Environment and Social Psychology (2024) Volume 9 Issue 4
doi: 10.54517/esp.v9i4.2307

ORIGINAL RESEARCH ARTICLE

Understanding mobile learning continuance after the COVID-19 pandemic: Deep learning-based dual stage partial least squares-structural equation modeling and artificial neural network analysis

Yakup Akgul[1,*], Ali Osman Uymaz[2], Pelin Uymaz[3]

[1] *Department of Business, Faculty of Economics, Administrative and Social Sciences, Alanya Alaaddin Keykubat University, Alanya 07425, Turkey*

[2] *Department of Human Resources Management, Faculty of Economics, Administrative and Social Sciences, Alanya Alaaddin Keykubat University, Alanya 07425, Turkey*

[3] *Department of Nursing, Faculty of Health Sciences, Alanya Alaaddin Keykubat University, Alanya 07425, Turkey*

*** Corresponding author:** Yakup Akgul, yakup.akgul@alanya.edu.tr

ABSTRACT

The influence of COVID-19 on educational processes has halted physical forms of teaching and learning and initiated online and mobile learning systems in most countries. The provision and usage of online and e-learning systems are becoming the main challenge for many universities during the COVID-19 pandemic. Due to the novelty of this situation, a substantial amount of research has been carried out to investigate the issue of m-learning adoption or acceptance. Nevertheless, little is known about studying to examine the continued use of m-learning, which is still in short supply and calls for further research. Five different theoretical models are integrated into this study to develop an integrated model that overcomes this limitation, including the technology acceptance model, the theory of planned behavior, the expectation-confirmation model, the Delone and McLean Information System Success Model, and the Unified Theory of Acceptance and Utilization of Technology 2. This conceptual framework shows novel relationships between variables by integrating trust, personal innovation, learning value, instructor quality, and course quality. Unlike extant literature, this study utilized a hybrid analysis methodology combining two-stage analysis using partial least squares structural equation modeling (PLS-SEM) and evolving artificial intelligence named deep learning (Artificial Neural Network [ANN]) on 250 usable responses. The sensitivity analysis results revealed that attitude has the most considerable effect on the continued use of m-learning, with 100% normalized importance, followed by perceived usefulness (88%), satisfaction (77%), and habit (61%). This research reveals that a "deep ANN architecture" may determine the non-linear relationships between variables in the theoretical model. Further theoretical and practical implications are also discussed.

Keywords: deep learning; non-linearity; artificial neural network; mobile learning; partial least squares-structural equation modeling

1. Introduction

Information and communication technology is a widely used technology today. A total of 4.1 billion people were online in 2019, representing 53.6% of the global population[1]. Smartphone penetration reached

ARTICLE INFO
Received: 4 December 2023 | Accepted: 3 January 2024 | Available online: 15 January 2024

CITATION
Akgul Y, Uymaz AO, Uymaz P. Understanding mobile learning continuance after the COVID-19 pandemic: Deep learning-based dual stage partial least squares-structural equation modelling and artificial neural network analysis. *Environment and Social Psychology* 2024; 9(4): 2307. doi: 10.54517/esp.v9i4.2307

66% in 2022[2]. Over the last two decades, the rapid adoption of mobile technologies has also led to a rise in internet usage. The higher penetration of mobile-based ICT has been critical to bridging society, integrating it, and allowing individuals to do their daily tasks remotely.

The concept of mobile learning can be described as follows: "the learning process carried out through the use of mobile devices (m-devices)". There have been several studies on e-learning adoption during the COVID-19 pandemic in higher education[3,4]. The paradigm of the education sector has been shifted by COVID-19. Many countries, such as Turkey, require remote education, including mobile learning, which carries many health risks. The effectiveness of mandatory m-learning programs is, however, not well understood. As a result, there is a need to investigate the aspects and mechanisms that influence students' experiences. There have been considerable studies in the extant literature on adopting mobile learning[5]. Nonetheless, there is still a growing interest in research into the long-term utility setting of m-learning.

The present study makes a major contribution in three ways: First, the significant effects of the antecedents and outcomes on continuing m-learning use represent a crucial contribution. Second, the current paper aims to create a novel hybrid model with the help of comprehensive constructs. In this regard, a conceptual model that incorporates the TAM, TPB, ECM, D & McLean IS success model, UTAUT2, etc. Trust (TRST) was added to our model since it is considered to be an essential need rather than a competitive advantage[6–9]. In the paper, UTAUT2 will be extended to include this major influence on technology adoption in mobile learning, contributing to the literature with a more holistic theoretical perspective. This paper proposes a revised version of UTAUT, which incorporates additional constructs such as price value, hedonic motivation, and habit to increase its explanatory power. The current work attempts to bridge a similar gap in the context of m-learning by adding variables such as course quality (CQ)[10], learning value (LV)[11], and instructor quality (INSQ)[10,12]. Personal innovativeness (PI) and social influence (SI) were added as additional constructs to address TAM's psychological science shortcomings, which may be due to the absence of psychological science components in TAM. Third, earlier research on m-learning has used a single-stage analysis such as SEM analysis[13–16]. There is a widely used linear model known as SEM that is utilized in many studies only to study linear correlations and is not considered appropriate for predicting the complexities involved in complex decision-making. However, to eradicate such limitations, as a complement to linear models, the second phase of the investigation involved creating an ANN with one hidden layer[17,18]. A two-phase analysis, comprised of one hidden layer, has been utilized to address this issue using machine learning approaches[19–27], which chose a single hidden layer, which a typical second stage ANN that is employed with a single hidden layer has been identified as a shallow architecture by Huang and Stokes[28]. Prior research topics that applied conventional shallow ANN approaches[29–31], it was recommended to use a deep learning dual-layer architecture[32–35]. Furthermore, the current study employs a deep learning technique that provides more insights than conventional ANNs[30,33,36,37]. Hence, by analyzing both linear and nonlinear compensatory associations through deep learning dual-stage approaches, this study fills an existing research gap. Because earlier m-learning research did not utilize the hybrid approach, adopting the deep learning dual-stage strategy in researching continuous intention in m-learning is regarded as a unique and novel way. The deep learning dual-stage approach's originality has provided a significant shift in methodology in the existing literature on mobile learning. **Figure 1** depicts the conceptual model.

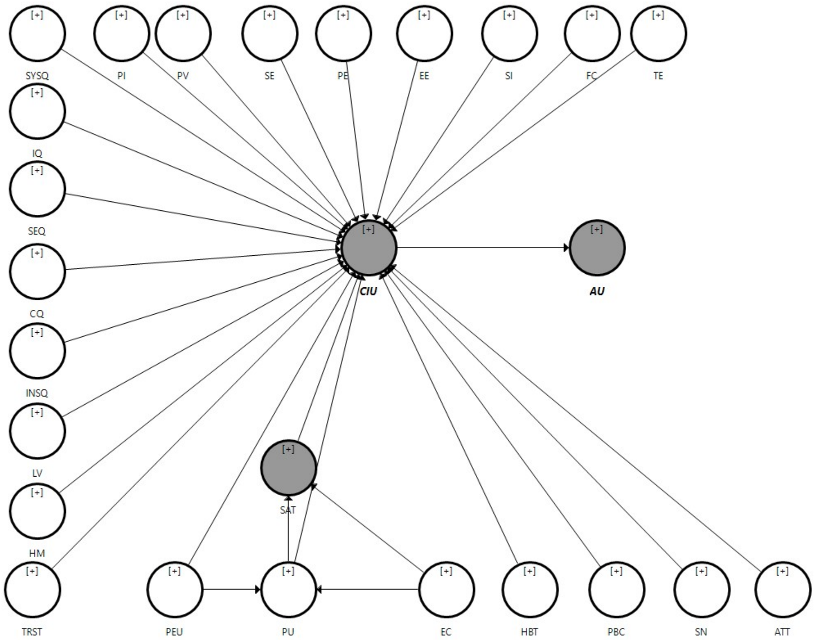

Figure 1. Research model.

2. Literature review

There is a wide range of theories to assess users' adoption of any new technology. Theory of Reasoned Action[38,39], Technology Acceptance model[40], Theory of Planned Behavior (TPB)[41] are among these theories. The theory of Reasoned Action (TRA), which was derived from social psychology[42], is the basis for many psychosocial theories, such as the Theory of Interpersonal Behavior (TIB), Theory of Planned Behavior (TPB), and Social Cognitive Theory (SCT). Diffusion of Innovation (DOI)[43], and Unified Theory of Acceptance and Use of Technology (UTAUT)[44]. A relatively more recent, comprehensive, and widely used model is the Unified Theory of Acceptance and Use of Technology (UTAUT) model. User adoption of technology can be explained by several theoretical frameworks, but the DeLone and McLean IS success model[45] is the most commonly used.

A selection of studies has been conducted on student acceptance of mobile learning systems using Partial Least Squares Structural Equation Modelling (PLS-SEM) and Artificial Neural Networks (ANN) (**Table 1**). These only focused on hybrid studies for online learning. For instance, the study by Al-Adwan et al.[46] investigated factors predicting students' intentions to use mobile learning using a framework based on the UTAUT. In their study, they found that effort expectations, trust expectations, performance expectations, system functionality, self-management, and social influence were significant determinants of m-learning adoption. In another study, the use of innovation diffusion theory (IDT) was used in another study by Park et al.[47] to investigate South Korean undergraduate students' acceptance of m-learning. They found that students' acceptance of m-learning was negatively influenced by their resistance to innovation, but positively influenced by compatibility, observability, relative advantage, and system quality. In another study, an examination of the effects of fear emotions on the adoption of technology by teachers and students during the COVID-19 pandemic was conducted by Al-Hamad et al.[48]. Experiments revealed significant predictors for using mobile learning platforms, including perceived fear, perceived ease of use, expectation confirmation, satisfaction, and perceived usefulness. Recently, a study by Alzaidi and Shehawy[49] examined student intentions to use mobile learning during COVID-19 in different cultural contexts, using the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Expectation-Confirmation Model (ECM). PE, SAT, SI, FC, and students' continued use of mobile learning are positively influenced by instructors' competencies. Moreover, PE, EE, and SI were all found to be positive predictors of behavioral intention (BI) to use technology in the context of Zimbabwe[50]. In another study, in their study, Chahal and Rani[51] investigated the factors that affect how students perceive e-learning and how they use it in their daily lives.

Table 1. Relevant and recent studies about mobile learning adoption.

Study	Technique applied	Area	Number of hidden layers	Constructs	Context	Sample size	How was the number of hidden neurons determined?	Network structure	Activation function hidden layer	Output layer
Al Ghuwairi et al.[52]	SEM-NN	Mobile learning		EE, FC, PE, and SF	Jordan	167	Automatically	9-1-1	Hyperbolic tangent	
Alhumaid et al.[26]	SEM-NN	Mobile learning		ATT, EC, PU, PEU, PBC, PF, SN, and INT	United Arab Emirates	280	Automatically	8-1-1	Sigmoid	Sigmoid
Yakubu et al.[23]	SEM-NN	Learning management systems	3:2	INSQ, CQ LV, SI, FC, SYSQ, PU, PEU, BI, and AU	Nigeria	1116	Automatically	5-3-2-1 1-3-2-1	Logistic function	Logistic function
AlHamad[19]	SEM-machine learning	Mobile learning		PU, PEU, ATT, SN, PBC, and INT	United Arab Emirates	489	Automatically			
Shukla[25]	SEM-NN	M-learning	1	CN, AFN, PE, EE, SI, FC, BI, MLUB	India	220	Automatically	5-1-1	Hyperbolic tangent	Identity
Al-Shihi et al.[53]	NN	Mobile learning	1	FLX, SL, EL, ENJL, SUL, and ECL	Oman	388	Automatically	6-1-1	Hyperbolic tangent	Identity
Alshurideh et al.[20]	SEM-machine learning	M-learning systems		PU, PEU, EC, SAT, SI, CI, and AU	United Arab Emirates	448				
Thongsri et al.[22]	SEM-NN	Online learning	1	SDL, ML, OCE, LC, and BI	Thailand	605	Automatically	4-1-1	Hyperbolic tangent	Hyperbolic tangent
Tan et al.[54]	SEM-NN	Mobile learning	1	PU, PEU, PIIT, SI, and BI	Malaysia	214	Automatically	1-1-1 2-1-1 3-1-1	Sigmoid	Sigmoid
Sharma et al.[55]	SEM-NN	E-learning management systems	1	IQ, IU, PI, SERQ, SYSQ, and TE	India	219	Automatically	5-1-1	Hyperbolic tangent	Identity
Akour et al.[21]	SEM-machine learning	Mobile learning platforms		PU, PEU, PF, SN, ATT, PBC, and INT	United Arab Emirates	1880				
Songkram and Chootongchai[27]	SEM-NN	Education as a service	2	PU, PEU, SERQ, SYSQ, and IQ	Thailand	1570	Automatically	4-2-1	Sigmoid function	Sigmoid function
Kumar et al.[24]	Sem-Ramsey's regression equation specification error test	Mobile learning		PU, PEU, ATT, MSE, WU, SN, and BI	Malaysia	171				
Elnagar et al.[56]	SEM NN	E-learning	2	POA, PU, PEU, PR, SE, EJ, and PC	United Arab Emirates	659	Automatically	7-2-1	Sigmoid function	Sigmoid function
Zhang et al.[57]	SEM NN	Mobile learning		CON, AFN, SON, ENN, MLC, and PINT	China	262				

Notes: TAM: Technology Acceptance Model; UTAUT: The Unified Theory of Acceptance and Use of Technology; SEM: Structural Equation Modelling; NN: Neural Network; ATT: Attitude; EC: Expectation Confirmation; PBC: Perceived Behavioral Control; PF: Perceived Fear; SN: Subjective Norm, INT: Intention to Use; SAT: Satisfaction; CI: Continuous Intention; CN: Cognitive Need; AFN: Affective Need; BI: Behavioral Intention; MLUB: M-Learning Use Behavior; EE: Effort Expectancy; PE: Performance Expectancy; SF: Social Factors; FC: Facilitating Conditions; FLX: Flexibility Learning; SL: Social Learning; EL: Efficiency Learning; ENJL: Enjoyment Learning; SUL: Suitability Learning, ECL: Economic Learning; IQ: Instructor Quality; CQ: Course Quality; LV: Learning Value, SI: Social Influence, SYSQ: System Quality, PU: Perceived Usefulness; PEU: Perceived Ease of Use; BI: Behavioral Intentions; AU: Actual Usage; MLC: Mobile Learning Continuance; PINT: Perceived Integration of Online-offline Learning; PIIT: Personal Innovativeness in Information Technology; POA: Post-Acceptance of e-learning technology; PR: Perceived Routine Use; SE: Self Efficiency, PC: Perceived Critical Mass; SDL: Self-Directed Learning, ML: Motivation for Learning; OCE: Online Communication Self-Efficacy; LC: Learner Control; SERQ: Service Quality; TE: Technology Experience; WU: WhatsApp Use; MSE: Mobile-Self Efficacy; SON: Social Need; ENN: Entertainment Need.

As a result of a recent systematic literature review, psychological factors, and student beliefs have a substantial influence on the continued use of mobile learning systems. A model that integrates five different theoretical models is proposed in this study as a solution to this limitation. D&M IS Success Model, TAM, TPB, ECM, and UTAUT2 were integrated. This conceptual framework integrates trust, personal innovativeness, learning value, instructor quality, and course quality.

2.1. Research model

Five different theoretical models, namely TAM, TPB, ECM, D&M IS Success Model, and UTAUT2 were integrated to develop the research model. Also, this conceptual framework integrated trust, personal innovativeness, learning value, instructor quality, and course quality. Both PU and PEU are considered to influence the intention to use mobile learning continuously. In the context of TPB, ATT, PBC, and SN have been found to significantly influence continual intention to use mobile learning. A significant correlation has been found between expectation confirmation in ECM and perceived usefulness and satisfaction, which in turn influence continuous intentions. Regarding the Delone and McLean IS success model (D&M IS Success Model), IQ, SYSQ, and SERQ have been proposed as factors that affect CI to use mobile learning. From the perspective of the UTAUT2, it has been proposed that performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), and habit (HB) has a significant impact on the continuous intention to use m-learning. Furthermore, trust, personal innovativeness, learning value, instructor quality, and course quality influence continuous intention to use mobile learning. A recent systematic review examined m-learning studies. The integration of TAM and ECM. In terms of acceptance of technology and post-adoption behavior, these two theories have been cited most often[58]. Furthermore, continuous intention is considered the key determinant of actual m-learning usage. Several additional factors and hypotheses are presented graphically in **Figure 2**, which were not explicitly presented in **Figure 1**. All these factors have been studied previously, but none have been presented in one paper before.

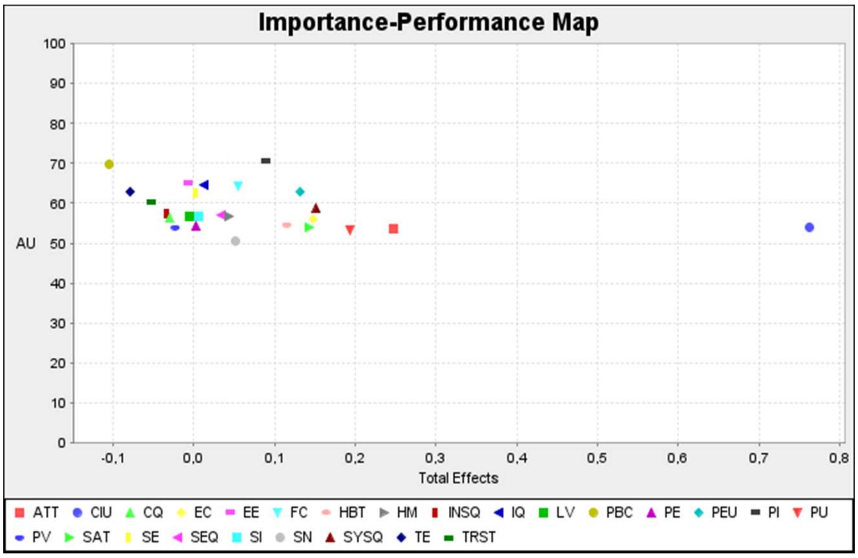

Figure 2. IPMA for AU.

3. Hypotheses development

A review of the most recent literature will enable us to propose a set of hypotheses that address important variables in mobile learning, such as: ATT; CIU; CQ; EC; EE; FC; HBT; HM; INSQ; IQ; LV; PBC; PE; PEOU; PI; PU; PV; SA; SE; SEQ; SI; SN; SYSQ; TE, and TRST. Moreover, we propose the following research model (see **Figure 1**), as a result of reviewing the previous literature described in the preceding sections. Students continued use of mobile learning after COVID 19 was the focus of the following hypotheses.

3.1. Attitude (ATT)

ATT refers to "one's desirability to use the system"[59]. Previous m-learning studies pointed out that ATT has a significant association with CIU[60–62]. We, therefore, propose the following:

H1: ATT positively and significantly influences on CIU.

3.2. Continuous intention to use (CIU)

CIU refers to "users' intention to continue using the information system"[63]. It has been indicated in previous studies that CI has a direct and significant impact on actual use (AU)[64,65]. Therefore, the following hypothesis is suggested:

H2: CIU positively and significantly influences on AU.

3.3. Course quality (CQ)

The output or information that can be received from the system in the form of reports is a significant indicator of its quality[45,66]. The quality of information obtained from an IS system is measured based on "dimensions such as accuracy, completeness, currency, efficiency, relevance, scope, and timeliness of information"[10]. Information quality refers to the quality of report contents and form that obtained from an IS system; its measurement includes "dimensions such as accuracy, completeness, currency, efficiency, relevance, scope and timeliness of information"[10,45,67].

H3: CQ positively and significantly influences on CIU.

3.4. Expectation confirmation (EC)

EC refers to "users' perceptions of the congruence between the expectation of information system usage and its actual performance"[63]. It was revealed in prior m-learning research that there is a significant impact of EC on satisfaction (SA)[68]. Previous research also triggered out that there is a significant relationship between EC and the perceived usefulness (PU) of m-learning[69,70]. Hence, we hypothesize the following:

H4: EC positively and significantly influences on PU.

H5: EC positively and significantly influences on SAT.

3.5. Effort expectancy (EE)

EE is defined as "the degree of ease associated with the use of the system"[35,71]. A person assumes that the utilization of technology would be effortless[72]. Effort expectancy is similar to complexity, ease of use, and perceived ease of use[44]. Previous studies indicated that effort expectancy significantly influences behavioral intention[34,73,74]. Furthermore, this construct is considered an essential determinant of learning behavioral intention to use e-learning systems[35,75–79]. Hence in this study, it was hypothesized that:

H6: positively and significantly influences on CIU.

3.6. Facilitating conditions (FC)

FC is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system"[44]. FC is provided external resources to facilitate the performance of a particular behavior[41]. UTAUT uses three items to capture the facilitating conditions: resources and knowledge, compatibility, and help[44]. Unlike some studies that found an insignificant influence on students' behavioral intention to use[17,80,81]. While some studies found significant relationship[23,82–84]. It was hypothesized that:

H7: FC positively and significantly influences on CIU.

3.7. Habit (HBT)

HBT is defined as "the extent to which people tend to perform behaviors automatically because of learning accumulated from their experience in using certain technology"[71]. According to Venkatesh and Davis[85] habit has been recognized as "an alternative determinant of technology usage along with behavioral intention". HB was found to affect BI toward using certain technology in IS research[86–89] and e-learning[90,91]. Therefore, the following hypothesis is postulated:

H8: HBT positively and significantly influences on CIU.

3.8. Hedonic motivation (HM)

HM is defined as "the fun or pleasure derived from using a technology"[71]. The hedonic motivation was added by Venkatesh et al.[71] to their new model to capture the role of intrinsic utilities. Venkatesh et al.[71] mentioned that the critical influence of hedonic motivation comes from the novelty-seeking and innovativeness existing in using new systems. Theoretically, HM was found to be an influential factor predicting the intention toward the adoption of technology in IS research[34,71,78,87,91,92]. Hence, the following hypothesis is formulated:

H9: HM positively and significantly influences on CIU.

3.9. Instructor quality (INSQ)

The key person's attitude can affect the user's behavior[93] Instructor quality (INSQ) dominates learners' attitudes towards e-learning[94], and this phenomenon reveals that the instructor is the key person that is important to learners' behaviors in the e-learning process. Learners' perceptions regarding an eLearning system are influenced by the quality of the instructor[94]. The instructor "is the key person that is important to learners' behaviors in the e-learning process"[10]. The instructors may play key roles in "learners' e-learning processes, and their teaching style, kindly help, and timely response"[10,94]. Hence, the following hypothesis is formulated:

H10: INSQ positively and significantly influences on CIU.

3.10. Information quality (IQ)

The desired properties of an IS's output are represented by the success dimension content and information quality[95]. The quality of information is frequently cited as a crucial determinant of user satisfaction[96–100], and for intention to use e-learning systems[10,100,101]. Hence, the following hypothesis is formulated:

H11: IQ positively and significantly influences on CIU.

3.11. Learning value (LV)

LV is "the students' positive perceptions about learning from the LMS influencing their intention to devote more time and effort to explore and obtain the required knowledge from the LMS"[11]. Learning value has a positive and substantial impact on students' behavioral intention to use mobile learning[11]. Hence, the following hypothesis is formulated:

H12: positively and significantly influences on CIU.

3.12. Perceive behavioral control (PBC)

PBC refers to "people's perception of the ease or difficulty of performing the behavior of interest"[41]. In previous m-learning research, PBC is found to have a significant impact on CI[60,62,102]. Thus, the following hypothesis is put forward:

H13: PBC positively and significantly influences on CI.

3.13. Performance expectancy (PE)

PE is "the degree to which an individual believes that using the system will help him or her to attain gains in job performance"[44]. Previous studies have found that performance expectancy to be a critical predictor for behavioral intention (BI) e-learning tools[9,35,77,78,100,103]. Hence, it was hypothesized that:

H14: PE positively and significantly influences on CIU.

3.14. Perceived ease of use (PEOU)

PEOU refers to "the degree to which a person believes that using a particular system would be free of effort"[40]. It has been shown in numerous studies conducted earlier that PEOU has a significant association with PU[61,65,104–106]. Furthermore, PEOU can have a stronger impact on the continuous intention (CI) to use m-learning[65,105–107]. Hence, the following hypotheses are suggested:

H15: PEOU positively and significantly influences on CIU.

H16: PEOU positively and significantly influences on PU.

3.15. Personnel innovativeness (PI)

Personal innovativeness is defined "as the form of openness to change"[108]. Personnel innovativeness has a positive and substantial impact on students' behavioral intention to use the mobile learning[51,109]. Therefore, we have proposed that:

H17: PI positively and significantly influences on CIU.

3.16. Perceived usefulness (PU)

PU refers the "the degree to which a person believes that using a particular system would enhance his or her job performance"[40]. Previous research indicated that PU has a significant relationship with SA[65,70]. It was also pointed out that PU is significantly affecting the CI to use m-learning[61,65,70,104,107]. Therefore, the following hypotheses are put forward:

H18: PU positively and significantly influences on CIU.

H19: PU positively and significantly influences on SA.

3.17. Price value (PV)

PV was defined as "a consumer's cognitive trade-off between the perceived benefits of the application and the monetary cost for using it"[35,71]. In other words, the price value is positive when the benefits of adopting a certain system are perceived to be greater than the monetary cost. Price value was found to have a positive effect on BI toward adopting certain technology in IS research[35,79], as well as in e-learning[90,91]. Accordingly, this study proposes the following hypothesis:

H20: PV positively and significantly influences on CIU.

3.18. Satisfaction (SA)

SA refers to "the affective attitude towards a particular computer application by an end user who interacts with the application directly"[110]. Several m-learning studies triggered out that SA has a significant impact on CI[65,69,70,102,111]. Hence, the following hypothesis is formulated:

H21: SA positively and significantly influences on CI.

3.19. Self-efficacy (SE)

SE was defined as "individuals' judgments about their capabilities to organize and execute the courses of action required to produce given attainments"[112]. In the social cognitive theory (SCT), self-efficacy is a type of self-assessment that helps the understanding of human behavior and performance in a certain task[113]. In the context of IT, self-efficacy has been defined as "an individual's perceptions of his or her ability to use computers in the accomplishment of a task rather than reflecting simple component skills"[114]. Prior studies have found self-efficacy to be a critical predictor that directly affects the user's behavioral intention[115,116] and e-learning adoption[117,118]. On the contrary, Venkatesh et al.[44] did not find a casual direct relationship between self- efficacy and behavioral intention. Hence, the following hypothesis is formulated:

H22: SE positively and significantly influences on CIU.

3.20. Service quality (SEQ)

SEQ is the "desirable characteristics of the system outputs; that is, management reports and Web pages. For example relevance, understandability, accuracy, conciseness, completeness, understandability, currency, timeliness, and usability"[119]. Service quality has been found to have a significant positive effect on satisfaction in the e-learning context[98,100,120–122], and on intention to use e-learning systems in some studies[96,100,101,123]. Therefore, it was hypothesized that:

H23: SEQ positively and significantly influences on CIU.

3.21. Social influence (SI)

SI is defined as "is defined as the degree to which an individual perceives that important others believe he or she should use the new system". Subjective norms, social factors, and images are all used by UTAUT to establish social influence[44]. In literature, social influence had been considered to have a significant relationship with intentions across various fields of application[106,124,125] but Tan et al.[54] findings deviated from the general belief with an insignificant relationship. It was hypothesized that:

H24: SI positively and significantly influences on CIU.

3.22. Subjective norms (SN)

SN refers to "the perceived social pressure to perform or not to perform the behavior"[41]. Previous studies in m-learning pointed out that SN has a significant effect on CI[126,127]. Hence, the following hypothesis is proposed:

H25: SN positively and significantly influences on CI.

3.23. System quality (SYSQ)

The degree of functionality of an educational system is measured by its system quality[45]. It is the "desirable characteristics of an information system, i.e ease of use, system flexibility, system reliability and ease of learning, as well as system features of intuitiveness, sophistication, flexibility and response times"[119]. Technical system quality has been found to have a significant positive effect on satisfaction in the e-learning context[96,97,99,100,121,128], and on intention to use e-learning system[10,100,101,123]. Hence, the following hypothesis is formulated:

H26: SYSQ positively and significantly influences on CIU.

3.24. Technology experience (TE)

It is stated that "prior experience in technology is the key antecedent in the acceptance of a new technology"[44]. Technology experience is found to have a significant impact on CIU[44,55]. Hence, the following hypothesis is formulated:

H27: TE positively and significantly influences on CIU.

3.25. Trust (TRST)

Trust was defined as "individual willingness to depend based on the beliefs in ability, benevolence, and integrity"[129]. Trust means a subjective expectation that someone or something is reliable and willing to accept vulnerability[130]. The particular interest in this construct could be attributed to the high uncertainty, intangibility, heterogeneity, and vagueness characterized by using the Internet and technologies[129]. Therefore, adding trust will complement the existing factors of the UTAUT2 and is expected to have a direct influence on behavioral intention toward using e-learning[78,131]. Hence, the following hypothesis is formulated:

H28: TRST positively and significantly influences on CIU.

4. Methodology

4.1. Measure of constructs

A convenient sampling technique was used to achieve the research's purpose[107,132]. To collect research data, validated items from existing studies were used as the basis of a self-administered questionnaire survey measured by a five-point Likert scale. **Table 1** contains all cited items.

4.2. Data collection and respondent profile

Because of the COVID-19 pandemic, an online questionnaire survey was utilized instead of face-to-face consultations to minimize the risk of health issues. Google Forms, the most popular online survey tool, was used to create and distribute the questionnaire. Effective responses exceed the requirement of a minimum sample size of 238 calculated by G*Power (Version 3.1.9.2) with a 0.95 power level, 0.05 alpha value, 0.15 impact size, and 25 predictors. The overall response rate was much higher than the minimum recommended sample size of 250. SEM analysis can be performed despite the modest size of the sample[133]. In Bentler and Chou[134], as well as Hair et al.[135], ten times the minimum threshold is recommended as a minimum size for such a study. Next, a pilot test is conducted to determine the scale's reliability and validity. Participants were asked to read the instructions section of the questionnaire before filling out the questionnaire to acknowledge confidentiality and declare the survey purpose.

Two sections were included in the online questionnaire. An anonymous profile of participants was collected in section one including their gender, age, and educational background. Second, a 5-point Likert scale was used to gather participants' opinions about mobile learning. In general, the demographic profile of respondents, females accounted for (60.5%) of the total sample, while male respondents (39.5%) of the total responses. Most of the respondents are between the ages of 21–30 (85.2%) and had either an undergraduate degree (84%) or vocational schools (8.6%).

5. Data analysis

5.1. Statistical analysis

This study employs deep learning-based dual-stage PLS-SEM and ANN methods to analyze the data as opposed to the existing literature that uses only structural equation modeling (SEM)[30,33]. PLS results will be used to rank significant variables based on the results of a deep learning-based hybrid approach. A PLS-SEM analysis will begin by testing hypotheses using the two-stage method (outer and inner models) recommended by Hair et al.[136]. As part of the second phase, researchers conduct sensitivity analyses to rank variables using ANN.

5.2. Common method variance (CMV)

CMV must be excluded from our study since the measuring scales were self-reported. All twenty-six constructs were first tested with Harman's single-factor analysis to ensure they were free of CMV[137]. Based on these findings, a single component explains only 28.92% of the variance, which indicates that no evidence for CMV has been found[137]. The variance inflation factors (VIFs) have been calculated as a result of the collinearity test. Multicollinearity is not a problem since the VIF is values under the threshold of 5[138,139].

5.3. Assessing the outer measurement model

A PLS-SEM analysis will begin by testing hypotheses using the two-stage method (outer and inner models) recommended by Hair et al.[136].

5.4. Measurement model results

From **Table 2**, convergent validity for all measurement model construct reliability were above the threshold value. Composite reliability (CR), Cronbach's alpha (α), and Djikstra Rhomba (rhoA) were above 0.7[140]. Except one item (PI2), the loadings of each item were above than the recommended value of >0.708[140]. From **Table 2**, average variance extracted (AVE) values exceeded the threshold values 0.5[140]. Thus, it appears that the data has no issues of convergent validity and reliability.

Table 2. Measurement model.

Construct	Variable	Loading	A	rho_A	CR	AVE	VIF	Sources
ATT	ATT1	0.925	0.920	0.920	0.949	0.862	3.271	Cheon et al.[60]; Davis[40]
	ATT2	0.932					3.476	
	ATT3	0.927					3.288	
AU	AU1	0.893	0.911	0.913	0.937	0.789	2.932	Ajzen and Fishbein[39]; Mohammadi[104]; Venkatesh et al.[44]
	AU2	0.895					3.146	
	AU3	0.872					2.445	
	AU4	0.893					2.967	
CIU	CIU1	0.894	0.947	0.950	0.958	0.792	3.675	Bhattacherjee[63]; Liaw and Huang[141]
	CIU2	0.928					5.148	
	CIU3	0.817					2.317	
	CIU4	0.929					5.584	
	CIU5	0.933					5.805	
	CIU6	0.830					2.438	
CQ	CQ1	0.796	0.871	0.875	0.906	0.659	1.843	Cheng[10]; Yakubu et al.[23]
	CQ2	0.804					1.977	
	CQ3	0.833					2.187	
	CQ4	0.817					2.080	
	CQ5	0.808					1.780	
EC	EC1	0.909	0.922	0.923	0.951	0.865	2.839	Bhattacherjee[63]; Liaw and Huang[141]
	EC2	0.947					4.531	
	EC3	0.934					3.847	

Table 2. (*Continued*).

Construct	Variable	Loading	A	rho_A	CR	AVE	VIF	Sources
EE	EE1	0.932	0.934	0.938	0.953	0.835	4.444	Venkatesh et al.[44]; Venkatesh et al.[71]
	EE2	0.899					3.164	
	EE3	0.931					4.036	
	EE4	0.891					3.282	
FC	FC1	0.842	0.918	0.920	0.936	0.708	2.716	Venkatesh et al.[44]; Venkatesh et al.[71]
	FC2	0.827					2.844	
	FC3	0.863					2.977	
	FC4	0.838					2.419	
	FC5	0.861					3.531	
	FC6	0.818					3.043	
HBT	HBT1	0.899	0.921	0.922	0.944	0.808	3.188	Venkatesh et al.[71]
	HBT2	0.870					2.533	
	HBT3	0.898					3.040	
	HBT4	0.928					4.024	
HM	HM1	0.870	0.899	0.912	0.930	0.769	2.635	Venkatesh et al.[71]
	HM2	0.917					3.685	
	HM3	0.786					2.038	
	HM4	0.927					3.978	
INSQ	INSQ1	0.864	0.919	0.921	0.939	0.755	2.549	Cheng[10]; Lwoga[12]; Yakubu et al.[23]
	INSQ2	0.884					2.903	
	INSQ3	0.855					2.546	
	INSQ4	0.875					2.937	
	INSQ5	0.867					2.792	
IQ	IQ1	0.845	0.864	0.876	0.907	0.709	2.010	Delone and McLean[45]; Sharma et al.[55]
	IQ2	0.861					2.024	
	IQ3	0.837					2.182	
	IQ4	0.824					2.089	
LV	LV1	0.830	0.915	0.918	0.937	0.747	2.243	Ain et al.[11]; Yakubu et al.[23]
	LV2	0.867					2.679	
	LV3	0.909					3.736	
	LV4	0.886					3.125	
	LV5	0.828					2.181	
PBC	PBC1	0.912	0.903	0.903	0.939	0.837	2.851	Cheon et al.[60], Davis[40]
	PBC2	0.920					2.952	
	PBC3	0.912					2.782	
PE	PE1	0.869	0.933	0.937	0.949	0.788	2.845	Venkatesh et al.[44]; Venkatesh et al.[71]
	PE2	0.895					3.322	
	PE3	0.829					2.312	
	PE4	0.929					5.088	
	PE5	0.914					4.410	
PEU	PEU1	0.894	0.938	0.940	0.953	0.801	3.804	Davis[40]
	PEU2	0.906					3.770	
	PEU3	0.898					3.644	
	PEU4	0.905					3.774	
	PEU5	0.872					2.904	
PI	PI1	0.926	0.904	0.907	0.940	0.837	3.073	Al-Busaidi[142]; Al-Busaidi[143]; Sharma et al.[55]; Schillewaert et al.[144]
	PI2*	0.682						
	PI3	0.919					3.121	
	PI4	0.903					2.622	
PU	PU1	0.933	0.953	0.954	0.964	0.843	5.147	Davis[40]
	PU2	0.927					4.998	
	PU3	0.930					5.156	
	PU4	0.920					4.293	
	PU5	0.881					3.185	

Table 2. (*Continued*).

Construct	Variable	Loading	Α	rho_A	CR	AVE	VIF	Sources
PV	PV1	0.823	0.854	0.864	0.901	0.696	2.533	Venkatesh et al.[71]
	PV2	0.883					2.942	
	PV3	0.816					2.638	
	PV4	0.811					2.575	
SAT	SAT1	0.936	0.911	0.915	0.944	0.850	4.461	Bhattacherjee[63]; Liaw and Huang[141]
	SAT2	0.949					4.916	
	SAT3	0.878					2.276	
SE	SE1	0.888	0.896	0.897	0.929	0.767	3.188	Zhang et al.[145]; Kim and Niehm[146];Tarhini et al.[78]
	SE2	0.912					3.602	
	SE3	0.924					4.360	
	SE4	0.770					1.617	
SEQ	SEQ1	0.885	0.890	0.892	0.924	0.752	2.692	Delone and McLean[45]; Sharma et al.[55]
	SEQ2	0.855					2.307	
	SEQ3	0.862					2.469	
	SEQ4	0.866					2.516	
SI	SI1	0.931	0.886	0.887	0.930	0.815	3.888	Venkatesh et al.[44]
	SI2	0.866					1.935	
	SI3	0.910					3.499	
SN	SN1	0.924	0.922	0.923	0.951	0.866	3.170	Ajzen and Fishbein[39]; Ajzen[41]; Cheon et al.[60]
	SN2	0.927					3.419	
	SN3	0.940					3.916	
SYSQ	SYSQ1	0.737	0.841	0.853	0.887	0.611	1.676	Delone and McLean[45]; Lwoga[12]; Sharma et al.[55]; Yakubu et al.[23]
	SYSQ2	0.751					1.691	
	SYSQ3	0.785					1.912	
	SYSQ4	0.792					2.024	
	SYSQ5	0.840					1.963	
TE	TE1	0.925	0.909	0.909	0.943	0.846	3.237	Al-Busaidi[142]; Sharma et al.[55]; Wan, and Fang[147]
	TE2	0.902					2.606	
	TE3	0.932					3.560	
TRST	TRST1	0.900	0.926	0.929	0.947	0.817	2.964	Venkatesh et al.[71]
	TRST2	0.909					3.268	
	TRST3	0.904					3.490	
	TRST4	0.903					3.321	

Note: * Deleted item; α: Cronbach's alpha; CR: Composite reliability: rhoA: Djikstra Rhomba; AVE: Average variance extracted; VIF: Variance inflated factor.

Discriminant validity comprises Fornell–Larcker, HTMT, and cross-loading. There is evidence of alignment of the Fornell-Larker condition with the AVEs and their square roots. It has a greater correlation between AVEs and their square roots[148]. Lastly, HTMT values for this study are below 0.9, indicating no lack of discrimination[135,149]. A discriminant validity conclusion can be drawn based on the results. The assessment of the measurement model found no problems related to validity or reliability. Therefore, structural models can be assessed and analyzed using the collected data.

5.5. Structural model assessment

Additionally, the authors also conducted tests the good fitness of the structural model by applying the root mean squared residual covariance matrix (RMStheta) ≤0.12, normed fit index (NFI) ≥0.90, and the standardized root mean square residual (SRMR) ≤0.08[140,150,151]. Finally, the study computed goodness of ft (GOF)[152]. The GOF of this study is 0.77, which indicates the model is effective and fits the data satisfactorily[153].

The bootstrapping procedure was utilized with 5000 subsamples to test the structural model. **Table 3** and **Figure 1** depict that of the 28 hypotheses proposed in the model, fourteen of the hypotheses were significant; the remaining fourteen hypotheses, however, were not significant. The structural model also explained for

88%, 68%, 68%, and 79 % of the variance in CIU, AU, PU, and SAT, respectively (see **Table 4**). R^2 value is 0.26, 0.13, and 0.02, indicating substantial, moderate, or weak levels of predictive accuracy, respectively[153]. Regarding the effect size f^2 and effects size q^2, 0.02, 0.15, and 0.35 represent small, medium, and large effects respectively. A value below 0.02 indicates that no effect has been observed[140,154,155]. **Table 4** and **Table 5** report the predictive relevance of the study (Q^2) and effect sizes (f^2 and q^2). Furthermore, we evaluated the model's predictive power using PLS predict[136,156]. There is a significant difference between the RMSE of the linear procedure and the RMSE of the naive linear procedure (**Table 4**). Consequently, Hair et al.[140] conclude that the empirical model is highly predictive.

Table 3. Hypothesis testing.

PLS path	*t*-value	Path coefficients	f^2	q^2
ATT -> CIU***	4.130	0.000	0.64	0.04
CIU -> AU***	36.051	0.000	-	-
CQ -> CIU	0.502	0.615	0.07	0
EC -> PU***	5.585	0.000	0.25	0.14
EC -> SAT***	6.559	0.000	0.6	0.17
EE -> CIU	0.116	0.908	2.22	0
FC -> CIU	0.960	0.337	0.28	0
HBT -> CIU**	2.223	0.026	0.04	0.01
HM -> CIU	0.993	0.321	0	0
INSQ -> CIU	0.718	0.473	0.19	0
IQ -> CIU	0.239	0.811	0.13	0
LV -> CIU	0.086	0.931	–0.55	0
PBC -> CIU**	2.073	0.038	0.67	0.01
PE -> CIU	0.032	0.974	–1.88	0
PEU -> CIU	0.674	0.500	2.1	0
PEU -> PU***	5.327	0.000	0.16	0.12
PI -> CIU**	2.078	0.038	1.4	0.01
PU -> CIU**	1.987	0.047	0	0.01
PU -> SAT***	8.517	0.000	0.82	0.28
PV -> CIU	0.622	0.534	0.07	0
SAT -> CIU***	2.903	0.004	0.13	0.01
SE -> CIU	0.029	0.977	0.1	0
SEQ -> CIU	0.699	0.485	0	0
SI -> CIU	0.153	0.878	0	0
SN -> CIU	1.128	0.259	0.04	0
SYSQ -> CIU***	3.045	0.002	0.07	0.02
TE -> CIU*	1.914	0.056	0.1	0.01
TRST -> CIU	1.225	0.221	0	0

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. f^2: effect size; q^2: effect size.

Table 4. PLS predict results.

Construct	PLS-SEM			Linear model benchmark	
	RMSE	MAE	Q²_predict	RMSE	MAE
AU	0.901	0.734	0.562	1.09	0.806

Table 5. Quality of structural model.

Endogenous constructs	Q²	R^2 (%)
ATT		
AU	0.526	0.68
CIU	0.679	0.88
CQ		
EC		
EE		
FC		
HBT		
HM		
INSQ		
IQ		
LV		
PBC		
PE		
PEU		
PI		
PU	0.562	0.68
PV		
SAT	0.666	0.79
SE		
SEQ		
SI		
SN		
SYSQ		
TE		
TRST		

Q^2: predictive relevance; R^2: coefficient of determination.

5.6. Importance performance map analysis

The Importance-performance map analysis (IPMA) was utilized as a post-hoc PLS analysis to detect the constructs that have high importance in the targeted variables yet underperform[157]. Results from **Table 6** and **Figure 2** depict that the highest importance is CIU (0.76), ATT (0.25), PU (0.19), SYSQ (0.15), and SAT (0.14). On performance, PI (70.70) indicates the highest performance, followed by, PBC (69.76), EE (65.09), IQ (64.55), FC (64.18), and TE (62.85).

Table 6. Importance performance map results.

Latent variables	Importance (total effect)	Performance (index value)
ATT	0.247	53.475
CIU	0.762	54.042
CQ	–0.030	56.294
EC	0.148	56.020
EE	–0.007	65.091
FC	0.055	64.181
HBT	0.115	54.610
HM	0.044	56.760
INSQ	–0.035	57.521
IQ	0.012	64.548
LV	–0.006	56.724
PBC	–0.105	69.756
PE	0.002	54.397
PEU	0.132	62.848
PI	0.089	70.707
PU	0.193	53.385
PV	–0.023	53.910
SAT	0.143	54.024
SE	0.001	62.458
SEQ	0.033	57.057
SI	0.006	56.894
SN	0.051	50.524
SYSQ	0.151	58.642
TE	–0.080	62.849
TRST	–0.053	60.336

6. Artificial neural network (ANN)

To identify nonlinear relationships between the variables, ANN analysis was also used in the present study. The ANN only used significant factors from the PLS-SEM results. Nonlinear relationships cannot be captured by the PLS-SEM structural equation model, despite its robustness for non-normal distributions. To capture linear and nonlinear relationships, neural network algorithms do not require a normal distribution[158]. Our nonlinear analysis and prediction were therefore based on ANNs. Haykin[159] states that "massively parallel distributed processor made up of simple processing units, which have a neural propensity for storing experimental knowledge and making it available for use"[159]. ANNs use a deep learning architecture built with dual layers that provide in-depth estimation results[33,34]. A non-normal distribution of exogenous and endogenous data supports the application of ANNs as well as the existence of non-linear relationships. ANN provides the researcher with several benefits: it addresses the linearity and nonlinearity among the predictors, prioritizes the factors based on their relative importance, and learns by input-output mapping[160]. A robust ANN is also resistant to outliers, noise, and small samples. Compared to other regression methods, ANN tends to have greater prediction accuracy[37,161].

6.1. Validation of ANN

IBM's SPSS neural network module was used to implement the ANN analysis. For activation functions and outcome layers, sigmoid functions were used. It is possible to reduce faults and increase prediction accuracy by implementing several phases of the learning procedure. Owing to the complexity of the models and several outputs, the current research model has been further sub-divided into four ANN models. For instance, Model 1 (output-CIU) contains nine input neurons: PI, PU, SAT, SYSQ, TE, ATT, HBT, PBC, and PEU. Model 2 (output-PU) contains two input neurons: EC and PEU. Model 3 (output-SAT) contains two input neurons: EC and PU. Finally, Model 4 (output-AU) has only one input neuron: CIU.

We applied 10-fold cross-validating technique to evade the possibility of over-fitting with 90% data for training and the remaining 10% of the data for testing, respectively[162]. Root Mean Square Error (RMSE) was used to measure the accuracy of the ANN model. As depicted in **Table 7**, the values of RMSE are found to be relatively low of the training and testing procedures, respectively.

Table 7. RMSE values for CIU, PU, SAT, and AU.

		Model 1 (R^2 = 92%)						**Model 2 (R^2 = 85%)**						**Model 3 (R^2 = 88 %)**						**Model 4 (R^2 = 86%)**				
		Input neurons: PI. PU. SAT. SYSQ. TE. ATT. HBT. PBC						Input neurons: EC. PEU						Input neurons: EC. PU			Input neurons: CIU							
		Output nodes: CIU						Output nodes: PU						Output nodes: SAT			Output nodes AU							
		Training			**Testing**			**Training**			**Testing**			**Training**			**Testing**			**Training**			**Testing**	
Neural network	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**
1	226	1.754	0.088	24	0.174	0.085	218	4.312	0.141	32	0.257	0.090	221	2.506	0.106	29	0.334	0.107	224	3.402	0.123	26	0.490	0.137
2	225	1.826	0.090	25	0.110	0.066	223	4.466	0.142	27	0.507	0.137	225	2.960	0.115	25	0.235	0.097	218	3.817	0.132	32	0.380	0.109
3	226	1.738	0.088	24	0.211	0.094	213	3.809	0.134	37	0.759	0.143	221	2.389	0.104	29	0.303	0.102	225	3.735	0.129	25	0.301	0.110
4	232	1.809	0.088	18	0.156	0.093	226	4.358	0.139	24	0.531	0.149	222	2.633	0.109	28	0.321	0.107	220	3.435	0.125	30	0.525	0.132
5	234	1.992	0.092	16	0.102	0.080	219	4.154	0.138	31	0.484	0.125	224	2.903	0.114	26	0.336	0.114	227	3.407	0.123	23	0.450	0.140
6	218	1.728	0.089	32	0.246	0.088	220	4.114	0.137	30	0.521	0.132	228	2.422	0.103	22	0.443	0.142	225	3.508	0.125	25	0.260	0.102
7	230	2.327	0.101	20	0.064	0.057	230	4.370	0.138	20	0.380	0.138	220	3.108	0.119	30	0.328	0.105	219	3.364	0.124	31	0.516	0.129
8	226	1.836	0.090	24	0.129	0.073	219	4.193	0.138	31	0.435	0.118	228	2.730	0.109	22	0.225	0.101	227	3.587	0.126	23	0.383	0.129
9	235	2.037	0.093	15	0.066	0.066	223	4.190	0.137	27	0.704	0.161	217	2.421	0.106	33	0.372	0.106	228	3.444	0.123	22	0.298	0.116
10	224	2.006	0.095	26	0.108	0.064	224	4.950	0.149	26	0.494	0.138	223	2.605	0.108	27	0.220	0.090	225	3.585	0.126	25	0.310	0.111
Mean		1.905	0.091		0.137	0.077		4.292	0.139		0.507	0.133		2.668	0.109		0.312	0.107		3.528	0.126		0.391	0.122
SD		0.187	0.060		0.004	0.013		0.294	0.004		0.144	0.019		0.251	0.005		0.070	0.014		0.152	0.003		0.099	0.013

6.2. Sensitivity analysis

Table 8 depicts the power of predictors in ANN models. The results indicate that ATT had the strongest power in predicting CIU, followed by PU. On the other hand, PEU exhibits the strongest prediction of PU, followed by EC. Also, PU exhibits the strongest prediction of SAT, followed by EC. Lastly, since CIU is the only predictor for AU. The normalized importance of the predictor is 100%. As depicted in **Figures 3–6**, the four ANN models were used in the sensitivity analysis.

Table 8. Sensitivity analysis for ANN Model 1, 2, and 3.

	ANN model 1 (output neuron: CIU)							ANN model 2 (output neuron: PU)			ANN model 3 (output neuron: SAT)		ANN model 4 (output neuron: AU)
Neural network	**PI**	**PU**	**SAT**	**SYSQ**	**TE**	**ATT**	**HBT**	**PBC**	**EC**	**PEU**	**EC**	**PU**	**CIU**
1	0.059	0.210	0.208	0.058	0.023	0.226	0.209	0.008	0.516	0.484	0.463	0.537	1.000
2	0.058	0.162	0.167	0.156	0.056	0.242	0.095	0.067	0.538	0.462	0.406	0.594	1.000
3	0.067	0.211	0.121	0.106	0.043	0.236	0.161	0.052	0.552	0.448	0.432	0.568	1.000
4	0.018	0.196	0.198	0.121	0.066	0.225	0.141	0.036	0.421	0.579	0.452	0.548	1.000
5	0.048	0.171	0.169	0.085	0.053	0.267	0.145	0.062	0.455	0.545	0.399	0.601	1.000
6	0.027	0.207	0.203	0.084	0.058	0.250	0.166	0.005	0.471	0.529	0.426	0.574	1.000
7	0.013	0.220	0.249	0.026	0.067	0.302	0.092	0.031	0.432	0.568	0.407	0.593	1.000
8	0.075	0.271	0.119	0.15	0.027	0.252	0.046	0.061	0.489	0.511	0.406	0.594	1.000
9	0.087	0.133	0.242	0.082	0.070	0.171	0.160	0.055	0.468	0.532	0.361	0.639	1.000
10	0.050	0.254	0.151	0.048	0.031	0.208	0.231	0.027	0.585	0.415	0.430	0.570	1.000
Average relative importance	0.050	0.204	0.183	0.092	0.049	0.238	0.144	0.040	0.493	0.507	0.418	0.582	
Normalized relative importance (%)	21%	85%	77%	38%	21%	100%	61%	17%	97%	100%	72%	100%	100%

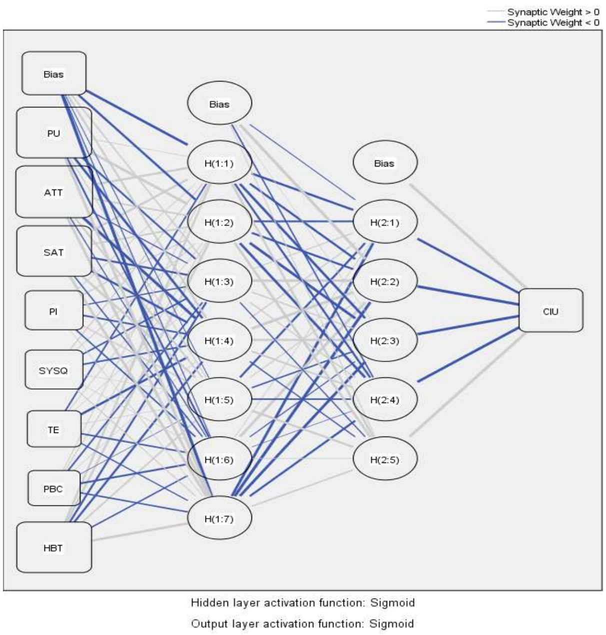

Figure 3. ANN model 1.

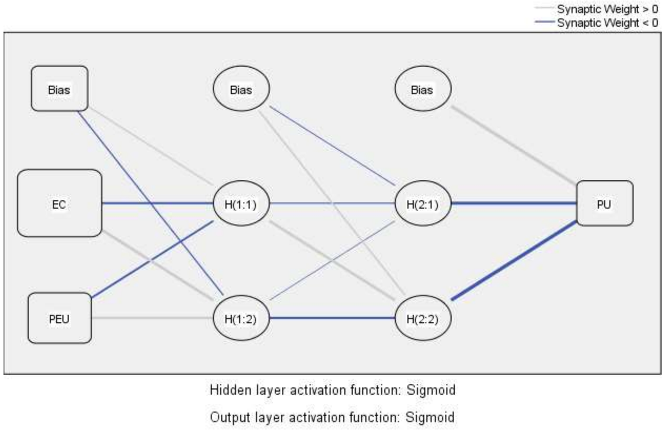

Figure 4 ANN model 2.

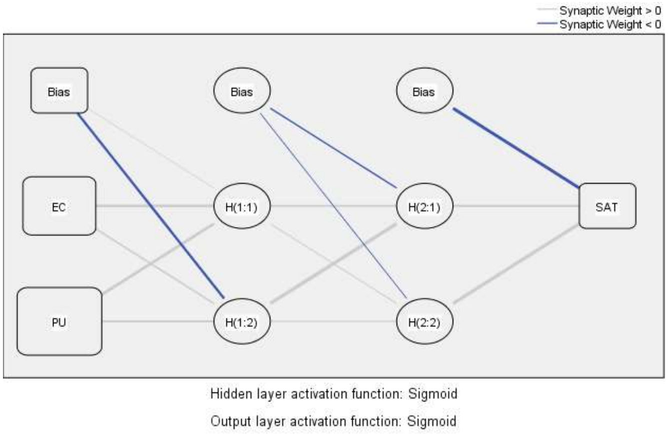

Figure 5. ANN model 3.

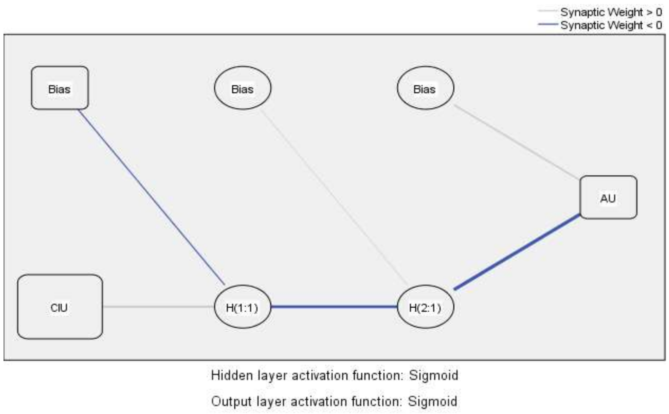

Figure 6. ANN model 4.

From the average synaptic weights of the input neurons in the tenfold neural network depicted in **Table 9**, it was found that attitude was the predictor with the greatest contribution, followed by satisfaction, perceived usefulness, and system quality. On the other hand, inhibitory hidden neurons H(2:1), H(2:2), H(2:3), H(2:4), and H(2:5) make up the five hidden neurons, with H(2:3) being the most inhibitory of all. Finally, we computed the goodness-of-fit index of the ANN models Lee et al.[30], Akgül and Uymaz[33]. This is similar to R^2 in SEM. The results reveal that the ANN models predict continuance intention with an accuracy of 92 %, PU (R^2:85%), SAT (R^2: 88%), and AU (R^2: 86%). This indicates that the ANN analysis represents endogenous constructs better than the PLS-SEM analysis since the R^2 value in the ANN analysis is higher. ANNs are capable of capturing non-linear relationships, which is largely due to the two-hidden-layer deep learning architecture.

Table 9. Average synaptic weights of the input and hidden neurons in the ten-fold ANN.

Parameter estimates															
Predictor		**Predicted**													
		Hidden layer 1							**Hidden layer 2**					**Output layer**	**Total contribution**
		H(1:1)	**H(1:2)**	**H(1:3)**	**H(1:4)**	**H(1:5)**	**H(1:6)**	**H(1:7)**	**H(2:1)**	**H(2:2)**	**H(2:3)**	**H(2:4)**	**H(2:5)**	**CIU**	
Input layer	(Bias)	0.574	–0.127	–0.378	–0.383	1.312	–0.033	–0.084							2.889
	HBT	–0.722	0.355	1.097	1.608	–0.273	–0.615	0.310							4.981
	PBC	0.019	0.525	1.120	1.777	0.822	0.357	0.590							5.210
	PEU	–0.080	0.705	0.888	1.612	–0.064	–0.513	0.436							4.297
	PI	–0.111	–0.115	0.548	1.511	–0.179	–0.064	0.564							2.863
	SYSQ	–0.196	0.382	0.883	1.730	–0.709	–0.825	0.861							5.586
	TE	0.547	0.613	0.407	2.022	0.318	0.024	0.311							4.242
	PU	–0.513	0.047	1.159	2.347	–0.605	–0.781	0.822							6.274
	SAT	–1.057	0.429	1.426	1.864	–0.654	–0.598	0.397							6.425
	ATT	–1.147	0.565	1.451	2.495	–1.006	–0.411	0.590							7.665
Hidden layer 1	(Bias)								–0.292	–0.451	–0.774	–0.234	0.444		
	H(1:1)								–1.058	–0.856	0.783	–3.508	1.253		
	H(1:2)								–1.553	–0.955	0.203	–5.752	2.050		
	H(1:3)								0.615	0.354	–1.458	2.100	–0.311		
	H(1:4)								0.363	0.556	–1.277	–1.434	0.053		
	H(1:5)								0.374	–0.205	–0.829	6.963	–1.508		
	H(1:6)								0.218	–0.278	–0.924	3.385	–0.295		
	H(1:7)								0.606	0.710	–0.747	2.780	–0.363		
Hidden layer 2	(Bias)													0.275	
	H(2:1)													5.209	
	H(2:2)													7.645	
	H(2:3)													–9.310	
	H(2:4)													–5.400	
	H(2:5)													–2.589	

The path coefficient and normalized relative importance are shown in **Table 10**. PLS-SEM and ANN models 1 and 2 results were inconsistent, except for ANN model 3 and 4. **Table 10** compares the results obtained by PLS-SEM and ANN. ANN and PLS-SEM were consistent in their results in terms of attitude as the biggest factor of continuous intention. There may be a difference because ANNs are better suited for capturing nonlinear relationships than other machine learning tools. There were only one or two predictors in both ANN models 3 and 4.

Table 10. Comparison between PLS-SEM and ANN results.

PLS path	Path coefficient	ANN results: normalized relative importance (%)	Ranking (PLS-SEM) [based on path coefficient]	Ranking (ANN) [based on normalized relative importance	Remark not match	RMSE (ANN)	RMSE (PLS-SEM)	ANN regression prediction	PLS-SEM regression prediction
Model 1 (Output: CIU)						0.077	0.43	92%	88%
PU -> CIU	0.17	85.49	3	2	not match				
ATT -> CIU	0.34	100	1	1	match				
SAT -> CIU	0.18	76.68	2	3	not match				
PI -> CIU	0.10	20.99	6	7	not match				
SYSQ -> CIU	0.16	38.46	4	5	not match				
TE -> CIU	-0.10	20.69	7	6	not match				
PBC -> CIU	-0.12	16.90	8	8	not match				
HBT -> CIU	0.15	60.58	5	4	not match				
Model 2 (Output: PU)						0.133	0.58	85%	68%
EC -> PU	0.45	97	1	2	not match				
PEU -> PU	0.42	100	2	1	not match				
Model 3 (Output: SAT)						0.107	0.54	88%	79%
EC -> SAT	0.41	72	2	2	match				
PU -> SAT	0.53	100	1	1	match				
Model 4 (Output: AU)						0.122	0.54	86%	68%
CIU -> AU	0.82	100	1	1	match				

The final step was to compare the PLS-SEM and ANN regression results according to the path coefficient strength and normalized relative importance ranking. An R^2 value indicating how well the predicted value matches the true value was used. ANN is found to have a higher R^2 than PLS-SEM according to **Table 10**. The prediction accuracy of ANN is high because it measures both linear and nonlinear relationships between variables[29,33,163,164]. Root means square error is the square root of the deviation between the observed value and the true value, divided by the square root of n, which is used to measure deviations between the observed value and the true value. PLS-SEM deviates more from ANN regression as depicted in **Table 10**. Using the SEM-ANN two-stage method, this paper provides further evidence of the effectiveness of the SEM-ANN two-stage method in predicting continuous mobile learning intentions.

7. Discussion

Mobile learning's continued use after COVID-19 is influenced by several factors. This is one of the few studies to attempt to integrate the literature to study the drivers of continuous intention. This integrated model combines the TAM, TPB, ECM, and D&M IS Success Models. Extending the UTAUT2 incorporated trust, personal innovation, learning value, instructor quality, and course quality to create a new relationship.

EC strongly influenced satisfaction and perceived usefulness with mobile learning. This research is also not aligned with prior studies' findings such as Al-Emran et al.[14]; Chen et al.[68]; Hong et al.[69]; Joo et al.[65]; Kim[102]; Oghuma et al.[70]. This outcome may be explained by the fact that students will surely behave better and be more pleased with m-learning systems when their expectations of m-learning benefits are confirmed. Providing mobile learning systems with the benefits students expect will increase their performance and satisfaction.

PEU, on the other hand, is empirically confirmed to have a crucial positive interaction, with PU as theorized. This study confirms previous results on mobile learning[14,15,61,65,104,105]. Surprisingly, our finding indicates that CIU is not significantly influenced by PEU. The latest studies' findings appear to be in contradiction with earlier findings[14,23,65,105,106,126]. The mobile learning platform may improve the performance and willingness of students to utilize it if they are convinced of its usefulness. To improve students' performance and satisfaction with these systems, developers, and designers need to place even more emphasis on these characteristics.

Similarly, this study reveals that perceived usefulness is important for ongoing intention[65,68,70,102,105,126,165,166]. PU contributes greatly to satisfaction, as previously demonstrated in other studies[15,65,68,70,104,167]. Having an m-learning system that improves students' performance might cause them to be more satisfied as a result of the experiential association between these two aspects.

The research findings also demonstrated that ATT and PBC have a significant impact on the continuing desire to utilize mobile learning. The findings are aligned with prior researches such as Cheon et al.[60]; Yadegaridehkordi et al.[61]; Yeap et al.[62]; Al-Emran et al.[14], PBC[60,62,102]. Regarding the relationship between SN and CIU, the results contradict[14,126,127]. Continuous intention (CIU) and actual usage (AU) are strongly correlated. This research therefore confirms CIU as a positive and significant factor in actual m-learning use, as earlies studies have shown[14,23,64,65]. It was found that, during the trial period, mobile learning had no effect on students' intentions to use it in educational activities, whether they had a positive or negative experience.

This study depicts that the quality of courses, instructors, and information can negatively affect continuous intention, as compared to previous studies[23]. Previous studies have indicated that instructors' attitudes impact learners' adoption of e-learning[10,94,96,104,120,121,168]. Service quality positively and significantly influences continuous intention. Previous studies have also reached similar conclusions[15]. There is a significant influence of system quality on continuous intention in several m-learning studies. Previous studies have confirmed the current results[10,23,100,101].

As a result, this study shows that students perceive mobile learning as satisfactory and compatible with their ongoing intentions when technology is perceived as satisfactory and compatible[15,65,69,70,102,111].

It was found that HM has a statistically insignificant and negative effect on the rejected hypotheses, inconsistent with prior studies[11,68,77,78,90,91,103]. Habit was found to affect continuous intention toward using mobile learning technology in mobile learning studies[78,87,90,91]. Similarly, consistent with Lewis et al.[90] and Raman and Don[91] were found to have a significant positive effect on CI. The current paper also does not support that continuous intention was not significantly influenced by price value.

Additionally, effort expectation seems to have some effect on behavioral intentions in Qatar, but not in the United States. Our results did not support the conclusions of previous studies[44,78,103,169].

Surprisingly, trust played a significant impact on continuous intention, one core construct that is not supported, which is not align with prior studies' findings of Tarhini et al., Mohd Alwi and Fan and El-Khatib et al.[78,170,171]. As part of this study, it was hypothesized that students would adopt a web-based learning system if they thought the benefits were greater than the costs.

Furthermore, this paper did not find an influential predictor of mobile learning continuous intention of self-efficacy different from past studies[78,172–175]. The variable of self-efficacy is used here to refer to the degree to which students are confident in their ability to accomplish certain learning tasks with the help of e-learning. Higher levels of SE are expected to increase the acceptance of e-learning platforms than lower levels. The findings of this study did not differ significantly from those of three previous ones regarding SN's positive effects.

It has been demonstrated in past studies of UTAUT2 that PE and EE are influential factors in the intention to continue using web-based learning tools, which contrasts with prior findings regarding performance expectations[15,25,58,75–78,126,176]. Regarding the effort expectancy[15,25,75,77,78,126,158,176].

Students' decisions to implement mobile learning technologies are typically influenced by pressure from both coworkers and students as well as superiors and lecturers. Mobile learning usage did not significantly correlate with social influence, contrary to our expectations. The current study's findings differ from previous studies[11,25,74,176,177–180].

A fairly positive and significant effect was also found between facilitating conditions and subjective norms on continuous intentions. Regarding the facilitating conditions, the finding contradicts the results of previous studies[11,25,74,175,177,180]. In keeping consistent with most related studies[14,15,181]. And in the context of subjective norm[126,127].

The current paper found the effect of PI on CIU. It is consistent with previous studies[51,109]. Finally, the study concluded that CIU is positively and significantly influenced by TE. The finding is in line with previous study[55].

8. Implication

Theoretical and practical implications

The use of deep learning methodology in this study enables a hybrid SEM-ANN technique, which differs from earlier empirical studies that were focused solely on SEM analysis. Research outcomes were robust because of a dual-stage analysis due to the increased statistical rigor. In terms of methodological contributions, this study utilizes a multi-analytical approach, which is regarded as an innovative approach in research methodology. PLS-SEM models are less predictive than ANN models. Deep learning ANNs provide better predictive power by identifying non-linear relationships between factors. Second, most importantly, this current study provides an amalgamation of the TAM, TPB, ECM, D&M IS Success Model, and UTAUT2 approaches to comprehend for predicting the mobile learning continuance, which has not been found in the existing literature. Because most previous research focuses on either m-learning adoption or acceptability, mobile learning, especially during the COVID-19 pandemic, is becoming increasingly important due to a lack of literature, this would be a highly valuable contribution to the mobile learning industry. Third, as these systems still require additional research to investigate the variables influencing their prolonged use, the current study contributes to the Türk literature by identifying the factors influencing their continued use. Fourth, the created model explains 88%, 68%, 68%, 79% of variance to CIU, AU, PU, and SAT, respectively. Taken together, the empirical findings suggest that the suggested theoretical model is more successful in explaining continued usage in general, and specifically in the context of m-learning. Fifth, this study verifies and increases the role of TAM (PU and PEU), TPB (ATT, PBC, and SN), ECM, the D&M IS Success Model, and the UTAUT2 components in affecting students' ongoing use of mobile learning platforms in Turkey contexts.

Both practitioners and scholars will benefit greatly from this study. First, the present study's findings revealed that students in Türk higher education had a strong desire to continue using mobile learning technologies in educational activities, providing factual evidence to support such efforts. As a result, the creation of "mobile-friendly" content is a necessary step in the ongoing desire to utilize these platforms. Second, Türk higher education policymakers could maximize the benefits of m-learning by developing their m-learning regulations and processes. Third, faculty members should examine the key mobile learning predictors while employing mobile learning services to increase mobile learning acceptability. Finally, the outcomes have significant practical implications for educational developers, policymakers, and practitioners interested in developing and improving mobile learning solutions during COVID-19.

9. Conclusion, limitation, and future lines of research

Even though many papers have been done on mobile learning adoption and acceptability, it is suggested that very little attention be paid to long-term mobile learning use. To bridge this gap, TAM, TPB, ECM, D&M IS Success Model, and UTAUT2, wherein trust, personal innovativeness, learning value, instructor quality, and course quality were integrated, and new relationships were assumed among the proposed research model variables, Three Turkish state universities were surveyed to test the proposed methodology. The acquired data were then submitted to a hybrid analytic approach that combined structural equation modeling (SEM) and a deep learning-based artificial neural network (ANN). This research has some drawbacks. The results of this study were impressive, but future studies will need to address many limitations. Based on the context of this study, which was conducted at a university, its findings cannot be applied to verify its general validity. However, similar studies could be conducted at other universities and by users of m-learning in a different field, such as the workplace. Second, the convenience sampling technique was used, which is another major limitation. Third, while this study focused primarily on students' mobile learning continuance, more studies on instructors' long-term use and acceptance of such systems have a lot of potential. Fourth, furthermore, this study was conducted in the setting of Turkey. As a result, the findings may not truly represent m-learning acceptability in other nations, given the wide range of variances. For example, cultural variations, technological readiness, and other attributes may influence technology acceptance. Fifth, the current research was limited to the use of a survey instrument as a data-gathering tool. A case study, focus group, and interview are recommended for future research to enhance the results. A sixth limitation of the study is that it utilized a quantitative research method, whereas qualitative evaluation may uncover other explanations for the correlation between the postulated constructs. As a result, future research should use a qualitative method to supplement its quantitative findings. More research using cross-sectional and cross-cultural techniques is needed to improve the predictive value of mobile learning. Further studies should examine cross-cultural effects and personal attributes (age, gender, and experience) to broaden this approach.

Author contributions

Conceptualization, YA, AOU and PU; methodology, YA and AOU; software, YA and AOU; validation, YA and AOU; formal analysis, YA and AOU; investigation, YA AOU, and PU; resources, YA, AOU and PU; data curation, YA and PU; writing—original draft preparation, YA, AOU and PU; writing—review and editing, YA, AOU and PU; visualization, YA, AOU and PU. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

References

1. International Telecommunication Union. Individuals using the Internet 2005–2019. Available online: https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx (accessed on 5 January 2024).
2. Statista. Global smartphone penetration rate as share of population from 2016 to 2022. Available online: https://www.statista.com/statistics/203734/global-smartphone-penetration-per-capita-since-2005/ (accessed on 5 January 2024).
3. Almaiah MA, Al-Khasawneh A, Althunibat A. Exploring the critical challenges and factors influencing the E-learning system usage during COVID-19 pandemic. Education and Information Technologies. 2020, 25(6): 5261-5280. doi: 10.1007/s10639-020-10219-y
4. Vladova G, Ullrich A, Bender B, et al. Students' Acceptance of Technology-Mediated Teaching – How It Was Influenced During the COVID-19 Pandemic in 2020: A Study From Germany. Frontiers in Psychology. 2021, 12. doi: 10.3389/fpsyg.2021.636086
5. Kumar BA, Chand SS. Mobile learning adoption: A systematic review. Education and Information Technologies. 2018, 24(1): 471-487. doi: 10.1007/s10639-018-9783-6
6. Acikgoz F, Vega RP. The Role of Privacy Cynicism in Consumer Habits with Voice Assistants: A Technology Acceptance Model Perspective. International Journal of Human–Computer Interaction. 2021, 38(12): 1138-1152. doi: 10.1080/10447318.2021.1987677
7. El-Masri M, Tarhini A. Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Educational Technology Research and Development. 2017, 65(3): 743-763. doi: 10.1007/s11423-016-9508-8
8. Türker C, Altay BC, Okumuş A. Understanding user acceptance of QR code mobile payment systems in Turkey: An extended TAM. Technological Forecasting and Social Change. 2022, 184: 121968. doi: 10.1016/j.techfore.2022.121968
9. Wong KT, Teo T, Goh PSC. Understanding the intention to use interactive whiteboards: model development and testing. Interactive Learning Environments. 2013, 23(6): 731-747. doi: 10.1080/10494820.2013.806932
10. Cheng Y. Effects of quality antecedents on e-learning acceptance. Internet Research. 2012, 22(3): 361-390. doi: 10.1108/10662241211235699
11. Ain N, Kaur K, Waheed M. The influence of learning value on learning management system use. Information Development. 2016, 32(5): 1306-1321. doi: 10.1177/0266666915597546
12. Lwoga ET. Critical success factors for adoption of web-based learning management systems in Tanzania. International Journal of Education and Development using ICT. 2014; 10(1): 4-21.
13. Al-Azawei A, Alowayr A. Predicting the intention to use and hedonic motivation for mobile learning: A comparative study in two Middle Eastern countries. Technology in Society. 2020, 62: 101325. doi: 10.1016/j.techsoc.2020.101325
14. Al-Emran M, Arpaci I, Salloum SA. An empirical examination of continuous intention to use m-learning: An integrated model. Education and Information Technologies. 2020, 25(4): 2899-2918. doi: 10.1007/s10639-019-10094-2
15. Alzahrani L, Seth KP. Factors influencing students' satisfaction with continuous use of learning management systems during the COVID-19 pandemic: An empirical study. Education and Information Technologies. 2021, 26(6): 6787-6805. doi: 10.1007/s10639-021-10492-5
16. Yuan YP, Wei-Han Tan G, Ooi KB, et al. Can COVID-19 pandemic influence experience response in mobile learning? Telematics and Informatics. 2021, 64: 101676. doi: 10.1016/j.tele.2021.101676
17. Sim JJ, Tan GWH, Wong JCJ, et al. Understanding and predicting the motivators of mobile music acceptance – A multi-stage MRA-artificial neural network approach. Telematics and Informatics. 2014, 31(4): 569-584. doi: 10.1016/j.tele.2013.11.005
18. Wong TC, Wong SY, Chin KS. A neural network-based approach of quantifying relative importance among various determinants toward organizational innovation. Expert Systems with Applications. 2011, 38(10): 13064-13072. doi: 10.1016/j.eswa.2011.04.113
19. AlHamad AQM. Predicting the intention to use Mobile learning: A hybrid SEM-machine learning approach. International Journal of Engineering Research & Technology. 2020; 9(3): 275-282.
20. Alshurideh M, Al Kurdi B, Salloum SA, et al. Predicting the actual use of m-learning systems: a comparative approach using PLS-SEM and machine learning algorithms. Interactive Learning Environments. 2020, 31(3): 1214-1228. doi: 10.1080/10494820.2020.1826982
21. Akour I, Alshurideh M, Al Kurdi B, et al. Using Machine Learning Algorithms to Predict People's Intention to

Use Mobile Learning Platforms During the COVID-19 Pandemic: Machine Learning Approach. JMIR Medical Education. 2021, 7(1): e24032. doi: 10.2196/24032

22. Thongsri N, Chootong C, Tripak O, et al. Predicting the determinants of online learning adoption during the COVID-19 outbreak: a two-staged hybrid SEM-neural network approach. Interactive Technology and Smart Education. 2021, 18(3): 362-379. doi: 10.1108/itse-08-2020-0165
23. Yakubu MN, Dasuki SI, Abubakar AM, et al. Determinants of learning management systems adoption in Nigeria: A hybrid SEM and artificial neural network approach. Education and Information Technologies. 2020, 25(5): 3515-3539. doi: 10.1007/s10639-020-10110-w
24. Kumar JA, Bervell B, Annamalai N, et al. Behavioral Intention to Use Mobile Learning: Evaluating the Role of Self-Efficacy, Subjective Norm, and WhatsApp Use Habit. IEEE Access. 2020, 8: 208058-208074. doi: 10.1109/access.2020.3037925
25. Shukla S. M-learning adoption of management students': A case of India. Education and Information Technologies. 2020, 26(1): 279-310. doi: 10.1007/s10639-020-10271-8
26. Alhumaid K, Habes M, Salloum SA. Examining the Factors Influencing the Mobile Learning Usage During COVID-19 Pandemic: An Integrated SEM-ANN Method. IEEE Access. 2021, 9: 102567-102578. doi: 10.1109/access.2021.3097753
27. Songkram N, Chootongchai S. Adoption model for a hybrid SEM-neural network approach to education as a service. Education and Information Technologies. 2022, 27(5): 5857-5887. doi: 10.1007/s10639-021-10802-x
28. Huang W, Stokes JW. MtNet: A multi-task neural network for dynamic malware classification. In: Caballero J, Zurutuza U, Rodríguez RJ (editors). *Detection of Intrusions and Malware, and Vulnerability Assessment*, Proceedings of the 13th International Conference, DIMVA 2016, 7–8 July 2016; San Sebastián, Spain. Springer; 2016. pp. 399–418. doi: 10.1007/978-3-319-40667-1_20
29. Akgül Y. Predicting the determinants of mobile payment acceptance: A hybrid SEM-neural network approach. In: Patel HS, Kumar AVS (editors). Applications of Artificial Neural Networks for Nonlinear Data. Engineering Science Reference; 2021. doi: 10.4018/978-1-7998-4042-8.ch006
30. Lee VH, Hew JJ, Leong LY, et al. Wearable payment: A deep learning-based dual-stage SEM-ANN analysis. Expert Systems with Applications. 2020, 157: 113477. doi: 10.1016/j.eswa.2020.113477
31. Leong LY, Hew TS, Ooi KB, et al. A hybrid SEM-neural network analysis of social media addiction. Expert Systems with Applications. 2019, 133: 296-316. doi: 10.1016/j.eswa.2019.05.024
32. Ashaari MA, Singh KSD, Abbasi GA, et al. Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: A multi-analytical SEM & ANN perspective. Technological Forecasting and Social Change. 2021, 173: 121119. doi: 10.1016/j.techfore.2021.121119
33. Akgül Y, Uymaz AO. Facebook/Meta usage in higher education: A deep learning-based dual-stage SEM-ANN analysis. Education and Information Technologies. 2022, 27(7): 9821-9855. doi: 10.1007/s10639-022-11012-9
34. Uymaz P, Uymaz AO, Akgül Y. Assessing the Behavioral Intention of Individuals to Use an AI Doctor at the Primary, Secondary, and Tertiary Care Levels. International Journal of Human–Computer Interaction. 2023, 1-18. doi: 10.1080/10447318.2023.2233126
35. Uymaz P, Uymaz AO. Assessing acceptance of augmented reality in nursing education. PLoS ONE. 2022, 17(2): e0263937. doi: 10.1371/journal.pone.0263937
36. Abbasi GA, Tiew LY, Tang J, et al. The adoption of cryptocurrency as a disruptive force: Deep learning-based dual stage structural equation modelling and artificial neural network analysis. PLoS ONE. 2021, 16(3): e0247582. doi: 10.1371/journal.pone.0247582
37. Liébana-Cabanillas F, Marinković V, Kalinić Z. A SEM-neural network approach for predicting antecedents of m-commerce acceptance. International Journal of Information Management. 2017, 37(2): 14-24. doi: 10.1016/j.ijinfomgt.2016.10.008
38. Kwak Y, Seo YH, Ahn JW. Nursing students' intent to use AI-based healthcare technology: Path analysis using the unified theory of acceptance and use of technology. Nurse Education Today. 2022, 119: 105541. doi: 10.1016/j.nedt.2022.105541
39. Ajzen I, Fishbein M. Understanding Attitudes and Predicting Social Behavior. Prentice-Hall Englewood Cliffs, N.J.; 1980.
40. Davis FD. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly. 1989, 13(3): 319. doi: 10.2307/249008
41. Ajzen I. The theory of planned behavior. Organizational Behavior and Human Decision Processes. 1991, 50(2): 179-211. doi: 10.1016/0749-5978(91)90020-t
42. Fishbein MA, Ajzen I. Belief, Attitude, Intention and Behaviour: An Introduction to Theory and Research. Addison-Wesley; 1975.
43. Rogers EM. Diffusion of innovations: Modifications of a model for telecommunications. In: Stoetzer MW, Mahler A (editors). The Diffusion of Innovations in Telecommunications (German). Springer; 1995. Volume 17. pp. 25-38. doi: 10.1007/978-3-642-79868-9_2

44. Venkatesh, Morris, Davis, et al. User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly. 2003, 27(3): 425. doi: 10.2307/30036540
45. The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. Journal of Management Information Systems. 2003, 19(4): 9-30. doi: 10.1080/07421222.2003.11045748
46. Berger H, Al Adwan A, Al Adwan AS. Solving the mystery of mobile learning adoption in higher education. International Journal of Mobile Communications. 2018, 16(1): 24. doi: 10.1504/ijmc.2018.10007779
47. Park SY, Lee HD, Kim SY. South Korean university students' mobile learning acceptance and experience based on the perceived attributes, system quality and resistance. Innovations in Education and Teaching International. 2016, 55(4): 450-458. doi: 10.1080/14703297.2016.1261041
48. Al-Hamad MQ, Mbaidin HO, AlHamad AQM, et al. Investigating students' behavioral intention to use mobile learning in higher education in UAE during Coronavirus-19 pandemic. International Journal of Data and Network Science. 2021, 5: 321-330. doi: 10.5267/j.ijdns.2021.6.001
49. Alzaidi MS, Shehawy YM. Cross-national differences in mobile learning adoption during COVID-19. Education + Training. 2022, 64(3): 305-328. doi: 10.1108/et-05-2021-0179
50. Zhou M, Dzingirai C, Hove K, et al. Adoption, use and enhancement of virtual learning during COVID-19. Education and Information Technologies. 2022, 27(7): 8939-8959. doi: 10.1007/s10639-022-10985-x
51. Chahal J, Rani N. Exploring the acceptance for e-learning among higher education students in India: combining technology acceptance model with external variables. Journal of Computing in Higher Education. 2022, 34(3): 844-867. doi: 10.1007/s12528-022-09327-0
52. Aloqaily A, Nawayseh MKA, Baarah AH, et al. A neural network analytical model for predicting determinants of mobile learning acceptance. International Journal of Computer Applications in Technology. 2019, 60(1): 73. doi: 10.1504/ijcat.2019.099502
53. Al-Shihi H, Sharma SK, Sarrab M. Neural network approach to predict mobile learning acceptance. Education and Information Technologies. 2018, 23(5): 1805-1824. doi: 10.1007/s10639-018-9691-9
54. Tan GWH, Ooi KB, Leong LY, et al. Predicting the drivers of behavioral intention to use mobile learning: A hybrid SEM-Neural Networks approach. Computers in Human Behavior. 2014, 36: 198-213. doi: 10.1016/j.chb.2014.03.052
55. Sharma SK, Sarrab M, Al-Shihi H. Development and validation of Mobile Learning Acceptance Measure. Interactive Learning Environments. 2016, 25(7): 847-858. doi: 10.1080/10494820.2016.1224250
56. Elnagar A, Alnazzawi N, Afyouni I, et al. An empirical study of e-learning post-acceptance after the spread of COVID-19. International Journal of Data and Network Science. 2022, 6(3): 669-682. doi: 10.5267/j.ijdns.2022.4.005
57. Zhang M, Chen Y, Zhang S, et al. Understanding mobile learning continuance from an online-cum-offline learning perspective: a SEM-neural network method. International Journal of Mobile Communications. 2022, 20(1): 105. doi: 10.1504/ijmc.2022.119995
58. Al-Emran M, Mezhuyev V, Kamaludin A. Technology Acceptance Model in M-learning context: A systematic review. Computers & Education. 2018, 125: 389-412. doi: 10.1016/j.compedu.2018.06.008
59. Karjaluoto H, Mattila M, Pento T. Factors underlying attitude formation towards online banking in Finland. International Journal of Bank Marketing. 2002, 20(6): 261-272. doi: 10.1108/02652320210446724
60. Cheon J, Lee S, Crooks SM, et al. An investigation of mobile learning readiness in higher education based on the theory of planned behavior. Computers & Education. 2012, 59(3): 1054-1064. doi: 10.1016/j.compedu.2012.04.015
61. Yadegaridehkordi E, Iahad NA, Baloch HZ. Success factors influencing the adoption of M-learning. International Journal of Continuing Engineering Education and Life-Long Learning. 2013, 23(2): 167. doi: 10.1504/ijceell.2013.054290
62. Yeap JAL, Ramayah T, Soto-Acosta P. Factors propelling the adoption of m-learning among students in higher education. Electronic Markets. 2016, 26(4): 323-338. doi: 10.1007/s12525-015-0214-x
63. Bhattacharya S. Artificial intelligence, human intelligence, and the future of public health. AIMS Public Health. 2022, 9(4): 644-650. doi: 10.3934/publichealth.2022045
64. Cheng M, Yuen AHK. Student continuance of learning management system use: A longitudinal exploration. Computers & Education. 2018, 120: 241-253. doi: 10.1016/j.compedu.2018.02.004
65. Joo YJ, Kim N, Kim NH. Factors predicting online university students' use of a mobile learning management system (m-LMS). Educational Technology Research and Development. 2016, 64(4): 611-630. doi: 10.1007/s11423-016-9436-7
66. DeLone WH, McLean ER. Information Systems Success: The Quest for the Dependent Variable. Information Systems Research. 1992, 3(1): 60-95. doi: 10.1287/isre.3.1.60
67. Kim TG, Lee JH, Law R. An empirical examination of the acceptance behaviour of hotel front office systems: An extended technology acceptance model. Tourism Management. 2008, 29(3): 500-513. doi: 10.1016/j.tourman.2007.05.016

68. Chen SC, Liu ML, Lin CP. Integrating Technology Readiness into the Expectation–Confirmation Model: An Empirical Study of Mobile Services. Cyberpsychology, Behavior, and Social Networking. 2013, 16(8): 604-612. doi: 10.1089/cyber.2012.0606
69. Hong S, Thong JYL, Tam KY. Understanding continued information technology usage behavior: A comparison of three models in the context of mobile internet. Decision Support Systems. 2006, 42(3): 1819-1834. doi: 10.1016/j.dss.2006.03.009
70. Oghuma AP, Chang Y, Libaque-Saenz CF, et al. Benefit-confirmation model for post-adoption behavior of mobile instant messaging applications: A comparative analysis of KakaoTalk and Joyn in Korea. Telecommunications Policy. 2015, 39(8): 658-677. doi: 10.1016/j.telpol.2015.07.009
71. Venkatesh, Thong, Xu. Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly. 2012, 36(1): 157. doi: 10.2307/41410412
72. Yadav R, Sharma SK, Tarhini A. A multi-analytical approach to understand and predict the mobile commerce adoption. Journal of Enterprise Information Management. 2016, 29(2): 222-237. doi: 10.1108/jeim-04-2015-0034
73. Zuiderwijk A, Janssen M, Dwivedi YK. Acceptance and use predictors of open data technologies: Drawing upon the unified theory of acceptance and use of technology. Government Information Quarterly. 2015, 32(4): 429-440. doi: 10.1016/j.giq.2015.09.005
74. Sharma SK, Al-Badi AH, Govindaluri SM, et al. Predicting motivators of cloud computing adoption: A developing country perspective. Computers in Human Behavior. 2016, 62: 61-69. doi: 10.1016/j.chb.2016.03.073
75. Gruzd A, Staves K, Wilk A. Connected scholars: Examining the role of social media in research practices of faculty using the UTAUT model. Computers in Human Behavior. 2012, 28(6): 2340-2350. doi: 10.1016/j.chb.2012.07.004
76. Teo T, Fan X, Du J. Technology acceptance among pre-service teachers: Does gender matter? Australasian Journal of Educational Technology. 2015, 31(3). doi: 10.14742/ajet.1672
77. Masa'deh R (Moh'd T, Tarhini A, Bany Mohammed A, et al. Modeling Factors Affecting Student's Usage Behaviour of E-Learning Systems in Lebanon. International Journal of Business and Management. 2016, 11(2): 299. doi: 10.5539/ijbm.v11n2p299
78. Tarhini A, Masa'deh R, Al-Busaidi KA, et al. Factors influencing students' adoption of e-learning: a structural equation modeling approach. Journal of International Education in Business. 2017, 10(2): 164-182. doi: 10.1108/jieb-09-2016-0032
79. Tarhini A, Teo T, Tarhini T. A cross-cultural validity of the E-learning Acceptance Measure (ElAM) in Lebanon and England: A confirmatory factor analysis. Education and Information Technologies. 2015, 21(5): 1269-1282. doi: 10.1007/s10639-015-9381-9
80. García Botero G, Nguyet DA, García Botero J, et al. Acceptance and Use of Mobile-Assisted Language Learning by Higher Education Language Teachers. Lenguaje. 2022, 50(1): 66-92. doi: 10.25100/lenguaje.v50i1.11006
81. Moran M, Hawkes M, Gayar OE. Tablet Personal Computer Integration in Higher Education: Applying the Unified Theory of Acceptance and use Technology Model to Understand Supporting Factors. Journal of Educational Computing Research. 2010, 42(1): 79-101. doi: 10.2190/ec.42.1.d
82. Blaise R, Halloran M, Muchnick M. Mobile Commerce Competitive Advantage: A Quantitative Study of Variables that Predict M-Commerce Purchase Intentions. Journal of Internet Commerce. 2018, 17(2): 96-114. doi: 10.1080/15332861.2018.1433911
83. Dwivedi YK, Rana NP, Jeyaraj A, et al. Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model. Information Systems Frontiers. 2017, 21(3): 719-734. doi: 10.1007/s10796-017-9774-y
84. Li W, Yuan K, Yue M, et al. Climate change risk perceptions, facilitating conditions and health risk management intentions: Evidence from farmers in rural China. Climate Risk Management. 2021, 32: 100283. doi: 10.1016/j.crm.2021.100283
85. Venkatesh V, Davis FD. A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science. 2000, 46(2): 186-204. doi: 10.1287/mnsc.46.2.186.11926
86. Agudo-Peregrina ÁF, Hernández-García Á, Pascual-Miguel FJ. Behavioral intention, use behavior and the acceptance of electronic learning systems: Differences between higher education and lifelong learning. Computers in Human Behavior. 2014, 34: 301-314. doi: 10.1016/j.chb.2013.10.035
87. Alalwan AA, Dwivedi YK, Rana NP, et al. Consumer adoption of Internet banking in Jordan: Examining the role of hedonic motivation, habit, self-efficacy and trust. Journal of Financial Services Marketing. 2015, 20(2): 145-157. doi: 10.1057/fsm.2015.5
88. Escobar-Rodríguez T, Carvajal-Trujillo E. Online drivers of consumer purchase of website airline tickets. Journal of Air Transport Management. 2013, 32: 58-64. doi: 10.1016/j.jairtraman.2013.06.018
89. Lee YH, Hsiao C, Hadi S. Enhancing e-learning Acceptance: An Empirical Examination on individual and system characteristics. Academy of Management Proceedings. 2012, 2012(1): 15828. doi: 10.5465/ambpp.2012.15828abstract

90. Lewis CC, Fretwell CE, Ryan J, et al. Faculty Use of Established and Emerging Technologies in Higher Education: A Unified Theory of Acceptance and Use of Technology Perspective. International Journal of Higher Education. 2013, 2(2). doi: 10.5430/ijhe.v2n2p22
91. Raman A, Don Y. Preservice Teachers' Acceptance of Learning Management Software: An Application of the UTAUT2 Model. International Education Studies. 2013, 6(7). doi: 10.5539/ies.v6n7p157
92. Brown, Venkatesh. Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle. MIS Quarterly. 2005, 29(3): 399. doi: 10.2307/25148690
93. Zhou T, Lu Y, Wang B. Integrating TTF and UTAUT to explain mobile banking user adoption. Computers in Human Behavior. 2010, 26(4): 760-767. doi: 10.1016/j.chb.2010.01.013
94. Ozkan S, Koseler R. Multi-dimensional students' evaluation of e-learning systems in the higher education context: An empirical investigation. Computers & Education. 2009, 53(4): 1285-1296. doi: 10.1016/j.compedu.2009.06.011
95. Petter S, McLean ER. A meta-analytic assessment of the DeLone and McLean IS success model: An examination of IS success at the individual level. Information & Management. 2009, 46(3): 159-166. doi: 10.1016/j.im.2008.12.006
96. Hassanzadeh A, Kanaani F, Elahi S. A model for measuring e-learning systems success in universities. Expert Systems with Applications. 2012, 39(12): 10959-10966. doi: 10.1016/j.eswa.2012.03.028
97. Kim K, Trimi S, Park H, et al. The Impact of CMS Quality on the Outcomes of E-learning Systems in Higher Education: An Empirical Study. Decision Sciences Journal of Innovative Education. 2012, 10(4): 575-587. doi: 10.1111/j.1540-4609.2012.00360.x
98. Roca JC, Chiu CM, Martínez FJ. Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. International Journal of Human-Computer Studies. 2006, 64(8): 683-696. doi: 10.1016/j.ijhcs.2006.01.003
99. Saba T. Implications of E-learning systems and self-efficiency on students outcomes: a model approach. Human-centric Computing and Information Sciences. 2012, 2(1). doi: 10.1186/2192-1962-2-6
100. Wang HC, Chiu YF. Assessing e-learning 2.0 system success. Computers & Education. 2011, 57(2): 1790-1800. doi: 10.1016/j.compedu.2011.03.009
101. Ramayah T, Ahmad NH, Lo MC. The role of quality factors in intention to continue using an e-learning system in Malaysia. Procedia - Social and Behavioral Sciences. 2010, 2(2): 5422-5426. doi: 10.1016/j.sbspro.2010.03.885
102. Kim B. An empirical investigation of mobile data service continuance: Incorporating the theory of planned behavior into the expectation–confirmation model. Expert Systems with Applications. 2010, 37(10): 7033-7039. doi: 10.1016/j.eswa.2010.03.015
103. Al-Gahtani SS. Empirical investigation of e-learning acceptance and assimilation: A structural equation model. Applied Computing and Informatics. 2016, 12(1): 27-50. doi: 10.1016/j.aci.2014.09.001
104. Mohammadi H. Social and individual antecedents of m-learning adoption in Iran. Computers in Human Behavior. 2015, 49: 191-207. doi: 10.1016/j.chb.2015.03.006
105. Sabah NM. Exploring students' awareness and perceptions: Influencing factors and individual differences driving m-learning adoption. Computers in Human Behavior. 2016, 65: 522-533. doi: 10.1016/j.chb.2016.09.009
106. Tan GWH, Ooi KB, Sim JJ, Phusavat K. Determinants of mobile learning adoption: An empirical analysis. Journal of Computer Information System. 2012, 52(3): 82–91. doi: 10.1080/08874417.2012.11645561.
107. Iqbal S, Qureshi IA. M-learning adoption: A perspective from a developing country. The International Review of Research in Open and Distributed Learning. 2012, 13(3): 147. doi: 10.19173/irrodl.v13i3.1152
108. van Raaij EM, Schepers JJL. The acceptance and use of a virtual learning environment in China. Computers & Education. 2008, 50(3): 838-852. doi: 10.1016/j.compedu.2006.09.001
109. Thompson R, Compeau D, Higgins C, et al. Intentions to use information technologies. In: Clarke S (editor). End User Computing Challenges and Technologies: Emerging Tools and Applications. Information Science Reference; 2008. pp. 79-101. doi: 10.4018/978-1-59904-295-4.ch006
110. Doll WJ, Hendrickson A, Deng X. Using Davis's Perceived Usefulness and Ease-of-use Instruments for Decision Making: A Confirmatory and Multigroup Invariance Analysis. Decision Sciences. 1998, 29(4): 839-869. doi: 10.1111/j.1540-5915.1998.tb00879.x
111. Wang RB, Du CT. Mobile Social Network Sites as innovative pedagogical tools: factors and mechanism affecting students' continuance intention on use. Journal of Computers in Education. 2014, 1(4): 353-370. doi: 10.1007/s40692-014-0015-9
112. Bandura A, Schunk DH. Cultivating competence, self-efficacy, and intrinsic interest through proximal self-motivation. Journal of Personality and Social Psychology. 1981, 41(3): 586-598. doi: 10.1037/0022-3514.41.3.586
113. Bandura A. Social Cognitive Theory: An Agentic Perspective. Annual Review of Psychology. 2001, 52(1): 1-26. doi: 10.1146/annurev.psych.52.1.1
114. Compeau DR, Higgins CA. Computer Self-Efficacy: Development of a Measure and Initial Test. MIS Quarterly. 1995, 19(2): 189. doi: 10.2307/249688

115. Downey J. Measuring general computer self-efficacy: The surprising comparison of three instruments in predicting performance, attitudes, and usage. In: Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS'06). 4–7 January 2006; Kauai, HI, USA. p. 210a. doi: 10.1109/hicss.2006.268
116. Hernandez B, Jimenez J, Jose Martin M. The impact of self-efficacy, ease of use and usefulness on e-purchasing: An analysis of experienced e-shoppers. Interacting with Computers. 2009, 21(1-2): 146-156. doi: 10.1016/j.intcom.2008.11.001
117. Yuen AHK, Ma WWK. Exploring teacher acceptance of e-learning technology. Asia-Pacific Journal of Teacher Education. 2008, 36(3): 229-243. doi: 10.1080/13598660802232779
118. Park SY. An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning. Journal of Educational Technology & Society. 2009, 12(3): 150-162.
119. Petter S, DeLone W, McLean E. Measuring information systems success: Models, dimensions, measures, and interrelationships. European Journal of Information Systems. 2008, 17(3): 236-263. doi: 10.1057/ejis.2008.15
120. Poulova P, Simonova I. E-learning Reflected in Research Studies in Czech Republic: Comparative Analyses. Procedia - Social and Behavioral Sciences. 2014, 116: 1298-1304. doi: 10.1016/j.sbspro.2014.01.386
121. Tajuddin RA, Baharudin M, Hoon TS. System Quality and its Influence on Students' Learning Satisfaction in UiTM Shah Alam. Procedia - Social and Behavioral Sciences. 2013, 90: 677-685. doi: 10.1016/j.sbspro.2013.07.140
122. Xu D, Huang WW, Wang H, et al. Enhancing e-learning effectiveness using an intelligent agent-supported personalized virtual learning environment: An empirical investigation. Information & Management. 2014, 51(4): 430-440. doi: 10.1016/j.im.2014.02.009
123. Li Y, Duan Y, Fu Z, et al. An empirical study on behavioural intention to reuse e-learning systems in rural China. British Journal of Educational Technology. 2011, 43(6): 933-948. doi: 10.1111/j.1467-8535.2011.01261.x
124. Park SY, Nam M, Cha S. University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. British Journal of Educational Technology. 2011, 43(4): 592-605. doi: 10.1111/j.1467-8535.2011.01229.x
125. Wang Y, Wu M, Wang H. Investigating the determinants and age and gender differences in the acceptance of mobile learning. British Journal of Educational Technology. 2008, 40(1): 92-118. doi: 10.1111/j.1467-8535.2007.00809.x
126. Dalvi-Esfahani M, Wai Leong L, Ibrahim O, et al. Explaining Students' Continuance Intention to Use Mobile Web 2.0 Learning and Their Perceived Learning: An Integrated Approach. Journal of Educational Computing Research. 2018, 57(8): 1956-2005. doi: 10.1177/0735633118805211
127. Huang RT, Hsiao CH, Tang TW, et al. Exploring the moderating role of perceived flexibility advantages in mobile learning continuance intention (MLCI). The International Review of Research in Open and Distributed Learning. 2014, 15(3). doi: 10.19173/irrodl.v15i3.1722
128. Alsabawy AY, Cater-Steel A, Soar J. IT infrastructure services as a requirement for e-learning system success. Computers & Education. 2013, 69: 431-451. doi: 10.1016/j.compedu.2013.07.035
129. Gefen D, Straub D, Boudreau MC. Structural Equation Modeling and Regression: Guidelines for Research Practice. Communications of the Association for Information Systems. 2000, 4. doi: 10.17705/1cais.00407
130. Chu TH, Chen YY. With Good We Become Good: Understanding e-learning adoption by theory of planned behavior and group influences. Computers & Education. 2016, 92-93: 37-52. doi: 10.1016/j.compedu.2015.09.013
131. Alalwan AA, Dwivedi YK, Williams MD. Customers' Intention and Adoption of Telebanking in Jordan. Information Systems Management. 2016, 33(2): 154-178. doi: 10.1080/10580530.2016.1155950
132. Iqbal MS, Khan SUD, Iqbal MZ. University students' perception of Ebola virus disease. Journal of Pharmaceutical Research International. 2020, 32(34): 132-140. doi: 10.9734/jpri/2020/v32i3430989
133. Myers ND, Ahn S, Jin Y. Sample Size and Power Estimates for a Confirmatory Factor Analytic Model in Exercise and Sport. Research Quarterly for Exercise and Sport. 2011, 82(3): 412-423. doi: 10.1080/02701367.2011.10599773
134. Bentler PM, Chou CP. Practical Issues in Structural Modeling. Sociological Methods & Research. 1987, 16(1): 78-117. doi: 10.1177/0049124187016001004
135. Hair J, Hollingsworth CL, Randolph AB, et al. An updated and expanded assessment of PLS-SEM in information systems research. Industrial Management & Data Systems. 2017, 117(3): 442-458. doi: 10.1108/imds-04-2016-0130
136. Shmueli G, Sarstedt M, Hair JF, et al. Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. European Journal of Marketing. 2019, 53(11): 2322-2347. doi: 10.1108/ejm-02-2019-0189
137. Podsakoff PM, MacKenzie SB, Lee JY, et al. Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology. 2003, 88(5): 879-903. doi: 10.1037/0021-9010.88.5.879
138. Ooi KB, Tan GWH. Mobile technology acceptance model: An investigation using mobile users to explore smartphone credit card. Expert Systems with Applications. 2016, 59: 33-46. doi: 10.1016/j.eswa.2016.04.015

139. Tan GWH, Ooi KB. Gender and age: Do they really moderate mobile tourism shopping behavior? Telematics and Informatics. 2018, 35(6): 1617-1642. doi: 10.1016/j.tele.2018.04.009
140. Hair JF, Hult GT, Ringle CM, Sarstedt M. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 2nd ed. Sage; 2016.
141. Liaw SS, Huang HM. Perceived satisfaction, perceived usefulness and interactive learning environments as predictors to self-regulation in e-learning environments. Computers & Education. 2013, 60(1): 14-24. doi: 10.1016/j.compedu.2012.07.015
142. Al-Busaidi KA. Learners' Perspective on Critical Factors to LMS Success in Blended Learning: An Empirical Investigation. Communications of the Association for Information Systems. 2012, 30. doi: 10.17705/1cais.03002
143. Al-Busaidi KA. An empirical investigation linking learners' adoption of blended learning to their intention of full e-learning. Behaviour & Information Technology. 2013, 32(11): 1168-1176. doi: 10.1080/0144929x.2013.774047
144. Schillewaert N, Ahearne MJ, Frambach RT, et al. The adoption of information technology in the sales force. Industrial Marketing Management. 2005, 34(4): 323-336. doi: 10.1016/j.indmarman.2004.09.013
145. Zhang S, Zhao J, Tan W. Extending TAM for online learning systems: An intrinsic motivation perspective. Tsinghua Science and Technology. 2008, 13(3): 312-317. doi: 10.1016/s1007-0214(08)70050-6
146. Kim H, Niehm LS. The Impact of Website Quality on Information Quality, Value, and Loyalty Intentions in Apparel Retailing. Journal of Interactive Marketing. 2009, 23(3): 221-233. doi: 10.1016/j.intmar.2009.04.009
147. Wan Z, Fang Y. The role of information technology in technology- mediated learning: A review of the past for the future. In: Proceedings of the 12th Americas Conference on Information Systems, AMCIS 2006; 4–6 August 2006; Acapulco, México. Volume 4, pp. 2018–2025.
148. Fornell C, Larcker DF. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research. 1981, 18(1): 39. doi: 10.2307/3151312
149. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science. 2014, 43(1): 115-135. doi: 10.1007/s11747-014-0403-8
150. Dijkstra TK, Schermelleh-Engel K. Consistent Partial Least Squares for Nonlinear Structural Equation Models. Psychometrika. 2013, 79(4): 585-604. doi: 10.1007/s11336-013-9370-0
151. Hu L, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal. 1999, 6(1): 1-55. doi: 10.1080/10705519909540118
152. Tenenhaus M, Vinzi VE, Chatelin YM, et al. PLS path modeling. Computational Statistics & Data Analysis. 2005, 48(1): 159-205. doi: 10.1016/j.csda.2004.03.005
153. Wetzels, Odekerken-Schröder, van Oppen. Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustration. MIS Quarterly. 2009, 33(1): 177. doi: 10.2307/20650284
154. Cohen J. A power primer. Psychological Bulletin. 1992, 112(1): 155-159. doi: 10.1037/0033-2909.112.1.155
155. Hew JJ, Tan GWH, Lin B, et al. Generating travel-related contents through mobile social tourism: Does privacy paradox persist? Telematics and Informatics. 2017, 34(7): 914-935. doi: 10.1016/j.tele.2017.04.001
156. Shmueli G, Ray S, Velasquez Estrada JM, et al. The elephant in the room: Predictive performance of PLS models. Journal of Business Research. 2016, 69(10): 4552-4564. doi: 10.1016/j.jbusres.2016.03.049
157. Ringle CM, Sarstedt M. Gain more insight from your PLS-SEM results. Industrial Management & Data Systems. 2016, 116(9): 1865-1886. doi: 10.1108/imds-10-2015-0449
158. Teo AC, Tan GWH, Ooi KB, et al. The effects of convenience and speed in m-payment. Industrial Management & Data Systems. 2015, 115(2): 311-331. doi: 10.1108/imds-08-2014-0231
159. Teo AC, Tan GW, Ooi KB, et al. The effects of convenience and speed in m-payment. Industrial management & data systems, 115(2): 311-331. doi: 10.1108/IMDS-08-2014-0231.
160. Talukder MdS, Sorwar G, Bao Y, et al. Predicting antecedents of wearable healthcare technology acceptance by elderly: A combined SEM-Neural Network approach. Technological Forecasting and Social Change. 2020, 150: 119793. doi: 10.1016/j.techfore.2019.119793
161. Liébana-Cabanillas F, Molinillo S, Ruiz-Montañez M. To use or not to use, that is the question: Analysis of the determining factors for using NFC mobile payment systems in public transportation. Technological Forecasting and Social Change. 2019, 139: 266-276. doi: 10.1016/j.techfore.2018.11.012
162. Asadi S, Abdullah R, Safaei M, et al. An Integrated SEM-Neural Network Approach for Predicting Determinants of Adoption of Wearable Healthcare Devices. Mobile Information Systems. 2019, 2019: 1-9. doi: 10.1155/2019/8026042
163. Yee-Loong Chong A, Liu MJ, Luo J, et al. Predicting RFID adoption in healthcare supply chain from the perspectives of users. International Journal of Production Economics. 2015, 159: 66-75. doi: 10.1016/j.ijpe.2014.09.034
164. Sternad Zabukovšek S, Kalinic Z, Bobek S, et al. SEM–ANN based research of factors' impact on extended use of ERP systems. Central European Journal of Operations Research. 2018, 27(3): 703-735. doi: 10.1007/s10100-018-

0592-1
165. Mac Callum K, Jeffrey L. The influence of students' ICT skills and their adoption of mobile learning. Australasian Journal of Educational Technology. 2013, 29(3). doi: 10.14742/ajet.298
166. Mac Callum K, Jeffrey L, NA K. Factors Impacting Teachers' Adoption of Mobile Learning. Journal of Information Technology Education: Research. 2014, 13: 141-162. doi: 10.28945/1970
167. Kim-Soon N, Ibrahim MA, Razzaly W, et al. Mobile Technology for Learning Satisfaction Among Students at Malaysian Technical Universities (MTUN). Advanced Science Letters. 2017, 23(1): 223-226. doi: 10.1166/asl.2017.7140
168. Oghuma AP, Libaque-Saenz CF, Wong SF, et al. An expectation-confirmation model of continuance intention to use mobile instant messaging. Telematics and Informatics. 2016, 33(1): 34-47. doi: 10.1016/j.tele.2015.05.006
169. Cheung R, Vogel D. Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. Computers & Education. 2013, 63: 160-175. doi: 10.1016/j.compedu.2012.12.003
170. Mohd Alwi NH, Fan IS. E-Learning and Information Security Management. International Journal for Digital Society. 2010, 1(2): 148-156. doi: 10.20533/ijds.2040.2570.2010.0019
171. El-Khatib K, Korba L, Xu Y, et al. Privacy and Security in E-Learning. International Journal of Distance Education Technologies. 2003, 1(4): 1-19. doi: 10.4018/jdet.2003100101
172. Chang S, Tung F. An empirical investigation of students' behavioural intentions to use the online learning course websites. British Journal of Educational Technology. 2007, 39(1): 71-83. doi: 10.1111/j.1467-8535.2007.00742.x
173. Chatzoglou PD, Sarigiannidis L, Vraimaki E, et al. Investigating Greek employees' intention to use web-based training. Computers & Education. 2009, 53(3): 877-889. doi: 10.1016/j.compedu.2009.05.007
174. Tarhini A, Arachchilage NAG, Masa'deh R, et al. A Critical Review of Theories and Models of Technology Adoption and Acceptance in Information System Research. International Journal of Technology Diffusion. 2015, 6(4): 58-77. doi: 10.4018/ijtd.2015100104
175. Tarhini A, Arachchilage NA, Abbasi MS. A critical review of theories and models of technology adoption and acceptance in information system research. International Journal of Technology Diffusion. 2015, 6(4): 58-77. doi: 10.4018/ijtd.2015100104
176. Al-Hujran O, Al-Lozi E, Al-Debei MM. Get ready to mobile learning: Examining factors affecting college students' behavioral intentions to use m-learning in Saudi Arabia. Journal of Business Administration. 2014, 10(1): 111-128. doi: 10.12816/0026186
177. Deng S, Liu Y, Qi Y. An empirical study on determinants of web based question-answer services adoption. Online Information Review. 2011, 35(5): 789-798. doi: 10.1108/14684521111176507
178. Tarhini A, Hone K, Liu X. Measuring the Moderating Effect of Gender and Age on E-Learning Acceptance in England: A Structural Equation Modeling Approach for An Extended Technology Acceptance Model. Journal of Educational Computing Research. 2014, 51(2): 163-184. doi: 10.2190/ec.51.2.b
179. Tarhini A, Hone K, Liu X. The effects of individual differences on e-learning users' behaviour in developing countries: A structural equation model. Computers in Human Behavior. 2014, 41: 153-163. doi: 10.1016/j.chb.2014.09.020
180. Teo T. A path analysis of pre-service teachers' attitudes to computer use: Applying and extending the technology acceptance model in an educational context. Interactive Learning Environments. 2010, 18(1): 65-79. doi: 10.1080/10494820802231327
181. Chao CM. Factors Determining the Behavioral Intention to Use Mobile Learning: An Application and Extension of the UTAUT Model. Frontiers in Psychology. 2019, 10. doi: 10.3389/fpsyg.2019.01652