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Factors Affecting Students' Acceptance of Mobile Learning Application in Higher Education during COVID-19 Using ANN-SEM Modelling Technique

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Abstract: Due to the COVID-19 pandemic, most universities around the world started to employ distance-learning tools. To cope with these emergency conditions, some universities in Jordan have developed "mobile learning platforms" as a new tool for distance teaching and learning for students. This experience in Jordan is still new and needs to be evaluated in order to identify its advantages and challenges. Therefore, this study aims to investigate students' perceptions about mobile learning platforms as well as to identify the crucial factors that influence students' use of mobile learning platforms. An online quantitative survey technique using Twitter was employed to collect the data. A two-staged ANN-SEM modelling technique was adopted to analyze the causal relationships among constructs in the research model. The results of the study indicate that content quality and service quality significantly influenced perceived usefulness of mobile learning platforms. In addition, perceived ease of use and perceived usefulness significantly influenced behavioral intention to use mobile learning platforms. The study findings provide useful suggestions for decision makers, service providers, developers, and designers in the ministry of education as to how to assess and enhance mobile learning platform quality and understanding of multidimensional factors for effectively using mobile learning platforms.

Keywords: e-learning; mobile learning platform; distance learning usage; COVID-19; Jordan

1. Introduction

Recently, the emergence of the COVID-19 has witnessed a high acceleration towards the use of information and communication technologies in educational institutions [1,2]. To cope with these sudden conditions, many educational institutions, including universities, have made distance electronic-platforms available to their students and teachers. However, the limited adoption and use of these new electronic-platforms among students is a considerable concern among teachers and parents [3]. The use of technologies during COVID-19 is beneficial for educational institutions and the more frequently and more diverse the technology being used the better. There is a growing paradigm shift towards technologically driven research, teaching and learning in order to improve a student's productivity [4].

According to many researchers [5–7], there are several factors that have been identified as hindrances of e-learning systems' usage, such as poor internet connectivity, uneasiness, infrastructure unavailability and lack of management support. This study seeks to investigate students' perceptions about mobile learning platforms available at Saudi universities as well as the main factors that influence them in using mobile learning platforms at Saudi higher education institutes. This study aims to investigate and answer the following questions:

(1) What factors influence students' use of mobile learning platform in Jordan?
(2) What factors hinder the use of mobile learning platforms in Jordan?
(3) What are the students' perceptions of mobile learning platforms as a higher distance-learning platform available in Jordan?

Significance of the Study

In recent times, e-learning systems have become the de-facto tool for teaching, learning and communicating between students and teachers in higher education. As such, universities that provide distance learning, including those in developing countries, have made great strides in availing e-learning systems to their students and teachers such as in Jordan and United Arab Emirates [8]. In Jordan, since March 2020, universities have started closures due to the spread of COVID-19, which has changed the learning process from traditional learning to distance learning [9]. A previous study conducted in Jordan on usage of e-learning systems showed limited utilization of these systems [10,11]. The assumption is that students play a major role in both using and accepting for usage mobile learning platforms and as such their perceptions are crucial if the ministry of education is to realize better usage of the mobile learning platform. By assessing students' perceptions about mobile learning platforms, this study will contribute to knowledge creation in the educational technologies discipline because there are few studies that have focused on mobile learning platform usage in higher education in Jordan. Thus, this study aims to determine students' perceptions on the mobile learning platform available at Saudi universities as well as factors that influence them to use mobile learning platforms at Jordan higher education. Findings from this study might present further recommendations to the Jordan education stakeholders for improved platform development and prompt further research towards the role of ICTs in learning universities in Jordan.

2. Literature Review

2.1. Value of M-Learning Systems in Higher Education during COVID-19

Several researchers have confirmed that incorporating m-learning systems in higher education ultimately improves access to quality education [12–14]. Others have argued that introducing m-learning platforms in learning process provides innovative ways of learning that engage the modern day learner [15–18]. The COVID-19 pandemic has also increased the need for m-learning systems in education as they provide a sustainable and risk-free method for learning and teaching [19–21]. The use of m-learning systems in education potentially brings a number of significant advantages. One of the major benefits of these systems is the provision of digital learning and learning resources anytime and anywhere for both students and teachers [21–23].

Several studies in the literature have summarized that e-learning systems are easy to use and learn through, can be used to access learning resources ubiquitously as long there is internet connectivity, can be downloaded and saved in computers and mobile phones as well as have high access speed and can provide links to other learning resources on the internet [24–26]. Effective use of e-learning systems can, therefore, be a panacea to the challenges in higher education especially during COVID-19 pandemic in Jordan and other countries where teaching and learning resources are in short supply, such as in Jordan [27–29]. Since e-learning platforms can quickly provide relevant and up to date information pertaining to learning materials and resources, they are of great value to the twenty-first century student who is faced with an ever-evolving academic landscape and has to continually update their knowledge in order to stay relevant.

For integrating e-learning systems and distance learning platforms successfully in higher education, all stakeholders, particularly students and teachers, play a major role [30]. The students and teachers have to be willing to utilize the e-learning systems, whereas the management has to continuously fund the information technology infrastructure improvements. Teachers can reach wider learners virtually through e-learning systems and distance learning platforms, such as mobile learning platforms. They can present the learning materials in many forms, such as videos, PowerPoint presentations, quizzes, chat-rooms, blogs and audio as part of the teaching philosophy. On the other hand, students can find, share and access learning materials for learning process enrichment. Social media and applications are also used in the teaching process as information and ideas sharing platforms [31]. Despite the results, the use of e-learning systems, especially in developing countries, is still minimum and further research to stimulate e-learning systems' usage is still necessary in Jordan [31].

2.2. The Use of Mobile Learning Platform and Technology Acceptance Models

There are several theoretical models that have been employed in previous studies to investigate the students' usage of numerous educational technologies in varied contexts such as mobile learning [31], distance learning [30] and e-learning [29]. These models include the technology acceptance model (TAM) [32], the theory of planned behavior and the UTAUT. For long time, these theoretical models played a major role to explain and understand the users' usage and acceptance of various educational technologies. For example, students' behavior towards an action can determine the level they accept or reject an innovation/technology; thus, Davis [32] explains behavioral intentions and attitudes through the TAM model constructs.

In our study, the proposed model is established from the technology acceptance model (TAM) [32]; the TAM model will help us to explain and understand the significant factors that influence students' usage of mobile learning platform in JORDAN. At the core, TAM is the most recent and widely used model, which uses five constructs including perceived usefulness, ease of use, attitude toward to use, intention to use and actual use as predictors of the technology usage and acceptance [33–37]. TAM model hypothesized that the two main determinants for an individual to use any new technology are the user's perceptions of ease of use as well as their perception on its usefulness [32].

A few studies have investigated students' perceptions of the mobile learning platform as a distance learning system during COVID-19 available at Saudi universities. Indeed, more research is necessary considering the increasing usage of these systems as well as their increasing importance during the COVID-19 pandemic. Therefore, this study attempts to fill the pertaining gap in the extant literature by identifying and analyzing the key determinants that would motivate the young children/students to use mobile learning platform learning in order to enhance their educational well-being and learning experiences during COVID-19 pandemic.

According to the literature, TAM model has been employed in previous studies to explore all factors of educational technology acceptance among students, such as mobile learning, virtual learning and e-learning [38–41]. A large number of studies also used the TAM model to understand e-learning systems' usage among students [42–46]. In addition, the TAM model has provided a high predictive validity in previous studies in exploring the main determinants of acceptance of various technologies [47–49]. Based on above justifications, we employed the TAM model in our study to explore students' perceptions about mobile learning platform usage in Jordan.

3. Development of the Proposed Theoretical Model

3.1. Constructs of the TAM Model

In this study, the proposed model in Figure 1 was developed by extending the TAM model in order to explain and understand the significant factors that influence students' usage of the mobile learning platform in JORDAN. Based on the above discussion, TAM is the most recent and widely used model, which uses five constructs, including perceived usefulness, ease of use, attitude toward to use, intention to use and actual use as predictors of the technology usage and acceptance [49–52]. TAM model as shown in Figure 2, hypothesized that the two main determinants for an individual to use any new technology are the user's perceptions of ease of use as well as their perception on its usefulness [32].

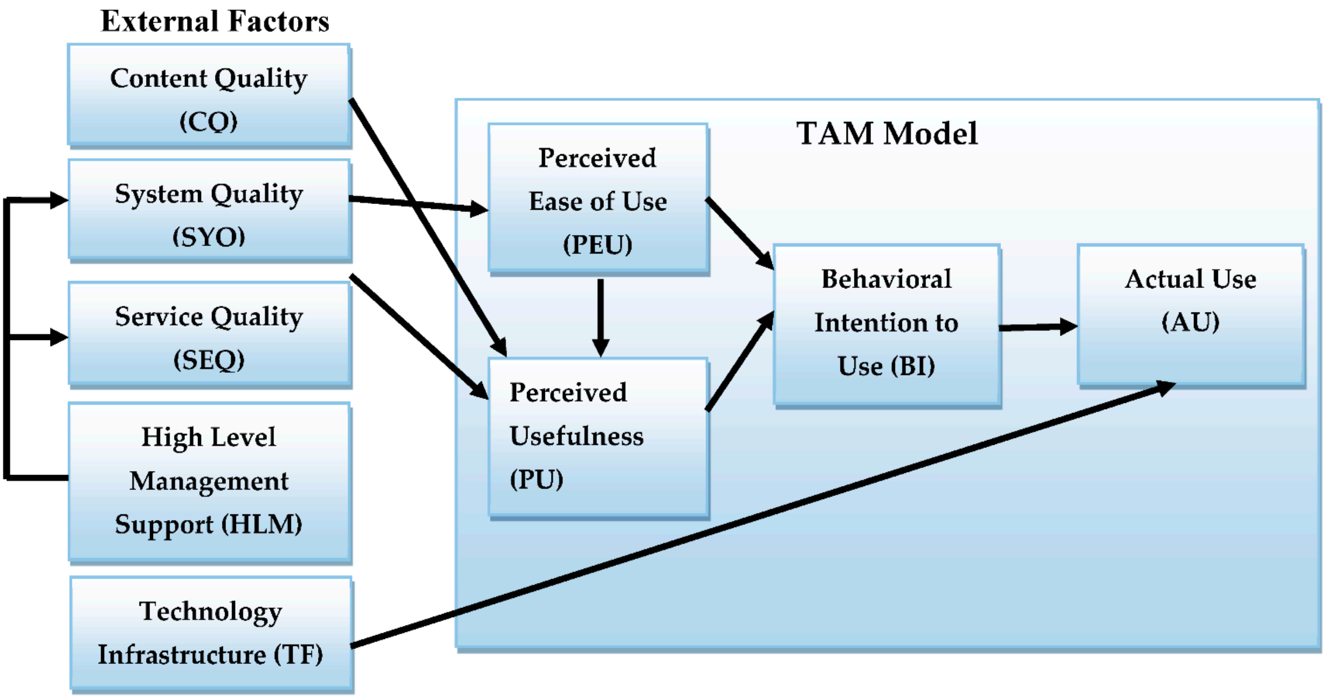

Figure 1. The Theoretical Model for examining the Usage of Mobile Learning Platform.

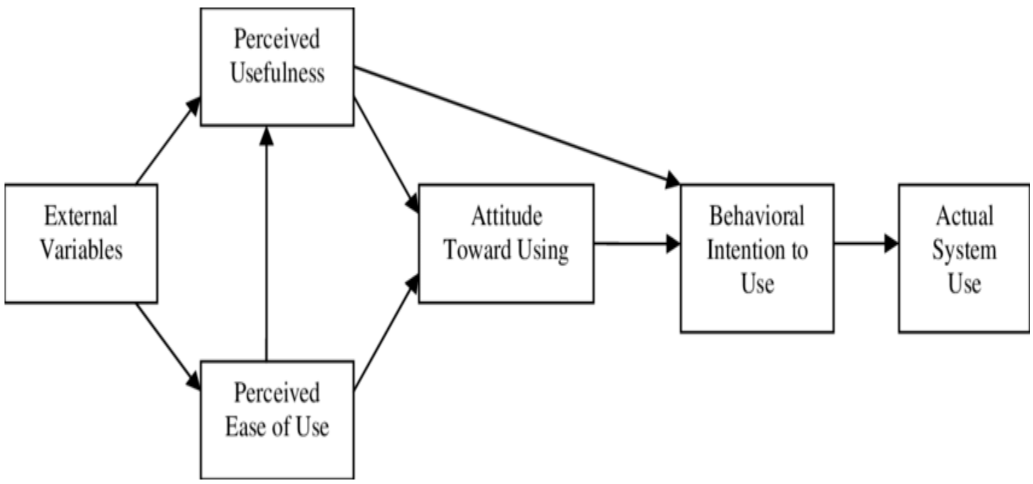

Figure 2. Technology Acceptance Model [32].

In the context of this study, perceived ease of use (PEU) is one of the major constructs to be used in the proposed model. Davis (1989) defined perceived ease of use (PEU) as the degree to which a person believes that using technology (mobile learning platform) will be free of effort. Perceived usefulness (PU) refers to the extent to which an individual believes that using a certain information system or technology enhances their job performance [32], is another construct to be used in our study. The construct PU in this study refers to students' perceptions concerning the degree to which using the Mobile learning platform would improve their learning performance. Both PEU and PU constructs are two fundamental constructs in the TAM that influence attitude towards using (ATU) a new technology [32]. ATU influences on the behavioral intention (BI) to use technology (Davis, 1989). This in turn influences the actual use (AU) of technology [32]. In the TAM model, PEU influences directly on PU and PU has a direct effect on ATU and BI to use technology [32]. In the context of this study, the technology being referred to is the mobile learning platform. From the above discussion on the TAM model, the following hypotheses were formulated:

Hypothesis 1 (H1): *PEU has a significant influence on PU to use mobile learning platforms.*

Hypothesis 2 (H2): *EU has a significant influence on BI to use mobile learning platforms.*

Hypothesis 3 (H3): *PU has a significant influence on BI to use mobile learning platforms.*

Hypothesis 4 (H4): *BI has a significant influence on AU to use mobile learning platforms.*

3.2. External Factors

In the proposed model for this study, we integrated five external factors with the TAM model constructs in order to identify the significant factors that influence students' usage of Mobile learning platform. According to the literature of technology usage and acceptance, which identified three important factors that influence use of technology in education: are content quality (CQ), system quality (SYQ) and service quality (SEQ). Several researchers in their studies have confirmed the importance of these constructs on their effect towards use of new technologies [53–56]. The assumption is that if a system, content and service is of high quality then the services and functionalities by such a system is also of a higher quality. In this case, if a mobile learning platform is a system, content and service is of high quality, then the learning content and activities provided by such a platform is also of a higher quality and thus will reflect positively on the learning performance of students. Therefore, we included these three external factors as antecedents to perceived usefulness and perceived ease of use. Based on that, we proposed the following hypotheses:

Hypothesis 5 (H5): *CQ has a positive effect on PU of Mobile learning platform.*

Hypothesis 6 (H6): *SYQ has a positive effect on PEU of Mobile learning platform.*

Hypothesis 7 (H7): *SEQ has a positive effect on PU of Mobile learning platform.*

Several researchers have asserted that high-level management support (HLM) is one of the critical factors for ensuring the usage of technology [57]. High-level management support (HLM) is defined as the degree to which senior management believe and understand the importance of information technology [58]. This factor is believed to play a crucial role in the success of technology usage among users [59]. According [60], 79% of the respondents indicated that HLM is one of the most important factors in the success of e-learning projects in Jordan. The full support of top managers will ensure richer resources in terms of financial support and technological resources to support the effective implementation of mobile learning platforms [61]. Furthermore, according to the study conducted by [62], top management support positively influences system quality and service quality. Based on this discussion, we hypothesized that HLM could positively impact the system and service quality of the mobile learning platform, which in turn will positively affect students' behavioral intention to use it and thus increase the actual use of the mobile learning platform; therefore, we proposed the following hypotheses:

Hypothesis 8 (H8): *HLM has a positive effect on SYQ of mobile learning platforms.*

Hypothesis 9 (H9): *HLM has a positive effect on SEQ of mobile learning platforms.*

Technology infrastructure (TF) is another external factor that can be included in our study. Ref. [63] confirmed that providing an excellent technology infrastructure has a significant influence on the accessibility and utilization of distance learning systems in higher education. In this study, TF refers to the provision of proper internet connectivity with unlimited bandwidth, computer availability etc. This means that providing suitable technology infrastructure will significantly motivate students to use mobile learning platforms; therefore, we proposed the following hypothesis:

Hypothesis 10 (H10): *TF has a positive effect on AU of mobile learning platforms.*

4. Research Methodology

In this study, a two-staged ANN-SEM modelling technique was used to predict the most significant factors that influence students' use of mobile learning platforms. Our study adopted the same steps of a research methodology from a study conducted by [64]. In several studies, ANN-SEM modelling techniques have been employed for predicting the users' usage and acceptance of educational technologies such as mobile learning and e-learning [65]. Despite the SEM technique being an advantageous data analysis method in that it simultaneously evaluates the measurement and structural models [21], it may oversimplify the complexities involved in the students' opinion towards to use of mobile learning platforms. This limitation in SEM can be addressed by employing the ANN modelling technique. ANN is capable of discovering non-linear and linear relations among variables [6]. Therefore, we are seeking to employ both models (ANN-SEM) in this study, in order to take advantage of the features in both models.

4.1. Data Collection

In this study, an online quantitative survey technique using the Twitter App was employed to collect the data. Online simple random sampling was used to select study participants and collect data via their Twitter accounts. For testing the hypotheses in the proposed model, a structural equation modelling (SEM) technique was adopted to examine causal relationships among constructs in the research model. The following sub-sections will present research participants, research measurements and data analysis method.

4.2. Research Participants

The study population comprised of 35,000 thousand students at Jordan universities, who were enrolled in the mobile learning platform. Online random sampling was employed to target 3000 students from seven universities at Jordan. This technique was used to mitigate against bias. The online survey was conducted between March and April of 2021. An online survey with the link was sent to the participants twitter accounts.

4.3. Research Measurements

The online survey was sent to the participants that included 30 items, measuring the nine constructs in the proposed model of this study. These items were drawn from validated scales in previous studies [6–9]. In order to suit the items with the context of this study, we modified the questions. All these items were phrased as questions and were adapted from other educational technologies usage and acceptance studies [1–5]. The measurements included 12 items for content quality, system quality and service quality that have been adopted from [2–4]. Four items for high level management support were adapted from a study conducted by [1] and 4 items for technology infrastructure were drawn from [3]. Lastly, 12 items for TAM constructs (perceived usefulness, ease of use, behavioural intention to use and actual use) were adopted from [32]. A five- point scale with the Likert model was utilized for measuring every item, ranging from "strongly disagree = 1" to "strongly agree = 5". For ensuring the validity and clarity of questions, we invited five experts in the domain of e-learning to examine the appropriateness and clarity of the online questionnaire, with the results indicating that the instructions and questions were completely understood.

4.4. Artificial Neural Network Modelling (ANN)

Due to the efficiency of the artificial neural network approach (ANN), it has been used on a variety of research domains with the help in predicting user behavior towards the use and acceptance of several systems and technologies. For example, ANN has been successfully applied in predicting mobile entertainment adoption [11], predicting a wearable healthcare devices adoption [12], predicting mobile banking adoption [13] and many other fields. Therefore, in this research, we can conclude that the ANN approach is also capable for predicting the most significant factors that influence students' use of mobile learning platforms effectively.

Artificial neural network (ANN) is an interconnected group of nodes, inspired by a simplification of neurons in a brain. According to Figure 3, each circular node represents an artificial neuron and an arrow represents a connection from the output of one artificial neuron to the input of another. The connections are called edges. Each connection, such as the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer) to the last layer (the output layer), possibly after traversing the layers multiple times. The output of each neuron is computed by some non-linear function of the sum of its inputs.

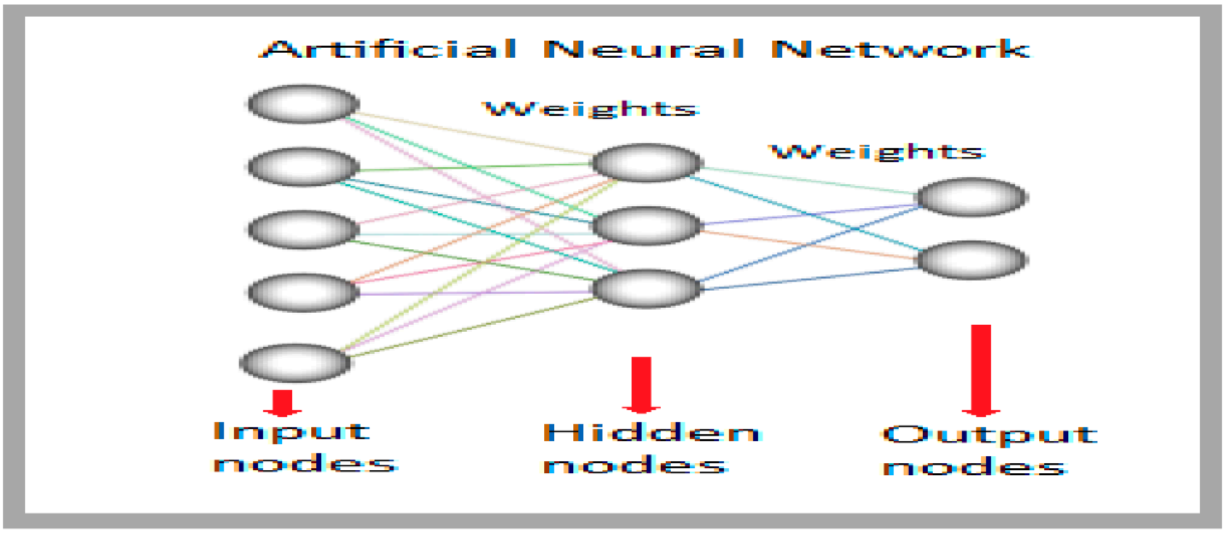

Figure 3. Artificial Neural Network Model.

The ANN model primarily consists of three layers, including input layers, hidden layers and output layers. Each artificial neuron is connected with multiple layers at the beginning of ANN model, which are known as input layers. The middle layer is known as hidden layers, which could contain large number of hidden layers in a network. Each layer has an activation function in the neural network model. The last layer is known as output layers.

Finally, ANN offers several features through using the back propagation neural network algorithm, which is supervised the learning process in the network. First, ANN has the capability to gain the knowledge through iterative learning process [15]. Second, ANN is capable of storing experimental knowledge and making it available for use [15].

Third, ANN is capable of discovering non-linear and linear relations among variables [6]. Fourth, the predicting performance of ANN is more powerful than statistical models such as structural equation modelling and multiple linear regression [6].

5. Data Analysis and Results

5.1. Reliability and Validity Analysis

The reliability and consistency of the constructs in the proposed model was measured using Cronbach's alpha reliability coefficient. Based on the results in Table 1, all values of Cronbach alpha were found to be exceeding the acceptable limit of 0.70 [59], this indicating satisfactory reliability for all constructs in the proposed research model.

Table 1. Results of Reliability and Convergent Validity Analysis.

Constructs	Cronbach's Alpha	Average Variance Extracted (AVE > 0.5)
PEU	0.901	0.752
PU	0.773	0.779
BI	0.887	0.829
AU	0.865	0.801
CQ	0.912	0.750
SYQ	0.897	0.882
SEQ	0.832	0.912
HLM	0.792	0.937
TF	0.873	0.918

For validity analysis, convergent and discriminant validity was used. Convergent validity was evaluated by using the criteria of average variance extracted (AVE). As shown in Table 1, the AVE values were above the minimum cut-off criteria of 0.5 (Hair, Black, Babin, & Anderson, 2010). According to [60], an AVE greater than 0.5 is acceptable. Therefore, the convergent validity values for the research constructs are acceptable.

Finally, discriminant validity was tested using the [57]: the square root of AVE values of each construct should be higher than the corresponding correlation values between two constructs [57] as highlighted in Table 2.

Table 2. Results of discriminant Validity Analysis.

	PEU	PU	BI	AU	CQ	SYQ	SEQ	HLM	TF
PEU	**0.936**								
PU	0.797	**0.958**							
BI	0.630	0.758	**0.964**						
AU	0.646	0.684	0.545	**0.978**					
CQ	0.759	0.769	0.563	0.689	**0.963**				
SYQ	0.769	0.792	0.643	0.707	0.790	**0.943**			
SEQ	0.530	0.623	0.506	0.643	0.527	0.614	**0.988**		
HLM	0.738	0.657	0.514	0.584	0.621	0.717	0.525	**0.960**	
TF	0.645	0.688	0.527	0.665	0.607	0.639	0.736	0.575	**0.968**

5.2. Structural Equation Modelling Analysis

The results of the SEM analysis indicated that all hypotheses in the proposed model were supported, as presented in Table 3. The results indicated that content quality factor (CQ) has a significantly positive effect on perceived usefulness (PU) (β-value = 0.327, $p < 0.001$), with this result supporting hypothesis H5. The results also found that system quality (SYQ) has a significantly positive effect on perceived ease of use (PEU) (β-value = 0.330, $p < 0.001$), this result means that H6 accepted. In addition, H7 was also supported according to the results, which indicated that service quality factor (SEM) has significant effect on perceived usefulness (PU) (β-value = 0.307, $p < 0.001$). The results also indicated that high level management support (HLM) has a significantly positive effect on system quality (SYQ) (β-value = 0.298, $p < 0.001$) and service quality (SEQ) (β-value = 0.281, $p < 0.001$), with these results supporting hypotheses H8 and H9. We also found that technology infrastructure (TF) has a significantly positive effect on actual use (AU) (β-value = 0.389, $p < 0.001$), with this result supporting H10. In addition, perceived ease of use (PEU) has a significant effect on both perceived usefulness (PU) and behavioral intention to use (BI) (β-value = 0.346, $p < 0.001$; β-value = 0.374, $p < 0.001$, respectively). We also found that perceived usefulness (PU) has a significantly positive effect on behavioral intention to use (BI) (β-value = 0.387, $p < 0.001$), and behavioral intention to use (BI) has a significantly positive effect on actual use (AU) (β-value = 0.392, $p < 0.001$). Thus, the results indicated that the hypotheses H1, H2, H3 and H4 were also supported. The results also indicated that the key factors explain 49% of variance in actual use of mobile learning platforms.

Table 3. Results of Structural Equation Modelling Analysis (** means the result is significant).

Hypotheses	Path			β	SE	*t*-Value	Results
H1	PEU	→	PU	0.346 **	0.043	4.717	Supported
H2	PEU	→	BI	0.374 **	0.039	4.133	Supported
H3	PU	→	BI	0.387 **	0.063	1.324	Supported
H4	BI	→	AU	0.392 **	0.057	3.468	Supported
H5	CQ	→	PU	0.327 **	0.072	3.014	Supported
H6	SYQ	→	PEU	0.330 **	0.066	5.065	Supported
H7	SEQ	→	PU	0.307 **	0.064	2.994	Supported
H8	HML	→	SYQ	0.298 **	0.066	5.837	Supported
H9	HML	→	SEQ	0.281 **	0.060	9.015	Supported
H10	TF	→	AU	0.389 **	0.071	4.023	Supported

5.3. *Artificial Neural Network Validation Analysis*

For starting the ANN analysis, we should first determine the independent variables for this study that represents the input layers (input neurons) and dependent variable (output layer) in the ANN model. For this study, the independent variables (CQ, SYQ, SEQ, HLM, TF, PEU, PU and BI) were the input layers (input neurons) of the ANN model. This means the number of input neurons (input layers) equal eight, which is the number of predictors. In construct, the output layer in the ANN model was the dependent variable, which is AU, as shown in Figure 4. This means the number of output neurons (output layers) equals one. The hidden layers (hidden neurons) are automatically generated using activation function (Sigmoid function). The number of hidden neurons is calculated based on the complexity of the problem to be solved by using SPSS software.

In this research, to test and analyze the ANN model, the SPSS software (Version 23.0) was used. The back propagation neural network algorithm was employed for the training process in the network. According to several recommendations from previous studies [52], the prediction accuracy of the trained network is measured using 10-fold cross-validation. In addition, the 10-fold cross-validation was employed to avoid model over-fitting. Based on that, a cross-validation with 10 folds was applied in this study, where 80% of the data points were utilized for training dataset and 20% of them for testing dataset of the network model.

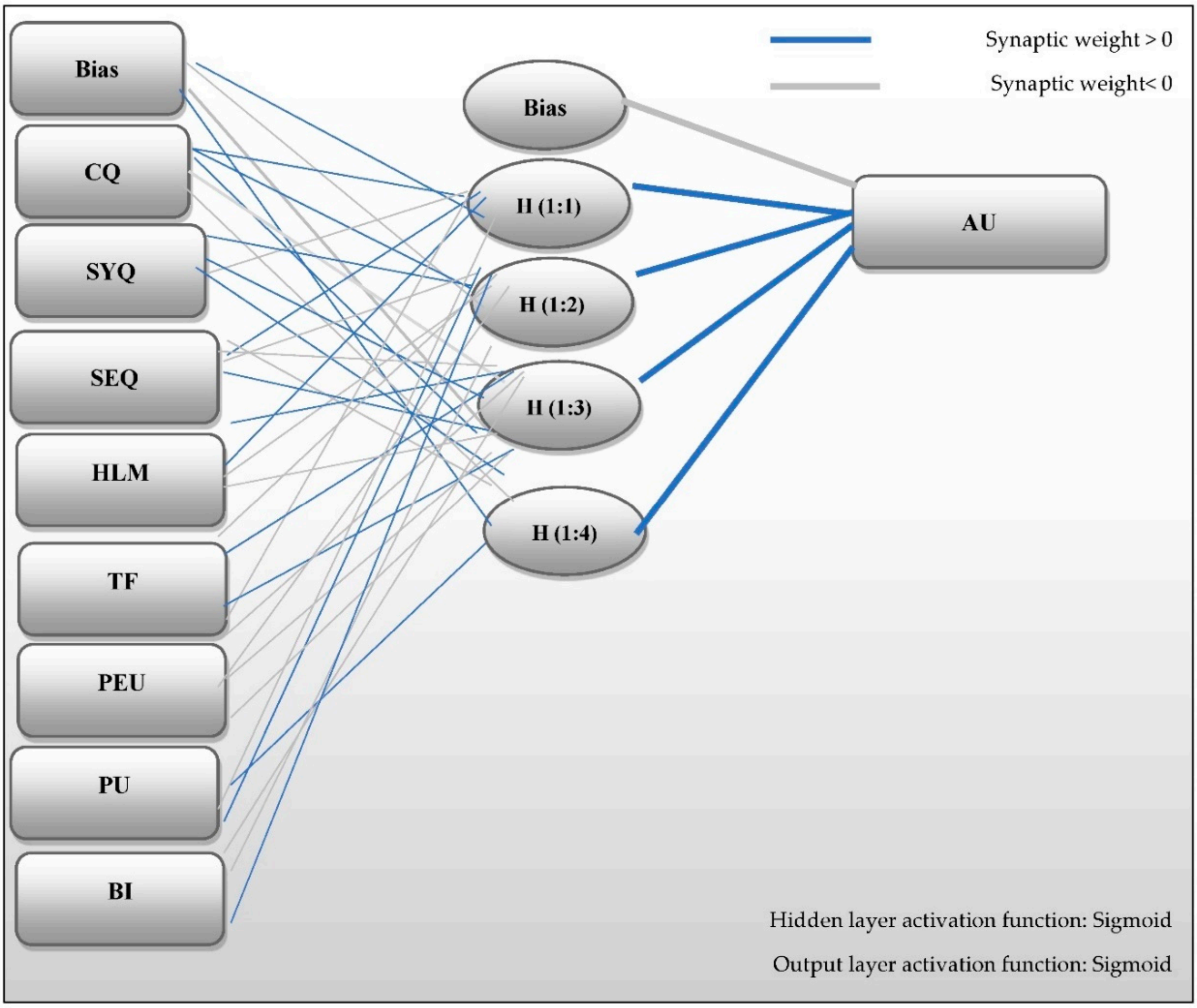

Figure 4. Neural Network Model.

In order to measure the accuracy of the ANN model prediction, the root mean square error (RMSE) was used. Thus, the prediction accuracy of the ANN model for both the training (80%) and testing (20%) data sets with 10 turns (10 folds) was computed using the RMSE. According to [53], the RMSE is calculated using Equations (1) and (2), where SSE is the sum of squared error, and MSE is the mean squared prediction error.

$$\mathrm{MSE} = \left[\frac{1}{\mathrm{N}}\right] \times \mathrm{SSE} \quad (1)$$

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \quad (2)$$

Based on the results in Table 4, the RMSE values were computed for both training and testing data sets in order to validate the ANN model for the relationships between input predictors (independent variables: CQ, SYQ, SEQ, HLM, TF, PEU, PU and BI) and the output (dependent variable: AU). According to [52], lower RMSE values represent higher predictive accuracy and better data fit. The results in Table 4 showed the average value of RMSE for training model equal 0.309 and the average value of RMSE for testing model is 0.905, and thus indicates that the ANN model used in this study is reliable in measuring and predicting the relationships between dependent and independent variables. Therefore, ANN model in this research is an accuracy model for predicting the most significant factors that influence students' use of mobile learning platforms effectively.

Table 4. Results of RMSE Values for ANN Model Validation.

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	0.131	0.323	0.118	0.918
ANN2	0.127	0.318	0.129	0.960
ANN3	0.131	0.323	0.166	0.910
ANN4	0.128	0.319	0.107	0.874
ANN5	0.124	0.314	0.110	0.886
ANN6	0.112	0.299	0.118	0.918
ANN7	0.112	0.299	0.115	0.906
ANN8	0.112	0.299	0.119	0.922
ANN9	0.112	0.299	0.107	0.874
ANN10	0.112	0.299	0.118	0.918
	Mean	**0.309**	**Mean**	**0.905**

5.4. Sensitivity Analysis

Sensitivity analysis was computed by the average of the importance of the independent variables that help in the prediction of dependent variables [17]. The results in Table 5 show that all eight independent variables are important to all 10 neural networks. Based on the results, content quality was the most influencing independent factor to predict the use of the mobile learning platform among students in Jordanian universities. The other independent factors (PEU, SYQ, PU, SEQ, BI, TF and HLM) were also important in predicting students' actual use of the mobile learning platform, respectively.

Table 5. Results of Independent Variables Importance.

Independent Variables	**Importance**	**Normalized Importance**
PEU	0.297	85.7
PU	0.231	66.2
BI	0.209	58.6
CQ	0.355	100.0
SYQ	0.247	71.3
SEQ	0.217	61.1
HLM	0.129	36.4
TF	0.157	44.2

6. Discussion

The success of mobile learning platforms depends on the acceptance, students' use, and their recommendations. Therefore, this research aimed to investigate students' perceptions about mobile learning platforms as well as to identify the main factors that influence them to use mobile learning platforms at Jordanian universities. This study examines the influence of five external factors (CQ, SYQ, SEQ, HLM and TF) with three constructs from the TAM model (PEU, PU and BI) on students' actual use of the mobile learning platform. The findings revealed that the TAM model is the most suitable model that can be used to predict the main factors that influence students' use of the mobile learning platform. The results of the study revealed that content quality and service quality significantly influenced perceived usefulness to use the mobile learning platform.

The results of the study revealed that perceived ease of use and perceived usefulness were significantly influencing behavioral intention to use mobile learning platforms. The results depicted that perceived usefulness is one of the most crucial factors contributing to behavioral intention to use mobile learning platforms. When students find mobile learning platforms facilitate their overall learning productivity, thereby, improving learning performance and effectiveness, their behavioral intention to adopt mobile learning platforms is enhanced. In addition, perceived ease of use was also found to be a significant predictor to behavioral intention to use mobile learning platforms among students. Along with it, the results manifested that mobile learning platforms and services should be easy to use and should require fewer efforts to engage students intuitively in order to increase their usage. The ease of use for using mobile learning platforms pertains to the ability of the user to choose what they want to learn, monitor their learning progress, record performance and navigate through unlimited content. Specifically, in case of underprivileged children, the higher they resonate with the content presentation, communication and portability of the mobile learning platform, the greater will be their usage. This is consistent with the result of the study conducted by Almaiah et al. [1].

The study findings indicate that content quality is the most crucial factor contributing to enhance students' use of mobile learning platforms. When students find mobile learning platforms enhancing their overall learning productivity, thereby, improving learning performance and effectiveness, their behavioral intention to use mobile learning platform is enhanced, and thus, motivating for them to use mobile learning platforms. Therefore, this study suggests that, to ensure the sustainability of mobile learning platform usage during COVID-19, developers and providers should provide their full support to analyze students' needs and requirements during the development and implementation of mobile learning platforms. This is consistent with the result of the study conducted by Almaiah et al. [2]. The results depicted that system quality significantly affected perceived ease of use to use mobile learning platforms. This result suggests that improvements in quality of functionalities of mobile learning systems will enhance students' actual use, consistent with Almaiah et al. [3]. In addition, system quality is a measure of the extent to which the system is flexible, user-friendly, easy to use, technically sound, etc. These characteristics of a system quality indirectly had a significant influence on actual use. A possible reason for this significant influence is the mediating effect of perceived ease of use. The direct impact of system quality on actual use might be insignificant. System quality thus affected actual use indirectly via perceived ease of use, rather than directly. Moreover, service quality significantly influenced on perceived usefulness to use mobile learning platforms. Our findings imply that service quality affects students' actual use in a positive way indirectly via perceived ease of use. Service quality provides a strong judgment on whether the mobile learning platform quality fits student needs, as well as learning activities being present and implemented effectively. Therefore, service quality may be considered as a threshold for evaluating how satisfied students are with mobile learning platforms. Therefore, mobile learning platform developers at universities should focus primarily on designing and providing high-quality services by analyzing students' needs. In addition, service quality had a positive effect on the actual use of the mobile learning platform, mediated by perceived usefulness. Our findings indicate service quality is necessary for successful usage of mobile learning platforms among students in Jordan. Therefore, this study suggests that, to ensure the sustainability of mobile learning platform usage during COVID-19, developers and providers should provide their full support to analyze students' needs and requirements during the development and implementation of mobile learning platforms. They should also guarantee that adequate resources are available for system upgrades to keep up with rapid technological changes. These results are consistent with a study conducted by Almaiah et al. [1].

Based on the findings of this study, high level management support has a significant and positive influence on the system quality and service quality of mobile learning platforms. This result implies that the achievement of high-quality mobile learning platforms that meet students' requirements and needs is not only dependent on system features, i.e., the availability of software and hardware, but also on the support of high level managers. Therefore, the findings of this study provide significant empirical evidence of the importance of this factor for mobile learning platform success. Refs. [42,43] indicated that management support is an important factor affecting e-learning success. Furthermore, the findings of this research revealed that there is clear evidence of a strong relationship between technology infrastructure and actual use of mobile learning platforms. This indicates that the availability of an excellent technology infrastructure has a significant influence on the accessibility and utilization of mobile learning platforms among students during COVID-19. In this study technology infrastructure refers to the provision of proper internet connectivity with unlimited bandwidth, computer availability, etc. This study suggests that providing suitable technology infrastructure will enable students to use mobile learning platforms effectively. Our findings are consistent with several researchers' findings, including [4,14], confirmed that technology infrastructure plays a crucial role in shaping student actual use of e-learning systems.

6.1. Significance of the Research

The significance of this research can be summarized as follows: first, this study is among the first to investigate a new distance learning platform called 'mobile learning platform' during COVID-19 in JORDAN, and will provide useful recommendations for researchers and practitioners to understand the essential factors that should be considered in promoting mobile learning platforms, which leads to increased students actual use of mobile learning platforms. Second, the proposed model in this study has made new contributions by taking into account the importance of quality factors in the evaluation of mobile learning platform quality. Third, this study provides practical suggestions for designers, developers and decision makers in universities as to how to enhance the actual use of mobile learning platforms and thus derives greater benefits from mobile learning platforms. Finally, the findings of this study confirm that quality factors, high level management support and technology infrastructure factors are important to mobile learning platform success, indicating that mobile learning platform quality alone cannot guarantee mobile learning platform positive contribution to the actual use of mobile learning platforms. This implies that universities in Jordan should balance quality factors, organizational factors, and technological factors.

6.2. Implications and Limitations of the Study

This research presents several theoretical and practical implications. In general, the study findings provide useful suggestions for decision makers, service providers, developers and designers in the ministry of education as to how to assess and enhance mobile learning platform quality and understanding of multidimensional factors for effectively using mobile learning platforms. First, leaders in the ministry of education need to support distance-learning projects during the COVID-19 pandemic by providing sufficient financial and technological resources. The full support of high-level managers will ensure richer resources in terms of financial support and technological resources to support the implementation of mobile learning platform project in an effective way. This will lead to improvements in system and service quality, which will positively affect students' behavior and thus increase the actual use of the system. Second, designers and developers of mobile learning platforms should focus on the factors that play a key role in improving the quality of mobile learning platforms, which in turn affects learning efficiency and student performance. Third, the study findings show how technological factors pertaining to students' actual use of mobile learning platforms are significant. Therefore, the use of mobile learning platforms should be supported by excellent technology infrastructure in universities and, thus, this will increase the actual use of the mobile learning platform among students. Fourth, the findings of this study can help designers and developers to develop mobile learning platforms by providing well-designed learning materials appropriate to students' knowledge, supporting different types of multimedia features and offering online discussion forums with instructors to answer students' questions regarding courses and learning materials. Such quality factors will promote students' satisfaction and the actual use of mobile learning platforms.

Despite this research provides several insights, further investigation is needed into the determinants of mobile learning platform usage among students. Future studies could investigate the teachers' perspectives and their requirements to use mobile learning platforms. In addition, there is a need to examine the existence of gender differences with respect to using mobile learning platforms, particularly in Jordan where notable gender disparity in smart and innovation industries is found.

7. Conclusions and Future Work

This study examined the factors influencing students' actual use of mobile learning platforms in Jordanian universities. The findings demonstrated the crucial determinants that would enhance the actual use of mobile learning platforms among students. The study has highlighted the applicability of the TAM model in explaining students' usage of mobile learning platforms. Furthermore, it extends the TAM model in the context of this study by adding five external factors (content quality, system quality, service quality, and high-level management support and technology infrastructure) with four TAM constructs. The results revealed that content quality and service quality were significant predictors of perceived usefulness to use the mobile learning platform. In addition, the study found that system quality was a significant predictor of perceived ease of use for the mobile learning platform. High-level management support had a significant and positive influence on the system quality and service quality of the Mobile learning platform. Furthermore, the findings of this research revealed that there is clear evidence of a strong relationship between technology infrastructure and actual use of mobile learning platforms.

The main advantages of this study can be summarized as follows: first, this study is among the first to investigate a new distance learning platform called 'mobile learning platform' during COVID-19 in Jordan, and thus will provide useful recommendations for researchers and practitioners to understand the essential factors that should be considered in promoting mobile learning platforms, which leads to increased students' actual use of mobile learning platform. Second, the proposed model in this study has made a new contribution by taking into account the importance of quality factors in the evaluation of mobile learning platform quality. Third, this study provides practical suggestions for designers, developers and decision makers in universities as to how to enhance the actual use of mobile learning platforms and thus derives greater benefits from mobile learning platforms.

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