived ease of use (PEU) is significantly positively influenced by system quality (SYQ) (β -value = 0.530, $p < 0.003$). This finding indicates that H6 is accepted. Furthermore, the results further corroborated H7, showing that PU is significantly impacted by the SEM (β -value = 0.507, $p < 0.003$).

Table 3. Findings from the analysis of structural equation modelling

Hypotheses	Path	β	SE	t-Value	Result
H1	PEU \rightarrow PU	0.347**	0.044	4.718	Reinforced
H2	PEU \rightarrow BI	0.375**	0.040	4.134	Reinforced
H3	PU \rightarrow BI	0.388**	0.064	1.325	Reinforced
H4	BI \rightarrow AU	0.393**	0.058	3.469	Reinforced
H5	CQ \rightarrow PU	0.328**	0.073	3.015	Reinforced
H6	SYQ \rightarrow PEU	0.331**	0.067	5.066	Reinforced
H7	SEQ \rightarrow PU	0.308**	0.065	2.995	Reinforced
H8	HML \rightarrow SYQ	0.299**	0.067	5.838	Reinforced
H9	HML \rightarrow SEQ	0.282**	0.061	9.015	Reinforced
H10	TF \rightarrow AU	0.390**	0.072	4.024	Reinforced

4.3 Analysis of artificial neural network certification

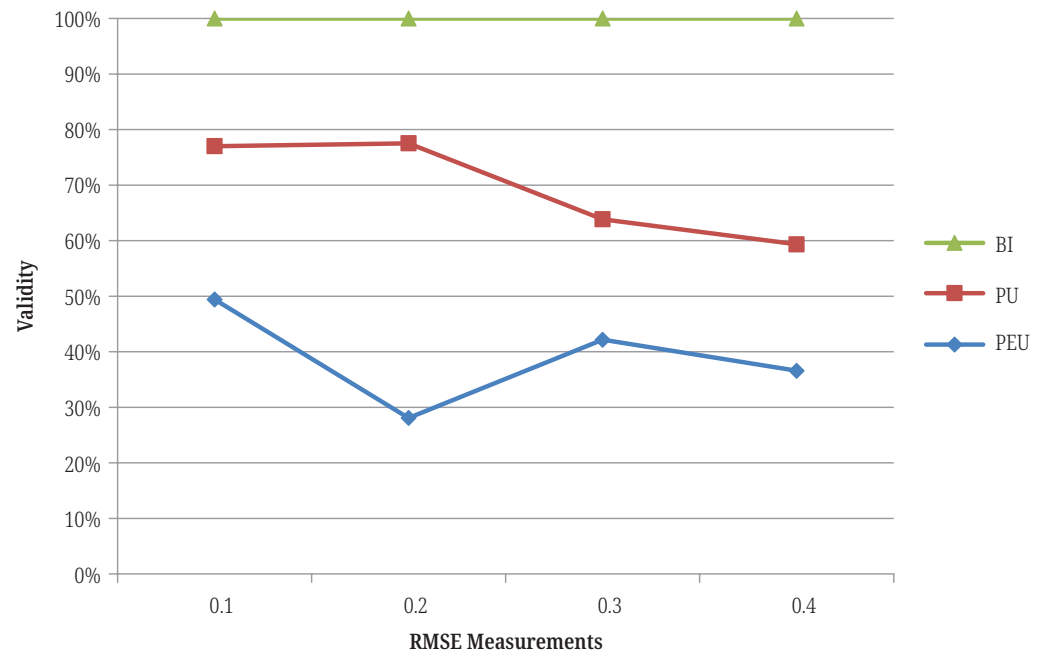


Fig. 6. The ANN models

In this study, SPSS software was used to test and analyze the artificial neural network (ANN) model presented in Figure 6. The network’s training procedure utilized the backpropagation neural network technique. Several recommendations from earlier research papers suggest using 10-fold cross-validation to assess the prediction accuracy of the trained network. Furthermore, the 10-fold cross-validation technique was utilized to prevent overfitting of the model. Based on this, ten-fold cross-validation was used in this study, with 80% of the data points allocated to the training set of the network model and 20% for testing.

The root mean square error was used to assess the accuracy of the ANN model’s predictions [14]. Therefore, the RMSE was used to calculate the prediction accuracy of the ANN with 10 turns (10 folds) for both the training (80%) and testing (40%) information sets. Equations (1) and (2) are used to determine the RMSE, where SSE represents the summation of squared errors and MSE stands for the mean square prediction errors.

$$MSE = \frac{2}{N * SSE} \tag{1}$$

$$RMSE = \sqrt{MSE} \tag{2}$$

Based on the results presented in Table 4, the ANN model was assessed to determine the relationship between input predictors by computing the RMSE values for both the test and training data sources. The average RMSE for the training model is 0.309, and the median RMSE for the testing model is 0.905. This indicates that the ANN model used in this study is reliable in identifying and predicting the relationships between independent and dependent variables [15]. As a result, this study’s ANN model predicts the key variables that have the most significant impact on how effectively learners utilize m-learning systems.

Table 4. Outcomes of ANN model validation using RMSE measurements

Input: CQ, SYQ, SEQ, HLM, TF, PEU, PU and BI Output: AU				
Neural Network	Training Dataset (80% of Data Sample 3000, N = 2400)		Testing Dataset (20% of Data Sample 3000, N = 600)	
	SSE	RMSE	SSE	RMSE
ANN1	1.132	1.324	1.119	1.919
ANN2	1.128	1.319	1.130	1.961
ANN3	1.132	1.324	1.167	1.911
ANN4	1.129	1.320	1.108	1.875
ANN5	1.125	1.315	1.111	1.887
ANN6	1.113	1.300	1.119	1.919
ANN7	1.113	1.300	1.116	1.907
ANN8	1.113	1.300	1.120	1.923
ANN9	1.113	1.300	1.108	1.875
ANN10	1.113	1.300	1.119	1.919
	Mean	1.310	Mean	1.906

5 CONCLUSIONS

The goal of this study is to determine how teaching methods operate in a m-learning environment that integrates classroom settings with digital learning resources. Based on the findings of earlier research, web-based formative assessment has been identified as a useful strategy that can help students identify their areas of weakness, motivating them to actively engage in learning and become familiar with the subject matter. Therefore, it would be interesting to examine how this method impacts students' cognitive loads and learning outcomes in a m-learning environment. Additionally, the study found that system quality had a significant impact on how users perceived the ease of use of the m-learning platform. The system and service quality of the m-learning platform were significantly and positively enhanced by high-level management assistance. Additionally, the research's conclusions demonstrated a strong correlation between technological infrastructure and the real-world application of m-learning systems.

This type of research suggests that many computer-assisted learning techniques or resources could be beneficial as an m-learning strategy to enhance students' learning outcomes in a real-world learning environment. It would be wise to investigate the effects or efficacy of employing several popular mind tools in m-learning settings, including concept maps, expert systems, databases, and spreadsheets. Furthermore, this methodology will be implemented in other courses, such as a university social science course and an elementary school natural science course.

The results highlighted the critical factors that could enhance students' actual utilization of m-learning platforms. The study has demonstrated how the TAM can be utilized to describe how students engage with m-learning platforms. It also includes five external components (content excellence, system excellence, excellent service, high-level leadership assistance, and technology infrastructure) along with four TAM concepts, expanding the TAM model within the scope of this study. The results

demonstrated that the quality of the services and content significantly predicted how useful users perceived the m-learning platform to be.

6 FUNDING STATEMENT

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7 REFERENCES

- [1] G. J. Hwang and H. F. Chang, "A formative assessment-based mobile learning approach to improving the learning attitudes and achievements of students," *Computers & Education*, vol. 56, no. 4, pp. 1023–1031, 2011. <https://doi.org/10.1016/j.compedu.2010.12.002>
- [2] C. H. Cheng and C. H. Chen, "Developing a mobile app-supported learning system for evaluating health-related physical fitness achievements of students," *Mobile Information Systems*, vol. 2018, 2018. <https://doi.org/10.1155/2018/8960968>
- [3] F. Ozdamli and N. Cavus, "Basic elements and characteristics of mobile learning," *Procedia-Social and Behavioral Sciences*, vol. 28, pp. 937–942, 2011. <https://doi.org/10.1016/j.sbspro.2011.11.173>
- [4] G. Vanthournout, D. Gijbels, L. Coertjens, V. Donche, and P. Van Petegem, "Students' persistence and academic success in a first-year professional bachelor program: The influence of students' learning strategies and academic motivation," *Education Research International*, vol. 2012, 2012. <https://doi.org/10.1155/2012/152747>
- [5] F. E. Louhab, A. Bahnasse, and M. Talea, "Towards an adaptive formative assessment in context-aware mobile learning," *Procedia Computer Science*, vol. 135, pp. 441–448, 2018. <https://doi.org/10.1016/j.procs.2018.08.195>
- [6] A. Aouf, L. Boussaid, and A. Sakly, "Same fuzzy logic controller for two-wheeled mobile robot navigation in strange environments," *Journal of Robotics*, vol. 2019, 2019. <https://doi.org/10.1155/2019/2465219>
- [7] N. P. Morris, "Podcasts and mobile assessment enhance student learning experience and academic performance," *Bioscience Education*, vol. 16, no. 1, pp. 1–7, 2010. <https://doi.org/10.3108/beej.16.1>
- [8] H. Lee, J. Park, and W. Chung, "Localization of outdoor mobile robots using curb features in urban road environments," *Mathematical Problems in Engineering*, vol. 2014, 2014. <https://doi.org/10.1155/2014/368961>
- [9] Y. Shin, J. Hur, D. Koo, and J. Yun, "Toward serverless and efficient encrypted deduplication in mobile cloud computing environments," *Security and Communication Networks*, vol. 2020, pp. 1–15, 2020. <https://doi.org/10.1155/2020/3046595>
- [10] K. Kang, "An adaptive framework for real-time ECG transmission in mobile environments," *The Scientific World Journal*, vol. 2014, 2014. <https://doi.org/10.1155/2014/678309>
- [11] M. A. Almaiah, E. M. Al-Lozi, A. Al-Khasawneh, R. Shishakly, and M. Nachouki, "Factors affecting students' acceptance of mobile learning application in higher education during COVID-19 using Ann-Sem modelling technique," *Electronics*, vol. 10, no. 24, p. 3121, 2021. <https://doi.org/10.3390/electronics10243121>
- [12] D. Keržič, J. K. Alex, R. Pamela Balbontín Alvarado, D. D. S. Bezerra, M. Cheraghi, B. Dobrowolska *et al.*, "Academic student satisfaction and perceived performance in the e-learning environment during the COVID-19 pandemic: Evidence across ten countries," *PLoS One*, vol. 16, no. 10, p. e0258807, 2021. <https://doi.org/10.1371/journal.pone.0258807>

- [13] M. Seraj and C. Y. Wong, "Lecturers' and students' perception on learning Dijkstra's shortest path algorithm through mobile devices," *International Journal of Interactive Mobile Technologies (IJIM)*, vol. 8, no. 3, pp. 19–24, 2014. <https://doi.org/10.3991/ijim.v8i3.3745>
- [14] C. L. Lai and G. J. Hwang, "High school teachers' perspectives on applying different mobile learning strategies to science courses: The national mobile learning program in Taiwan," *International Journal of Mobile Learning and Organisation*, vol. 9, no. 2, pp. 124–145, 2015. <https://doi.org/10.1504/IJMLO.2015.070704>
- [15] T. H. Laine and M. Joy, "Survey on context-aware pervasive learning environments," *International Journal of Interactive Mobile Technologies (IJIM)*, vol. 3, no. 1, pp. 70–76, 2008. <https://doi.org/10.3991/ijim.v3i1.680>

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