Asian Social Science; Vol. 17, No. 12; 2021
ISSN 1911-2017 E-ISSN 1911-2025
Published by Canadian Center of Science and Education

The Mediating Effect of Intention to Use on the Relationship between Mobile Learning Application and Knowledge and Skill Usage

Azizi Mohd Noor[1], Nik Hasnaa Nik Mahmood[1] & Wan Normeza Wan Zakaria[1]

[1] Razak Faculty of Technology and Informatics, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia

Correspondence: Azizi Mohd Noor, Razak Faculty of Technology and Informatics, Universiti Teknologi Malaysia, 54100 Kuala Lumpur, Malaysia. Tel: 60-13-332-1109. E-mail: azizimohdnoor@graduate.utm.my

Received: October 2, 2021 Accepted: October 17, 2021 Online Published: November 29, 2021

doi:10.5539/ass.v17n12p31 URL: https://doi.org/10.5539/ass.v17n12p31

Abstract

Mobile learning (m-learning) has evolved as an alternative way of training delivery in a variety of businesses and sectors. Mobile device technology is continuously developing and improving, resulting in more mobile device use. In a corporate setting, the usage of mobile devices as learning aids has become a new delivery technique. Telekom Malaysia (TM) has also adopted this learning tool for staff training. This research has been conducted to determine the mediating effect of intention to use on the relationship between mobile learning applications and knowledge and skill usage. There are five objectives for this research. Hypotheses have been generated to be tested according to the Technology Acceptance Model (TAM) and Kirkpatrick Evaluation Model. The questionnaire was used for data collection. SmartPLS version 3.2.8 and IBM SPSS Statistics version 26 statistical software were used in the analysis. The finding revealed that there was an effect of perceived ease of use (PEOU) and perceived usefulness (PU) on TM employee knowledge and skill usage. In addition, the study also found there was a mediating effect of Intention to Use (ITU) on the relationship between PEOU and PU with TM employee knowledge and skill usage.

Keywords: Mobile learning (m-learning), Intention to use, Technology Acceptance Model (TAM), knowledge, skill usage.

1. Introduction

Mobile learning has become the new learning delivery method in various industries and sectors. Telekom Malaysia (TM) has also adopted mobile learning tool for staff training. Telekom Malaysia Berhad (TM) is Malaysia's digital infrastructure and national connectivity provider, as well as the country's leading integrated telco, providing a comprehensive suite of communication services and solutions in fixed (telephony and broadband), mobile (content), WiFi, ICT, Cloud, and smart services. The company emphasizes providing a better customer experience through continuous customer service quality improvements and innovations while also focusing on increased operational efficiency and productivity. While operating in a highly competitive environment, TM is motivated by the creation of shareholder value. In 2020, TM had more than 21,000 employees (Telekom Malaysia Corporate Profile).

There are challenges in getting the Telekom Malaysia employees to attend the conventional face-to-face training, especially for the front-liners such as the sales team, service installer, repairer, and other critical scopes of work due to their daily work commitment. The employees need to have a different way of learning to learn anytime and anywhere without interrupting their daily tasks. In view of this, the EduBite mobile learning apps have become one of TM's new learning delivery solutions. Therefore, the proposed study is vital to identify the factors that affected mobile learning implementation in the Telekom Malaysia organization. Employees would accept mobile learning if they PEOU and PU. Both factors affect ITU mobile learning, which leads to knowledge acquisition and skill usage.

Though mobile learning has been widely discussed, the majority of previous studies have been carried out in countries such as Taiwan (Hwang et al., 2010), New Zealand (Lu & Viehland, 2008), Macedonia (Fetaji & Fetaji, 2008), China (Liu et al., 2010), and Thailand (Vate-U-Lan, 2008). Mobile learning studies from the perspective of a developing country such as Malaysia are still in their infancy. Those who have studied mobile learning have primarily looked at it from the perspectives of library services (Cummings et al., 2010; Hahn, 2008; Walsh, 2009), higher education (Cook et al., 2007; Fetaji & Fetaji, 2008), Museums (Hsu et al., 2006), and further education (Savill-Smith et al., 2006). However, the elements that influence people's intentions to use mobile learning in the context of telecommunication organizations have remained largely unexplained.

66 percent of smartphone users and 20 percent of tablet users had smartphones and tablets in 2018. Access to the internet is primarily accomplished through mobile devices (including tablets and smartphones). By 2025, around 71% of the world's population will have access to mobile internet (GSMA, 2018). Given the expanding number of mobile users and the potential of mobile technologies, it is critical to explore the factors that influence the intention to utilise mobile devices for corporate or organizational learning goals. Nonetheless, evaluating the intention to use mobile learning in an organization is still not widely considered. As a result, this research aims to identify the role of intention to use (ITU) in mediating between mobile learning application and knowledge and skill usage in a telecommunication organization. Specifically, five research objectives had been determined; (RO1) To examine the effect of PEOU and PU on the Intention to Use (ITU) of mobile learning. (RO2) To determine the effect of Intention to Use (ITU) of mobile learning on TM employee knowledge. (RO3) To determine the effect of Intention to Use (ITU) of mobile learning on TM employee skill usage. (RO4) To examine the effect of PEOU and PU of mobile learning on TM employee knowledge and skill usage. (RO5) To examine the mediating effect of Intention to Use (ITU) of mobile learning on the relationship between PEOU and PU with TM employee knowledge and skill usage.

2. Literature Review

García et al. (2019) suggested that to predict whether users will have an intention to use mobile learning as a tool of human capital training in organisations, it is necessary to consider the following factors: the influence of their circle of reference (subjective norm), whether m-learning is important to their work (job relevance), whether the results are tangible (PU and PEOU). Subjective norm and job relevance are major factors in defining m-learning PU (after PEOU). PEOU of m-learning appears to be strongly associated with how enjoyable the learning process is and whether the learner believes that they have control over it. In the results presented above, PEOU appears to be a very strong predictor of both PU and BI, with PU being the key driver of Behavioral intention. Although user acceptability has garnered a lot of attention in past study, Ong et al. (2004) discovered that more work was needed to analyse or validate previous findings, particularly in different technologies, user groups, and/or organisational contexts. They presented perceived credibility as a novel construct to investigate the applicability of the technology acceptance model (TAM) in understanding engineers' decisions to adopt e-learning and to address a practical technology management issue. The results, based on a sample of 140 engineers from six worldwide companies, clearly corroborate the extended TAM's ability to predict engineers' intention to adopt e-learning.

Moreover, Venkatesh (2000), in his study on “Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model,” found while past study has demonstrated that simplicity of use is significant in affecting user acceptance and usage behaviour, recent studies show that it has been overlooked in prior research. Still, relatively little study has been done to examine how this view evolves and shifts over time. System-specific PEOU is adjusted and tested in the current research using the adjustment-based theoretical model. According to the model, three main sources of early impressions of system ease of use include: control (internal and external—both conceptualised as computer self-efficacy, the former by virtue of the conditions used to facilitate ease of use, the latter through the intrinsic desire to use computers), and intrinsic motivation (conceptualised as computer playfulness) (conceptualised as computer anxiety). When more experience is gained, it is assumed that the objective usability of the system will alter to reflect the general views about computers and computer use, while anchoring to external control and the current system environment. The concept was tested by implementing it in three separate firms and gathering data over three months from 246 people. According to the proposed research model, which was well supported at all sites of measurement, and which explained up to sixty percent of the variances in system-specific PEOU, our existing understanding accounts for only half of the system-specific perceived ease of use.

Meanwhile, Wang et al. (2006) in their research on predicting consumer ITU mobile service stated that to help consumers understand which aspects influence their intent to utilise m-services, there is a necessity for study. The research, based on TAM, TPB, and Luarn & Lin's (2005) mobile banking acceptance model, refines and validates an integrated model for predicting user intention to use m-service. To test the research model, an analysis of 258 individuals in Taiwan was completed utilising the structural equation modelling approach. Results significantly confirm the suggested model's claim that customers are more likely to use m-service after engaging with it. The paper explores several issues relevant to m-service adoption and acceptance studies.

Furthermore, Yoon and Kim (2007) found that, although PEOU and PU have been consistently valued in IT decisions over the past few decades, context, user type, and technological attributes will alter the adoption rate of a new IT. They introduced convenience as a new factor that reflects the characteristic of ubiquitous computing technology. In addition, they chose wireless Local Area Network ubiquitous computing is still in its nascent stages, and so uses TAM as a means to evaluate the Extended TAM in a ubiquitous computing context.

Tan et al. (2014) previously published a paper titled "Predicting the drivers of behavioural intention to use mobile learning: A hybrid SEM-Neural Networks approach." The study employs a "hybrid Structural Equation Modeling–Artificial Neural Networks (SEM–ANN) technique" to empirically analyse the elements that impact a user's intention to adopt mobile learning (m-learning). SEM input units and the Root Mean Square of Errors (RMSE) produced a feed-forward-back-propagation multi-layer perceptron ANN that demonstrated a high level of prediction accuracy. In order to assess the normalised relevance of all relevant determinants, all relevant variables were employed in a sensitivity analysis. Because of the popularity of this new technology, understanding why it was embraced can be explained using the Technology Acceptance Model (TAM). the study attempts to overcome the study's weaknesses by incorporating two new constructs: personal innovativeness in information technology (PIIT) and social influences (SI). Of the 400 surveys distributed to mobile users, 216 questionnaires were returned. The study finds that there is a strong link between the intention to use m-learning and overall student learning. In contrast, for PIIT, SI, and the control variables age, gender, and academic credentials, the findings are inconclusive. The findings are relevant to companies that make mobile devices, such as phone carriers and universities, as well as governments, who may want to plan their future adoption plans. In addition, the study further extended TAM from a market with a developing economy from the aspect of psychology.

Moreover, a book by Kim (2009) aimed at exploring the influential factors of customers in accepting biometrics and to moderate impacts of demographic factors on their intention to use biometrics in the hospitality industry. Meanwhile, Gibson et al. (2008) evaluated the extent to which the TAM could satisfactorily explain faculty acceptance of online education by conducting a survey. The data showed that PU is a strong pointer of faculty willingness to use online education technology; nevertheless, the effects of the additional power offered by PEOU are small when compared to those found in PU. In addition to that, Barkhi et al. (2008) claimed, "TAM postulates that PU is an important determinant of user attitude about acceptance of technologies that can lead to the ITU the technology and actual usage."

Kuciapski (2017) investigated to better understand how employees were adopting mobile technology for knowledge transfer. In order to train employees for using mobile technology for competency development, their knowledge and preparedness to use mobile technology is not yet sufficient. The research aims to discover why mobile devices and software are more likely to be used for knowledge transfer within the knowledge management process. Design/methodology/approach using literature research, a conceptual model was created to describe the relationship between UTAUT and various relative usability (RU) and user autonomy characteristics (UA). In order to test the validity of the model, a survey of 371 employees from 21 different sectors was utilised. Findings The UTAUT paradigm explains employer acceptance of mobile technology for knowledge transfer. User autonomy in selecting and utilising applications, as well as user experience, plays a role in user desire to use mobile devices and software for knowledge transfer. Restrictions/implications This approach explains why 55% of employees want to adopt mobile technologies for knowledge sharing. Despite its high acceptance theories, additional variables should be studied. The study also does not examine sector-specific m-learning acceptability. Consequences Employees should be able to choose solutions that are convenient for them, use preferred platforms, customise apps, and use devices and software in varied contexts. They should not be simplified and should have the same capability and efficiency as online and desktop programmes, even if learning them takes more time. Mobile solutions that support UA and RU let employees capture, distribute, and use knowledge effectively. Originality/value The developed methodology offers a practical option for enhancing mobile technology acceptance for knowledge transfer. As a result of this study, two new predictors for technology acceptability in knowledge transfer have been introduced: UA and RU.

Furthermore, the study in Indonesia by Sidik and Syafar (2020) found that the total benefits provided by mobile learning are more than advantageous for educational productivity. Also, mobile learning is absolutely required to be ready for Indonesia's Higher Education Industry 4.0. Mac Callum and Jeffrey (2013), who also found the study indicated that ICT (information and communications technology) abilities directly correlate with intentions to utilise mobile learning. Cebeci et al. (2019) in their research on understanding the intention to use Netflix, found that knowledge is related to both PEOU and PU. Bailey et al. (2017); Kim et al. (2010); Liu and Tai (2016); Sánchez-Prieto et al. (2017) also found that knowledge is related to both PEOU and PU. Izuagbe et al. (2019) discovered a substantial correlation between PEOU and e-Skills. The researchers were able to discover that e-Skills and PEOU both display a strong link, and that library users have a strong desire to accept new technologies. Akintolu et al. (2019), also found that participants have a good attitude toward using mobile devices for educational reasons. In addition, the participants found that mobile technology can be both engaging and beneficial in achieving success in adult literacy programs. Dias and Victor (2017), Sharples et al. (2005), and Wagner and Kozma (2005) all corroborated that mobile phones facilitate community-centered learning, which means that the learner considers it valuable to be relevant and can also be used to accomplish socio-economic goals such as those related to health and family care. Yusoff et al. (2009) found that E-library usage was also found to be positively correlated with PU. Usage level will be higher if students feel that a system is useful. this discovery has come about as a consequence of an independent study that discovered a strong positive association between PU and actual usage (Adams et al., 1992; Davis, 1989; Igbaria et al., 1995; Igbaria et al., 1997; Mathieson, 1991; Ndubisi et al., 2001; Ramayah & Aafaqi, 2004; Ramayah et al., 2004; Ramayah et al., 2003; Segars & Grover, 1993).

Previous studies showed that PU and PEOU all indirectly influence knowledge and skill through their intention to use mobile learning, which is consistent with previous studies. (Chiou et al., 2009; Jahangir & Begum, 2008; Liu et al., 2010; Lu et al., 2005; Taylor & Todd, 1995; Venkatesh & Davis, 2000). The intention to use (ITU) has played a partial mediation role in the relationship. These findings confirm previous research that revealed that the more the potential user's intention to use, the more likely he or she will begin utilising such mobile learning technology. (Brown et al., 2003; Chiou et al., 2009; Davis et al., 1989; Karim et al., 2006; Liu et al., 2010; Lu et al., 2005; Luarn & Lin, 2005). In accordance with prior research findings (Cheng & Yuen, 2018; Joo et al., 2016), where intention significantly impacts actual use, the empirical findings validate the significance of intention to use mobile learning.

This study introduces knowledge and skill usage variables in the research model, which will be discussed in section 3. Kirkpatrick Evaluation Model was proposed in explaining learning and training effectiveness which include knowledge and skill gained from the learning or training. Donald Kirkpatrick proposed this model, which focuses on measuring four different outcomes or levels expected from an effective training programme. Reaction, learning, behaviour, and results are the four levels. The reaction is how well the trainees liked the training program. Learning examines whether the trainees gained any knowledge, attitude, or skills as a result of the training; behaviour assesses the extent to which the trainees' job behaviour changed as a result of the training, and results attempt to determine the extent to which the outcomes (i.e., effects on the business or institution) have been influenced by the training programme. This model is the most preferred evaluation framework as it helps in understanding the training evaluation in a very systematic way and one of the best evaluation methods (Bates, 2004; Dorri et al., 2016). Moreover, Salas and Cannon-Bowers (2001) found that the Kirkpatrick Evaluation Model is the most popular framework for guiding evaluations. The statements have been supported by Alsalamah and Callinan (2021), where the Kirkpatrick model is useful, appropriate, and applicable in various contexts. It is adaptable to many training environments and achieves high performance in evaluating training. The overview of publications on the Kirkpatrick model shows that research using the model is an active and growing area. Rafiq (2015) has found in his study on training evaluation in an organization using the Kirkpatrick evaluation model that the participants had applied skills and knowledge they had learned from training.

All of the above reviews by various authors discussed the variables in relation to the research model: perceived ease of use, perceived usefulness, intention to use, knowledge, and skill usage. The reviews had discussed the TAM-related study and the Kirkpatrick evaluation model of the learning, including knowledge and skill usage.

3. Research Model and Hypotheses Development

Technology Acceptance Model (Davis, 1989) in Figure 1 and Kirkpatrick's Evaluation model (Kirkpatrick & Kirkpatrick, 2006) in Figure 2 are two independent theoretical models integrated into this study to create a research model that may be applied to various situations. According to TAM, the intention to use mobile learning is determined by perceived usefulness (PU) and perceived ease of use (PEOU).

In the original model, TAM is constructed from several indicators, including perceived ease of use (PEOU), perceived usefulness (PU), attitudes towards using (Attitude), behavioral intention (Intention to use), and actual usage (Use) as per Figure 1. PEOU and PU affect attitude towards using and influence the intention to use, which finally will reflect the actual usage. In addition, many researchers have extended TAM by incorporating new constructs into the model (Ahmad et al., 2010; Hanafizadeh et al., 2012). On the other hand, some studies were conducted after modifying a few factors from the original TAM (Wang et al., 2006; Zejno & Islam, 2012). As a result, this study has modified the Technology Acceptance Model by combining attitude with the intention to use to become intention to use. The indicator of Use in this study is known as Skill usage, and a new additional indicator is a knowledge. When mobile learning technology is accepted, the employees will use it and gain knowledge and skill. Knowledge and skill variables have been introduced in this study to indicate the outcome of intention to use mobile learning. To support these variables, Rafiq (2015) has investigated the training evaluation in an organization using Kirkpatrick Model. The results showed that the participants had applied skills and knowledge they had learned from training. Therefore, this study uses TAM and incorporates variables such as knowledge and skill usage as dependent variables. The research model tested in this study is shown in Figure 3.

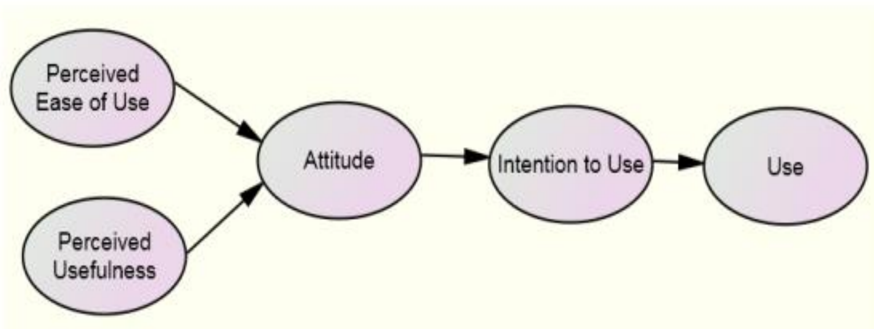

Figure 1. Technology Acceptance Model (TAM) (Davis, 1989)

To further evaluate the knowledge and skill usage of mobile learning, Kirkpatrick Evaluation Model is used. Kirkpatrick Evaluation Model has 4 levels (Refer to Figure 2). Level 1 is reaction/satisfaction towards the training. Level 2 is to measure the learning before and after the training. Level 3 measures the behaviour (application) at the workplace after the training, and Level 4 measures the impact of the training on the division performance. In the context of this study, Level 2 is applied to measure knowledge before and after the training. While Level 3 is applied to evaluate skill usage of mobile learning after completion of the training.

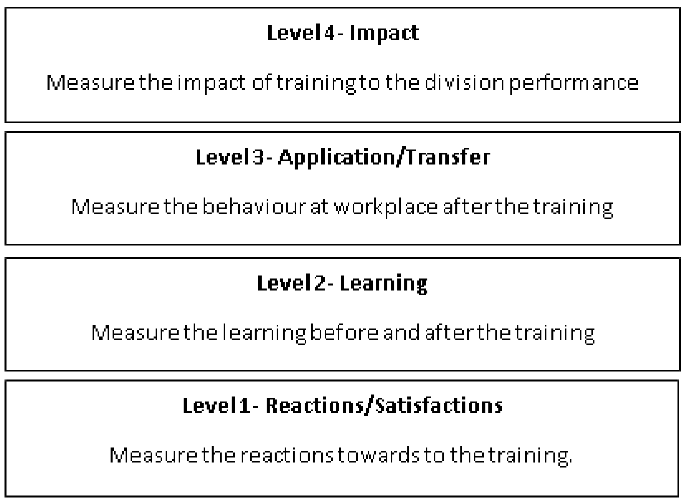

Figure 2. Kirkpatrick Evaluation Model (Kirkparick and Kirkpatrick, 2006)

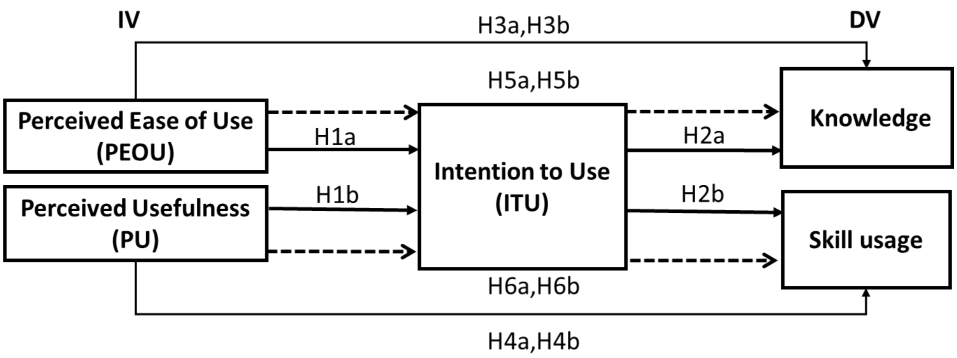

Figure 3. Research model

Based on findings from previous studies related to the relationship between PEOU, PU, ITU with knowledge and skill usage, TAM, and Kirkpatrick Evaluation Model, six hypotheses have been developed as depicted in the research model (Refer to Figure 3).

Therefore, the following hypotheses are suggested:

H1a There is an effect of PEOU on ITU. This hypothesis was supported by García et al. (2019); in their study on the determinants of the acceptance of mobile learning as an element of human capital training in organizations, they found that perceived ease of use of mobile learning had a positive and direct effect on the intention to use it. Several studies have demonstrated a significant effect of perceived ease of use on intention to use (Ong et al., 2004; Venkatesh, 2000; Wang et al., 2006; Yoon & Kim, 2007).

H1b There is an effect of PU on ITU. This hypothesis was supported by García et al. (2019), who found that the perceived usefulness of mobile learning had a positive and direct effect on the intention to use it. Kim (2009) studied exploring the influential factors of customers in accepting biometrics and moderate impacts of demographic factors on their intention to use biometrics also supports this hypothesis.

H2a There is an effect of ITU on Knowledge. Kuciapski (2017) supported this hypothesis, who found an impact on the employees' intention to use mobile devices and software for knowledge acquisition. Sidik and Syafar (2020) also found that the number of the benefits offered positively by mobile learning are favorable for productive learning.

H2b There is an effect of ITU on Skill usage. This hypothesis was supported by Mac Callum and Jeffrey (2013), who found a direct relationship between intention to adopt mobile learning and basic ICT skills. Also supported by Kumar and Mantri (2021) on evaluating engineering educators' attitudes regarding using Augmented reality interactive tabletop environment (ARITE) to improve laboratory skills, educators are enthusiastic about using ARITE to teach laboratory skills in embedded system courses.

H3a There is an effect of PEOU on knowledge. This hypothesis was supported by Yusoff et al. (2009), who found that PEOU of e-library affects the knowledge of search domain. Prior research of Hong et al. (2002), Thong et al. (2004), and Ramayah (2006) on user acceptance of digital libraries or e-library also supported this research hypothesis.

H3b There is an effect of PEOU on Skill usage. This hypothesis was supported by Izuagbe et al. (2019), who discovered a substantial correlation between PEOU and e-Skills. Mac Callum and Jeffrey (2014) also supported the hypothesis that ease of use and digital skills are significant factors influencing lecturers' propensity to utilize educational technologies.

H4a There is an effect of PU on Knowledge. This hypothesis reflects those of Akintolu et al. (2019), who also found that participants showed a positive attitude regarding the usage of mobile technologies for educational purposes. Dias and Victor (2017), Sharples et al. (2005), and Wagner and Kozma (2005) all corroborated that mobile phones facilitate community-centered learning, which means that the learner considers it valuable to be relevant and can also be used to accomplish socio-economic goals such as those related to health or family care.

H4b There is an effect of PU on Skill usage. This hypothesis has been supported by Yusoff et al. (2009), who also found that PU was also found to be positively related to the actual skill usage of the e-library. This hypothesis support prior research that has found a direct positive relationship between PU and actual usage (Adams et al., 1992; Davis, 1989; Igbaria et al., 1995; Igbaria et al., 1997; Mathieson, 1991; Ramayah & Aafaqi, 2004).

H5a There is a mediating effect of Intention to Use (ITU) on the relationship between PEOU on Knowledge.

H5b There is a mediating effect of Intention to Use (ITU) on the relationship between PEOU on Skill usage.

H6a There is a mediating effect of Intention to Use (ITU) on the relationship between PU on Knowledge.

H6b There is a mediating effect of Intention to Use (ITU) on the relationship between PU on Skill usage.

H5a, H5b, H6a, and H6b hypothesized that PU and PEOU all indirectly influence the actual use (knowledge and skill) through intention to use mobile learning, which is consistent with prior research (Chiou et al., 2009; Jahangir & Begum, 2008; Liu et al., 2010; Lu et al., 2005; Taylor & Todd, 1995; Venkatesh & Davis, 2000). These hypotheses have been supported by prior research, which also found that the more intention to use the potential user has, the more likely he or she starts using such mobile learning technology (Brown et al., 2003; Chiou et al., 2009; Davis et al., 1989; Karim et al., 2006; Liu et al., 2010; Lu et al., 2005; Luarn & Lin, 2005).

3.1 PEOU

"The degree to which a person believes that using a certain system would be devoid of effort, according to the definition of perceived ease of use (PEOU)" (Davis, 1989). Several studies have demonstrated that PEOU has a statistically significant correlation with PU (Joo et al., 2016; Mohammadi, 2015; Sabah, 2016; Seliaman & Al-Turki, 2012) (Tan et al., 2012; Yadegaridehkordi et al., 2013). A further benefit of PEOU is that a more significant impact on the continuous intention (CI) to use m-learning (Iqbal & Qureshi, 2012; Joo et al., 2016; Sabah, 2016; Tan et al., 2012).

3.2 PU

"Perceived usefulness is defined as the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). According to a previous study, PU has a statistically significant connection. (Ibrahim et al., 2017; Joo et al., 2016; Mohammadi, 2015; Oghuma et al., 2015). It has also been pointed out that PU has a considerable impact on the CI's decision to employ mobile learning (Alzaza, 2013; Iqbal & Qureshi, 2012; Joo et al., 2016; Kim, 2010; Mac Callum & Jeffrey, 2013, 2014; Mohammadi, 2015; Oghuma et al., 2015; Sabah, 2016; Tan et al., 2012; Yadegaridehkordi et al., 2013).

3.3 Intention to Use

Intention to use is defined by Davis and Cosenza (1993), Fishbein and Ajzen (1975); Fishbein and Ajzen (1979), and Malhotra and Galletta (1999) as a function of beliefs, it's more likely for individuals to have favourable or unfavourable attitudes towards the action. Behavioral intention (BI) or ITU is defined by Davis and Cosenza (1993), Fishbein and Ajzen (1975); Fishbein and Ajzen (1979) as behavioural intents are the aims, aspirations, and expected responses to the attitude object. They are referred to as behavioural intentions.

3.4 Knowledge

"Knowledge is defined as the remembering of previously learned material. This may involve the recall of a wide range of material, from specific facts to complete theories, but all that is required is bringing to mind the necessary data. When it comes to cognitive domain outcomes, knowledge represents the lowest level of achievement." (Bloom, 1956). Examples of learning objectives at this level include: common understanding terms, understanding specific facts, understanding techniques and procedures, fundamental understanding concepts, and understanding principles. Moreover, according to The European Qualifications Framework (EQF) (2008), knowledge is obtained by learning, which entails the absorption of information. Knowledge is all that relates to a field of employment or study. Knowledge can be classified as theoretical or factual based on the six digital competency elements within this framework. In this scope of the study, the researcher measures the knowledge gained on the six digital competency elements before and after the usage of mobile learning.

3.5 Actual Use/Skill Usage

The actual use in this study is referred to as skill usage. The ability to accomplish a task is described as skill, but the term also refers to a dimension of improving ability in the performance of that task. When the word "skill" is used in conjunction with the word "competence," it awakens images of expertise, mastery, and quality, which are all associated with the concept of competence. According to The European Qualifications Framework (EQF) (2008), skills are the effective application of information and know-how to fulfill tasks and solve problems. This approach categorises skills as either cognitive (including the use of logical, intuitive, and creative thinking) or practical (involving the use of hands-on experience). The purpose of this research is to look into the skills that have emerged as a result of using mobile learning as a learning tool.

4. Method

4.1 Data Collection

In a technology adoption study, the quantitative approach has been the most used method (Al-Emran et al., 2018b). A questionnaire survey was issued to TM employees in Klang Valley, Malaysia, for this study. The questionnaires were taken from three TM branches such as TM Kuala Lumpur, TM Petaling Jaya, and TM Selangor within Klang Valley. In such instances, surveys with questionnaires are thought to be the most appropriate way for examining the relationships between the dimensions in a research model. (Al-Emran et al., 2018a). The information was gathered from TM employees in various scopes of work. The G*Power tool and Cohen (1992) were used to determine the minimum sample size that was necessary (Faul et al., 2009). The effect size is 0.15, the error type is 0.05, the power is 0.99, and the number of predictors is 4. These are the G*Power parameters. The minimal sample size necessary was determined to be 107. As a result, 150 employees took part in the research and completed the survey. Only 137 valid responses were kept and could thus be analysed.

4.2 Instrument

The employees' intention to use mobile learning applications was investigated through a questionnaire survey.

There are five research instruments in this study. (1) Perceived ease of use (PEOU) (2) Perceived usefulness (PU) (3) Intention to use (ITU), (4) Knowledge, and (5) Skill usage. Instruments (1), (2), and (3) have been adopted from the previous researcher (Cheon et al., 2012; Davis, 1989; Islam, 2011a; Islam, 2011b). Instruments (1) and (2) have 7 items each. Instrument (3) has 5 items. At the same time, instrument (4) has 10 test questions, and instrument (5) has 30 items. Instrument (4) and (5) had been adopted from Telekom Malaysia organization in 2018 and has been validated by the subject matter expert from the industry. The research instruments (1), (2), (3), and (5) utilized a "5-point Likert scale". All items had been validated by university academia and also the industry subject matter expert.

5. Results

5.1 Data Analysis/Findings

In this work, the data was analysed using the partial least squares-structural equation modelling (PLS-SEM) method, which was applied with the SmartPLS V.3.2.8 software (Ringle et al., 2015). In order to examine the acquired data, a two-step evaluation approach was used, which included both the measurement model and the structural model (Hair et al., 2017). There are a number of factors that contributed to the decision to use PLS-SEM in this investigation. In the first place, PLS-SEM is considered the ideal approach if study seeks to advance an existing hypothesis (Urbach & Ahlemann, 2010). Second, PLS-SEM is the best method for the exploration of difficult models (Hair et al., 2016). Third, instead of looking at the model separately, a PLS-SEM approach looks at the entire model as a unified entity (Goodhue et al., 2012). Fourth, as PLS-SEM enables for both the measurement and structural modelling to be done at the same time, it provides more precise estimations (Barclay et al., 1995).

5.2 Demographic Analysis

There have been 137 totally completed valid questionnaires. Demographic analysis shows that female respondents represented a higher percentage of the total sample (63.5%) as compared to the male respondents (36.5%). This result signifies that most of TM's Klang Valley employees who attended the mobile learning were female. 67 respondents (48.9%) were from 36 until 45 years old, which represents the highest percentage. There were 38 respondents (27.7%) from 26 to 35 years old, 27 respondents (19.7%) from 46 to 55 years old, 4 respondents (2.9%) from 56 to 60 years old, and only 1 respondent (0.7%) from less than 26 years old. According to the respondents' position in the TM's Klang Valley. 53 employees were Exec Band 1 (38.7%), 49 employees were Non-Exec (35.8%), 27 employees (19.7%) were Exec Band 2, and 8 employees or (5.8%) were Exec Band 3. 73 respondents (53.3%) were educated at the Degree level. It represents more than half of the total respondents. The number of respondents with a Diploma was 38 or (27.7%), 12 respondents or (8.8%) were Master holders, 12 respondents or (8.8%) were SPM/Sijil holders, and only 1 or (0.7%) respondent was a Ph.D./Professional. Last but not least, is regarding the respondents working experience in Telekom Malaysia (TM). 56 respondents or (40.9%) had worked for more than 15 years in TM. Then, followed by 52 respondents or (38.0%) with 11 to 15 years working experience, 22 respondents or (16.1%) had between 6 to 10 years working experience, and only 7 respondents (5.1%) had worked from 1 to 5 years in TM.

5.3 Reflective Measurement Model Assessment

Hair et al. (2017) suggested using a standard measurement model to calculate both construct reliability (Cronbach's alpha and composite reliability) and validity (convergent and discriminant validity). This table demonstrates that the values for Cronbach's alpha from the results in Table 1 range between 0.875 and 1.000, all above the threshold value of 0.7. (Nunnally & Bernstein, 1994). Included in the findings shown in Table 1 were the results from the composite reliability (CR) analyses, which showed values ranging from 0.923 to 1.000, all above the recommended value of 0.7 (Kline, 2015). Following these findings, the reliability of the construction was affirmed, and all constructs were found to be error-free. Convergent validity is measured using the factor loading and average variance extracted (AVE). (Hair et al., 2017). Factor loadings yielded results greater than the value of 0.7 suggested. Further, in Table 1, it can be seen that AVE's values (0.667-1.000) are greater than the threshold value of 0.5. Since these findings are in hand, it has been proven that all constructs have converged in their levels of validity. Fornell-Larker criterion, cross-loadings, and the Heterotrait-Monotrait ratio are three potential measurement methods to use in the measurement of discriminant validity (HTMT) (Hair et al., 2017). Table 2 shows that the Fornell-Larker criterion confirms the requirement because all AVEs have square roots greater than their correlation with other constructs. (Fornell & Larcker, 1981). Table 3 shows that, since the indicator loadings on each construct are higher than the loadings of the constructs' corresponding variables, the cross-loadings criterion is also met.

Table 4 shows the Heterotrait-Monotrait (HTMT) ratio generated results. After the bootstrapping procedure, there is no HTMT rate straddle at a value of 1. Therefore, from the three assessments, it is concluded that each latent measurement was discriminating against the other. Last but not least, three essential steps to assess the reflective measurement model had been completed through internal consistency, convergent validity, and discriminant validity. The value from composite reliability, Cronbach alpha, factor loadings, Average Variance Extracted, Fornell & Lacker criterion, cross-loading criterion, and HTMT inference for the reflective measurement model fulfilled the recommended guidelines or the minimum threshold value. Based on all results obtained, the reflective measurement model has a good level of internal consistency, convergent validity, and discriminant validity. The indicators for each latent construct were valid and fit. Thus, the data gathered can be further evaluated in the structural model.

Table 1. Summary of Convergent validity results

Constructs	Cronbach's Alpha	Composite Reliability	AVE
ITU	0.947	0.959	0.826
Knowledge	1.000	1.000	1.000
PEOU	0.907	0.941	0.843
PU	0.875	0.923	0.800
Skill usage	0.983	0.984	0.667

Table 2. Summary of Fornell-Larcker scale results

	ITU	Knowledge	PEOU	PU	Skill usage
ITU	0.909				
Knowledge	0.283	1.000			
PEOU	0.816	0.235	0.918		
PU	0.862	0.217	0.838	0.895	
Skill usage	0.606	0.155	0.596	0.599	0.817

Table 3. Cross-loading results

	ITU	Knowledge	PEOU	PU	Skill usage
PEOU1	0.773	0.216	**0.916**	0.763	0.559
PEOU2	0.732	0.243	**0.930**	0.749	0.525
PEOU3	0.741	0.187	**0.908**	0.796	0.557
PU1	0.763	0.239	0.781	**0.879**	0.590
PU2	0.801	0.199	0.756	**0.920**	0.532
PU3	0.749	0.145	0.712	**0.884**	0.485
ITU1	**0.908**	0.258	0.679	0.745	0.515
ITU2	**0.928**	0.263	0.768	0.797	0.604
ITU3	**0.931**	0.297	0.795	0.793	0.542
ITU4	**0.913**	0.214	0.772	0.833	0.557
ITU5	**0.861**	0.255	0.685	0.744	0.530
CF1	0.551	0.216	0.476	0.512	**0.797**
CF2	0.529	0.223	0.449	0.463	**0.770**
CF3	0.519	0.248	0.464	0.527	**0.718**
CF4	0.522	0.174	0.542	0.539	**0.749**
CF5	0.449	0.085	0.437	0.418	**0.710**
CO1	0.465	0.170	0.419	0.451	**0.820**
CO2	0.477	0.167	0.475	0.473	**0.818**

CO3	0.432	0.102	0.443	0.444	**0.800**
CO4	0.427	0.068	0.374	0.426	**0.729**
CO5	0.402	0.065	0.330	0.405	**0.764**
DL1	0.483	0.102	0.513	0.482	**0.863**
DL2	0.476	0.041	0.507	0.497	**0.857**
DL3	0.387	-0.089	0.363	0.408	**0.735**
DL4	0.530	0.168	0.516	0.495	**0.834**
DL5	0.541	0.070	0.544	0.514	**0.866**
IDT1	0.451	0.042	0.386	0.432	**0.794**
IDT2	0.525	0.160	0.500	0.536	**0.875**
IDT3	0.473	0.123	0.463	0.492	**0.857**
IDT4	0.470	0.137	0.483	0.478	**0.882**
IDT5	0.524	0.171	0.476	0.500	**0.853**
LA1	0.540	0.178	0.556	0.578	**0.830**
LA2	0.538	0.201	0.607	0.546	**0.862**
LA3	0.490	0.106	0.511	0.481	**0.838**
LA4	0.547	0.115	0.548	0.522	**0.829**
LA5	0.581	0.138	0.563	0.548	**0.846**
TL1	0.446	0.056	0.487	0.465	**0.826**
TL2	0.499	0.155	0.527	0.477	**0.821**
TL3	0.476	0.087	0.513	0.464	**0.844**
TL4	0.468	0.096	0.501	0.484	**0.859**
TL5	0.493	0.081	0.496	0.507	**0.846**
Knowledge	0.283	**1.000**	0.235	0.217	0.155

Table 4. Summary of Heterotrait-Monotrait ratio (HTMT) results

	ITU	Knowledge	PEOU	PU	Skill usage
ITU					
Knowledge	0.291 CI.90 (0.169,0.416)				
PEOU	0.879 CI.90 (0.814,0.935)	0.246 CI.90 (0.088,0.382)			
PU	0.946 CI.90 (0.892,0.983)	0.232 CI.90 (0.110,0.368)	0.941 CI.90 (0.891,0.991)		
Skill usage	0.623 CI.90 (0.496,0.738)	0.158 CI.90 (0.076,0.270)	0.627 CI.90 (0.509,0.736)	0.642 CI.90 (0.502,0.771)	

5.4 Assessment of Structural Model

After verifying the measurement model, the next step is constructing a structural model. The researcher needs to use a bootstrapping method of 5000 re-samples to accurately estimate both the coefficient of determination (R^2) and the path coefficients. (Hair et al., 2017). Path coefficients, t-values, and p values are provided in **Table 5** for each hypothesis. All the hypotheses are obviously supported.

Hypothesis 1a ($\beta = 0.315$, $t = 2.823$) proved that PEOU has a significant relationship with ITU mobile learning. **Hypothesis 1b** ($\beta = 0.598$, $t = 5.740$) shows the significant relationship between the PU and ITU mobile learning. **Hypothesis 2a** ($\beta = 0.283$, $t = 3.756$) shows the significant relationship between ITU and knowledge. Representing that ITU effects the knowledge gained after the use of mobile learning. **Hypothesis 2b** ($\beta = 0.606$, $t = 8.799$) shows the significant relationship between ITU and skill. Revealing that the ITU mobile learning positively affects skill. **Hypothesis 3a** ($\beta = 0.089$, $t = 2.226$) shows the significant relationship between PEOU and knowledge. Indicating that the PEOU mobile learning significantly affects knowledge. **Hypothesis 3b** (β =

0.191, t = 2.534) shows the significant relationship between PEOU and skill. Indicating that the PEOU mobile learning significantly affects the skill. **Hypothesis 4a** (β =0.169 , t =2.930) shows the significant relationship between PU and knowledge. Indicating that the PU of using mobile learning increases knowledge. **Hypothesis 4b** (β = 0.362, t = 4.587) shows the significant relationship between PU and skill. Indicating that the PU of using mobile learning enhances the skill. **Hypothesis 5a** (β =0.089 , t =2.226) proves the significant path between PEOU, ITU, and knowledge; triggering out that there is a mediating effect of ITU mobile learning on the relationship between PEOU on knowledge. According to the Variance Accounted For (VAF) calculation, PEOU -> ITU -> knowledge has been found to have a VAF percentage at 50.04%, which is partial mediation (Hair et al., 2017). **Hypothesis 5b** (β = 0.191, t = 2.534) proves the significant path between PEOU, ITU, and skill; triggering out that there is a mediating effect of ITU mobile learning on the relationship between PEOU on Skill. According to the Variance Accounted For (VAF) calculation, PEOU -> ITU -> Skill has been found to have a VAF percentage at 49.98%, which is partial mediation (Hair et al., 2017). **Hypothesis 6a** (β =0.169 , t =2.930) shows the significant path between PU, ITU, and knowledge; revealing that there is a mediating effect of ITU on the relationship between PU on knowledge. According to the Variance Accounted For (VAF) calculation, PU -> ITU -> knowledge has been found to have a VAF percentage at 50.03%, which is also partial mediation (Hair et al., 2017). **Hypothesis 6b** (β = 0.362, t = 4.587) demonstrates the significant path between PU, ITU, and skill; revealing that there is a mediating effect of ITU on the relationship between PU on Skill actual usage. According to the Variance Accounted For (VAF) calculation, PU -> ITU -> SKILL has been found to have a VAF percentage at 50.03%, which is also partial mediation (Hair et al., 2017).

Based on the (R^2) results in **Table 6,** it indicates that the PEOU and PU explain 77.3% of the variance in ITU. It is also revealed that, PEOU and PU explain 36.7% of the variance in the actual Skill use of mobile learning. PEOU and PU explain 8% of the variance in knowledge. Conforming to the recommended values of (R^2) (Chin, 1998), the obtained (R^2) values are acceptable, with a substantial or large effect on ITU and Skill usage, and also a weak effect on knowledge.

Table 5. Summary of Hypotheses testing results

Hypotheses	Relationship	Beta Value	T Statistics Value	P Value	Remarks
H1a	PEOU -> ITU	0.315	2.823	0.005	Supported
H1b	PU -> ITU	0.598	5.740	0.000	Supported
H2a	ITU -> Knowledge	0.283	3.756	0.000	Supported
H2b	ITU -> Skill usage	0.606	8.799	0.000	Supported
H3a	PEOU -> Knowledge	0.089	2.226	0.026	Supported
H3b	PEOU -> Skill usage	0.191	2.534	0.012	Supported
H4a	PU -> Knowledge	0.169	2.930	0.004	Supported
H4b	PU -> Skill usage	0.362	4.587	0.000	Supported
H5a	PEOU -> ITU -> Knowledge	0.089	2.226	0.026	Supported
H5b	PEOU -> ITU -> Skill usage	0.191	2.534	0.012	Supported
H6a	PU -> ITU -> Knowledge	0.169	2.930	0.004	Supported
H6b	PU -> ITU -> Skill usage	0.362	4.587	0.000	Supported

Table 6. Summary coefficient of determination, R^2

	R Square	R Square Adjusted	Remark, R^2
ITU	0.773	0.769	Substantial
Knowledge	0.080	0.073	Weak
Skill usage	0.367	0.362	Substantial

6. Discussion

The main purpose of this study was to determine the mediating effect of intention to use on the relationship between mobile learning applications and knowledge and skill usage. This has been accomplished through the theoretical model of the Technology Acceptance Model (TAM) and Kirkpatrick Evaluation model.

The results from Smartpls analysis indicated that, the **PEOU** and **PU** have a significant positive effect on the

ITU mobile learning **(RO1-H1a,H1b).** The significant relationship between PEOU, PU, and ITU was also supported in previous research (Davis, 1989; Davis et al., 1989; García et al., 2019). Several studies have demonstrated a significant effect of PEOU on ITU (Ong et al., 2004; Venkatesh, 2000; Wang et al., 2006; Yoon & Kim, 2007). Moreover, Nikou and Economides (2017) found that PEOU significantly influences behavioral ITU mobile-based assessment via mobile devices in their study. Meanwhile, Tan et al. (2014), in their research on "predicting the drivers of behavioral intention to use mobile learning" revealed that, PEOU is positively related to the ITU mobile learning. Moreover, a study by Kim (2009) aimed at exploring the influential factors of customers in accepting biometrics and to moderate impacts of demographic factors on their intention to use biometrics. Meanwhile, Gibson et al. (2008) conducted a survey to determine the extent to which the TAM was capable of elucidating faculty acceptance of online education. Faculty acceptance of online education technology is strongly predicted by PU, according to the findings. However, PEOU provides little additional projecting power over and above that provided by PU. In addition to that, Barkhi et al. (2008) claimed, "TAM postulates that perceived usefulness is an important determinant of user attitude about acceptance of technologies that can lead to the intention to use the technology and actual usage."

The finding shows that there is an effect of ITU on employee knowledge (R02-H2a). This finding has been supported by Kuciapski (2017). He found an employees' intentions to use mobile devices and software for knowledge transfer are affected by this factor. The study in Indonesia by Sidik and Syafar (2020) found that when it comes to productive learning, the number of advantages provided by mobile learning is substantial and favourable.

This study has also found that there is an effect of ITU on Skill usage (RO3-H2b). This finding was also reported by Mac Callum and Jeffrey (2013), who also found that a direct relationship was found between basic ICT skills and the ITU mobile learning in the study. **There is an effect of PEOU on knowledge (RO4-H3a).** This result reflects those of Cebeci et al. (2019) in their research on understanding the intention to use Netflix, who also found that knowledge is related to both PEOU and PU. They are consistent with previous research (Bailey et al., 2017; Kim et al., 2010; Liu & Tai, 2016; Sánchez-Prieto et al., 2017). People who have self-efficacy of using Netflix or any other new technology, perceive that they can use it without having a problem. Furthermore, people with knowledge of a specific thing are important to perceive it as user-friendly and beneficial.

From the results, there is also a significant effect of PEOU on skill usage (RO4-H3b). The finding has been supported by Izuagbe et al. (2019). Izuagbe et al. (2019) discovered that there is a significant correlation between PEOU and e-Skills. They came to the conclusion that there is a strong correlation between e-Skills and PEOU, as well as between librarians' intention to accept technology and their ability to learn new technologies. This finding verified Mac Callum and Jeffrey (2014) findings that the ease with which educational technologies can be used, as well as digital skills, are important factors in determining whether or not lecturers will use educational technologies. **There is an effect of PU on knowledge (RO4-H4a).** This result reflects those of Akintolu et al. (2019), who also found that participants showed a positive attitude regarding the usage of mobile technologies/learning for educational purposes. Thus, the participants found that mobile technology can be both engaging and beneficial in achieving success in adult literacy programs. Dias and Victor (2017), Sharples et al. (2005), and Wagner and Kozma (2005) all corroborated that mobile phones facilitate community-centered learning, which means that the learner considers it valuable to be relevant and can also be used to accomplish socio-economic goals such as those related to health or family care.

The study results also pointed out that, there is an effect of PU on skill usage (RO4-H4b). In other words, this finding revealed that when the actual usage has been applied, it will develop the skill. When the employees perceived that mobile learning is useful, they will apply the knowledge learned and develop the skill. This result reflects those of Yusoff et al. (2009), who also found that the amount of time spent at the e-library was also found to be positively related to the amount of PU. Therefore, students who believe that a system is beneficial are more likely to use it. Previous research has discovered a direct positive relationship between PU and actual usage, which has discovered a positive relationship between PU and actual usage. (Adams et al., 1992; Davis, 1989; Igbaria et al., 1995; Igbaria et al., 1997; Mathieson, 1991; Ndubisi et al., 2001; Ramayah & Aafaqi, 2004; Ramayah et al., 2004; Ramayah et al., 2003; Segars & Grover, 1993).

Furthermore, the research results showed that there is a mediating effect of ITU mobile learning on the relationship between PEOU and PU on knowledge and skill usage (RO5-H5a,H5b,H6a & H6b). This study's findings indicate that the intention to use mobile learning has an indirect impact on knowledge and skill, which is consistent with previous research. PU and PEOU all have an indirect impact on knowledge and skill through their ITU mobile learning. (Chiou et al., 2009; Jahangir & Begum, 2008; Liu et al., 2010; Lu et al., 2005; Taylor

& Todd, 1995; Venkatesh & Davis, 2000). The intention to use (ITU) has played a partial mediation role for the relationships. These findings corroborate previous research, which discovered that the greater the potential user's desire to use mobile learning technology, the more likely it is that he or she will begin using it. (Brown et al., 2003; Chiou et al., 2009; Davis et al., 1989; Karim et al., 2006; Liu et al., 2010; Lu et al., 2005; Luarn & Lin, 2005). In accordance with the conclusions reached in previous studies (Cheng & Yuen, 2018; Joo et al., 2016), in cases where ITU has a significant impact on actual use, the empirical findings in this study provided compelling evidence that ITU mobile learning has a significant impact on actual use. The reason for this finding is that TM employees had a positive experience with mobile learning when it was used in corporate learning activities. They will continue to use it for their capability development as this type of learning gives them easy access and useful knowledge for their work-related needs. Thus, it will also develop their required skills.

7. Contribution to the Theory and Practical Implication

There is a noteworthy theoretical contribution made in this research. This research is valuable, particularly in reflecting the contribution to the body of knowledge. In particular, The present study adds and advances existing knowledge, specifically on employee’s acceptance of mobile learning technology compared to the previously TAM model study related to acceptance of IT/IS technology (Davis et al., 1989; Muchran & Ahmar, 2019). In addition to the current TAM, this study has added one new item in TAM, which is knowledge. The findings from this study have several contributions to organizations' practices, namely in training delivery methods and training policy. Adherence with the findings, mobile learning shall be considered a new learning methodology to deliver training to employees on top of the existing training delivery method such as face-to-face physical classroom and online learning. This research also helps policymakers in enhancing their existing training policy at the organization to accept mobile learning training hours as official calculated training hours, although the training is conducted outside the classroom. Therefore, the annual training budget shall be allocated to enhance the mobile learning modules, user experience, platform, and networking. To conclude, based on the research finding which revealed that ITU mediates the relationship between perceived ease of use (PEOU) and perceived usefulness (PU) with knowledge and skill usage, it implies that the training and development division is able to accelerate individual capability development by using mobile learning as a training tool.

8. Future Research

Despite the statistically significant results obtained in the current study, it also identifies some shortcomings that should be taken into consideration in future research. First and foremost, this study was limited by the fact that the data was gathered from only one source: Telekom Malaysia organisation. The present study urges future researchers to replicate this study in a different context, such as changes in different sectors such as education, healthcare, factories, or the public. Second, this study examines only three predictors to see the impact on knowledge and skill. Therefore, the researcher suggested that more predictors or exogenous variables be introduced in future research. Third, the study should consider qualitative research techniques.

9. Conclusion

Mobile learning has become one of the popular training delivery methods in organizations. Employees have accepted mobile learning as a new way of learning. The employees had increased their knowledge and skills after using mobile learning. The main reason for deploying mobile learning is to cater to the challenges of employees to attend the official face-to-face physical training in the organization due to their daily work commitment. Mobil Learning can be an important learning tool for staff development and organization excellent performance. The rapid development of mobile technology has pushed the implementation of mobile learning in the organization. The pandemic of Covid-19 and the globalization of the market compelled the organization to establish an online presence and adapt its business processes to this new reality or new normal.

References

Adams, D. A., Nelson, R. R., & Todd, P. A. (1992). Perceived usefulness, ease of use, and usage of information technology: A replication. *MIS quarterly*, 227-247. https://doi.org/10.2307/249577

Ahmad, T. B. T., Madarsha, K. B., Zainuddin, A. M. H., Ismail, N. A. H., & Nordin, M. S. (2010). Faculty's acceptance of computer based technology: Cross-validation of an extended model. *Australasian Journal of Educational Technology, 26*(2). https://doi.org/10.14742/ajet.1095

Akintolu, M., Adelore, O., & Nzima, D. (2019). Attitude of learners toward the use of mobile technology for adult literacy programme. *African Journal of Gender, Society & Development*, *8*(1), 63. https://doi.org/10.31920/2050-4284/2019/8n1a3

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018a). *PLS-SEM in information systems research: A* *comprehensive methodological reference.* International Conference on Advanced Intelligent Systems and Informatics,

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018b). Technology Acceptance Model in M-learning context: A systematic review. *Computers & education*, *125*, 389-412. https://doi.org/10.1016/j.compedu.2018.06.008

Alsalamah, A., & Callinan, C. (2021). The Kirkpatrick model for training evaluation: Bibliometric analysis after 60 years (1959–2020). *Industrial and Commercial Training*, *ahead-of-print* (ahead-of-print). https://doi.org/10.1108/ICT-12-2020-0115

Alzaza, N. S. (2013). *Mobile learning services acceptance model among higher education students.* https://doi.org/10.12816/0012314

Bailey, A. A., Pentina, I., Mishra, A. S., & Mimoun, M. S. B. (2017). Mobile payments adoption by US consumers: An extended TAM. *International Journal of Retail & Distribution Management*. https://doi.org/10.1108/IJRDM-08-2016-0144

Barclay, D., Higgins, C., & Thompson, R. (1995). *The partial least squares (PLS) approach to casual modeling: Personal computer adoption ans use as an Illustration.*

Barkhi, R., Belanger, F., & Hicks, J. (2008). A model of the determinants of purchasing from virtual stores. *Journal of Organizational Computing and Electronic Commerce*, *18*(3), 177-196. https://doi.org/10.1080/10919390802198840

Bates, R. (2004). A critical analysis of evaluation practice: The Kirkpatrick model and the principle of beneficence. *Evaluation and program planning*, *27*(3), 341-347.

Bloom, B. S. (1956). Taxonomy of educational objectives. Vol. 1: Cognitive domain. *New York: McKay*, *20*, 24.

Brown, I., Cajee, Z., Davies, D., & Stroebel, S. (2003). Cell phone banking: Predictors of adoption in South Africa—an exploratory study. *International journal of information management*, *23*(5), 381-394. https://doi.org/10.1016/S0268-4012(03)00065-3

Cebeci, U., Ince, O., & Turkcan, H. (2019). Understanding the Intention to Use Netflix: An Extended Technology Acceptance Model Approach. *International Review of Management and Marketing*, *9*(6), 152-157. https://doi.org/10.32479/irmm.8771

Cheng, M., & Yuen, A. H. K. (2018). Student continuance of learning management system use: A longitudinal exploration. *Computers & education*, *120*, 241-253. https://doi.org/10.1016/j.compedu.2018.02.004

Cheon, J., Lee, S., Crooks, S. M., & Song, J. (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behavior. *Computers & education*, *59*(3), 1054-1064. https://doi.org/10.1016/j.compedu.2012.04.015

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern methods for business research*, *295*(2), 295-336.

Chiou, W.-C., Lin, C.-C., Perng, C., & Tsai, J.-T. (2009). *E-Learning usability measurement-using technology acceptance model and usability test.* 10th Asia Pacific Industrial Engineering & Management Systems Conference, Kitakyushu, Japan. ,

Cohen, J. (1992). Statistical power analysis. *Current directions in psychological science*, *1*(3), 98-101. https://doi.org/10.1111/1467-8721.ep10768783

Cook, J., Bradley, C., Lance, J., Smith, C., & Haynes, R. (2007). Generating learning contexts with mobile devices. In N. Pachler (Ed.), *Mobile learning: Towards a research agenda. WLE Centre Occasional Papers in Work-based Learning 1* (pp. 55-74), WLE Centre, London.

Cummings, J., Merrill, A., & Borrelli, S. (2010). The use of handheld mobile devices: Their impact and implications for library services. *Library Hi Tech*. https://doi.org/10.1108/07378831011026670

Davis, D., & Cosenza, R. (1993). *Business Research for Decision Making*. Wadsworth Publishing Company.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, *35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Dias, L., & Victor, A. (2017). Teaching and learning with mobile devices in the 21st century digital world: Benefits and challenges. *European Journal of Multidisciplinary Studies, 2*(5), 339-344. https://doi.org/10.26417/ejms.v5i1.p339-344

Dorri, S., Akbari, M., & Dorri Sedeh, M. (2016). Kirkpatrick evaluation model for in-service training on cardiopulmonary resuscitation. *Iranian journal of nursing and midwifery research*, *21*(5), 493-497. https://doi.org/10.4103/1735-9066.193396

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior research methods*, *41*(4), 1149-1160. https://doi.org/10.3758/BRM.41.4.1149

Fetaji, M., & Fetaji, B. (2008). *Universities go mobile—Case study experiment in using mobile devices.* ITI 2008-30th International Conference on Information Technology Interfaces,

Fishbein, M., & Ajzen, I. (1975). Belief, Attitude, Intention and Behaviour: An Introduction to Theory and Research, Reading, Mass: Addision-Wesley. *Fransson, N., and Garling*, 369-382.

Fishbein, M., & Ajzen, I. (1979). *A theory of reason action: Some application sand implications* (H. Howe and M. Page (Eds.) ed.). University of Nebraska Press, .

Fornell, C., & Larcker, D. F. (1981). *Structural equation models with unobservable variables and measurement error: Algebra and statistics.* In Sage Publications Sage CA: Los Angeles, CA.

García, M. V., Blasco López, M. F., & Sastre Castillo, M. Á. (2019). Determinants of the acceptance of mobile learning as an element of human capital training in organisations. *Technological Forecasting and Social Change*, *149*, 119783. https://doi.org/10.1016/j.techfore.2019.119783

Gibson, S. G., Harris, M. L., & Colaric, S. M. (2008). Technology acceptance in an academic context: Faculty acceptance of online education. *Journal of Education for Business*, *83*(6), 355-359. https://doi.org/10.3200/JOEB.83.6.355-359

Goodhue, D. L., Lewis, W., & Thompson, R. (2012). Does PLS have advantages for small sample size or non-normal data? *MIS quarterly*, 981-1001. https://doi.org/10.2307/41703490

GSMA. (2018). The mobile economy. Retrieved from https://www.gsma.com/mobileeconomy/wp-content/uploads/2018/02/The-Mobile-Economy-Global-2018.pdf.

Hahn, J. (2008). Mobile learning for the twenty-first century librarian. *Reference Services Review*. https://doi.org/10.1108/00907320810895369

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2016). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Sage. https://doi.org/10.15358/9783800653614

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Sage. https://doi.org/10.15358/9783800653614

Hanafizadeh, P., Behboudi, M., Koshksaray, A. A., & Tabar, M. J. S. (2012). Mobile-banking adoption by Iranian bank clients. *Telematics and Informatics*, *31*(1), 62-78.

Hong, W., Thong, J. Y., Wong, W.-M., & Tam, K.-Y. (2002). Determinants of user acceptance of digital libraries: An empirical examination of individual differences and system characteristics. *Journal of management information systems*, *18*(3), 97-124.

Hsu, T. Y., Ke, H. R., & Yang, W. P. (2006). Knowledge-based mobile learning framework for museums. *The electronic library*. https://doi.org/10.1108/02640470610707240

Hwang, G.-J., Wu, P.-H., Zhuang, Y.-Y., Kuo, W.-L., & Huang, Y.-M. (2010). *An investigation on students' cognitive load and learning achievements for participating in a local culture mobile learning activity.* 2010 6th IEEE International Conference on Wireless, Mobile, and Ubiquitous Technologies in Education,

Ibrahim, M. A., Kim-Soon, N., Ahmad, A. R., & Sirisa, N. M. X. (2017). Mediating roles of attitude on intention to use M-learning among students at Malaysian technical universities. *Advanced Science Letters*, *23*(4), 2795-2798. https://doi.org/10.1166/asl.2017.7657

Igbaria, M., Iivari, J., & Maragahh, H. (1995). Why do individuals use computer technology? A Finnish case study. *Information & management*, *29*(5), 227-238. https://doi.org/10.1016/0378-7206(95)00031-0

Igbaria, M., Zinatelli, N., Cragg, P., & Cavaye, A. L. (1997). Personal computing acceptance factors in small firms: A structural equation model. *MIS quarterly*, 279-305. https://doi.org/10.2307/249498

Iqbal, S., & Qureshi, I. A. (2012). M-learning adoption: A perspective from a developing country. *International Review of Research in Open and Distributed Learning*, *13*(3), 147-164. https://doi.org/10.19173/irrodl.v13i3.1152

Islam, A. (2011a). Online database adoption and satisfaction model. *Saarbrücken: Lambert Academic Publishing*, 50.

Islam, A. Y. M. A. (2011b). Viability of the extended technology acceptance model: An empirical study. *Journal of Information and Communication Technology*, *10*, 85-98.

Izuagbe, R., Ibrahim, N., Lilofa, O., Olawoyin, O., Nwokeoma, N., Promise, I., & Osayande, O. (2019). Effect of perceived ease of use on librarians' e-skills: Basis for library technology acceptance intention. *Library & Information Science Research*, 100969. https://doi.org/10.1016/j.lisr.2019.100969

Jahangir, N., & Begum, N. (2008). The role of perceived usefulness, perceived ease of use, security and privacy, and customer attitude to engender customer adaptation in the context of electronic banking. *African journal of business management*, *2*(2), 32-40.

Joo, Y. J., Kim, N., & Kim, N. H. (2016). Factors predicting online university students' use of a mobile learning management system (m-LMS). *Educational Technology Research and Development*, *64*(4), 611-630. https://doi.org/10.1007/s11423-016-9436-7

Karim, N. S. A., Darus, S. H., & Hussin, R. (2006). Mobile phone applications in academic library services: A students' feedback survey. *Campus-Wide Information Systems*.

Kim, B. (2010). An empirical investigation of mobile data service continuance: Incorporating the theory of planned behavior into the expectation–confirmation model. *Expert Systems with Applications*, *37*(10), 7033-7039. https://doi.org/10.1016/j.eswa.2010.03.015

Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. *Computers in Human behavior*, *26*(3), 310-322. https://doi.org/10.1016/j.chb.2009.10.013

Kim, J. (2009). *A Comprehensive Structural Model of Factors Influencing Customers' Intention to Use Biometrics in the Hospitality Industry.* ERIC.

Kirkpatrick, D., & Kirkpatrick, J. (2006). *Evaluating training programs: The four levels.* Berrett-Koehler Publishers.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications. https://doi.org/10.1038/156278a0

Kuciapski, M. (2017). A model of mobile technologies acceptance for knowledge transfer by employees. *Journal of Knowledge Management*, *21*(5), 1053-1076. https://doi.org/10.1108/JKM-03-2016-0136

Kumar, A., & Mantri, A. (2021). Evaluating the attitude towards the intention to use ARITE system for improving laboratory skills by engineering educators. *Education and Information Technologies*. https://doi.org/10.1007/s10639-020-10420-z

Liu, G.-S., & Tai, P. T. (2016). A study of factors affecting the intention to use mobile payment services in Vietnam. *Economics World*, *4*(6), 249-273. https://doi.org/10.17265/2328-7144/2016.06.001

Liu, Y., Li, H., & Carlsson, C. (2010). Factors driving the adoption of m-learning: An empirical study. *Computers & education*, *55*(3), 1211-1219. https://doi.org/10.1016/j.compedu.2010.05.018

Lu, J., Yao, J. E., & Yu, C.-S. (2005). Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology. *The Journal of Strategic Information Systems*, *14*(3), 245-268. https://doi.org/10.1016/j.jsis.2005.07.003

Lu, X., & Viehland, D. (2008). *Factors influencing the adoption of mobile learning.*

Luarn, P., & Lin, H.-H. (2005). Toward an understanding of the behavioral intention to use mobile banking. *Computers in Human behavior*, *21*(6), 873-891. https://doi.org/10.1016/j.chb.2004.03.003

Mac Callum, K., & Jeffrey, L. (2013). The influence of students' ICT skills and their adoption of mobile learning. *Australasian Journal of Educational Technology*, *29*(3). https://doi.org/10.14742/ajet.298

Mac Callum, K., & Jeffrey, L. (2014). Factors impacting teachers' adoption of mobile learning. *Journal of Information Technology Education*, *13*. https://doi.org/10.28945/1970

Malhotra, Y., & Galletta, D. F. (1999). *Extending the technology acceptance model to account for social influence: Theoretical bases and empirical validation.* Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences. 1999. HICSS-32. Abstracts and CD-ROM of Full Papers,

Mathieson, K. (1991). Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior. *Information systems research*, *2*(3), 173-191. https://doi.org/10.1287/isre.2.3.173

Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human behavior*, *45*, 359-374. https://doi.org/10.1016/j.chb.2014.07.044

Muchran, M., & Ahmar, A. S. (2019). Application of TAM model to the use of information technology. *arXiv preprint arXiv:1901.11358*.

Ndubisi, N. O., Jantan, M., & Richardson, S. (2001). Is the technology acceptance model valid for entrepreneurs? Model testing and examining usage determinants. *Asian Academy of Management Journal*, *6*(2), 31-54.

Nikou, S. A., & Economides, A. A. (2017). Mobile-based assessment: Investigating the factors that influence behavioral intention to use. *Computers & education*, *109*, 56-73. https://doi.org/10.1016/j.compedu.2017.02.005

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory*. McGraw-Hill. https://doi.org/10.1037/018882

Oghuma, A. P., Chang, Y., Libaque-Saenz, C. F., Park, M.-C., & Rho, J. J. (2015). Benefit-confirmation model for post-adoption behavior of mobile instant messaging applications: A comparative analysis of KakaoTalk and Joyn in Korea. *Telecommunications Policy*, *39*(8), 658-677. https://doi.org/10.1016/j.telpol.2015.07.009

Ong, C.-S., Lai, J.-Y., & Wang, Y.-S. (2004). Factors affecting engineers' acceptance of asynchronous e-learning systems in high-tech companies. *Information & management*, *41*(6), 795-804. https://doi.org/10.1016/j.im.2003.08.012

Rafiq, M. (2015). Training evaluation in an organization using Kirkpatrick model: A case study of PIA. *Journal of Entrepreneurship & Organization Management*, *4*(3), 152-162. https://doi.org/10.4172/2169-026X.1000151

Ramayah, T. (2006). Interface characteristics, perceived ease of use and intention to use an online library in Malaysia. *Information development*, *22*(2), 123-133.

Ramayah, T., & Aafaqi, B. (2004). Role of self-efficacy in e-library usage among students of a public university in Malaysia. *Malaysian Journal of Library & Information Science*, *9*(1), 39-57.

Ramayah, T., Aafaqi, B., & Ignatius, J. (2004). *E-library usage among students of a public University in Malaysia.* The Proceedings of the International Conference on Management Education,

Ramayah, T., Jantan, M., & Aafaqi, B. (2003). *Internet usage among students of institutions of higher learning: The role of motivational variables.* The proceedings of The 1st International conference on Asian Academy of Applied Business conference,

Ringle, C. M., Wende, S., & Becker, J. M. (2015). *SmartPLS 3. Boenningstedt: SmartPLS GmbH.* Retrieved from http://www.smartpls.com

Sabah, N. (2016). Exploring students' awareness and perceptions. *Comput. Human Behav.*, *65*, 522-533. https://doi.org/10.1016/j.chb.2016.09.009

Salas, E., & Cannon-Bowers, J. A. (2001). The science of training: A decade of progress. *Annual review of psychology*, *52*(1), 471-499.

Sánchez-Prieto, J. C., Olmos-Migueláñez, S., & García-Peñalvo, F. J. (2017). MLearning and pre-service teachers: An assessment of the behavioral intention using an expanded TAM model. *Computers in Human behavior*, *72*, 644-654. https://doi.org/10.1016/j.chb.2016.09.061

Savill-Smith, C., Attewell, J., & Stead, G. (2006). *Mobile Learning in practice: Piloting a Mobile Learning teacher's toolkit in further education colleges.* Learning and Skills Network.

Segars, A. H., & Grover, V. (1993). Re-examining perceived ease of use and usefulness: A confirmatory factor analysis. *MIS quarterly*, 517-525. https://doi.org/10.2307/249590

Seliaman, M. E., & Al-Turki, M. (2012). Mobile learning adoption in Saudi Arabia. *World Academy of Science, Engineering and Technology*, *69*(9), 391-293.

Sharples, M., Taylor, J., & Vavoula, G. (2005). *Towards a theory of mobile learning.* Proceedings of mLearn, Sidik, D., & Syafar, F. (2020). Exploring the factors influencing student's intention to use mobile learning in Indonesia higher education. *Education and Information Technologies*, *25*(6), 4781-4796. https://doi.org/10.1007/s10639-019-10018-0

Tan, G. W.-H., Ooi, K.-B., Leong, L.-Y., & Lin, B. (2014). Predicting the drivers of behavioral intention to use mobile learning: A hybrid SEM-Neural Networks approach. *Computers in Human behavior, 36*, 198-213. https://doi.org/10.1016/j.chb.2014.03.052

Tan, G. W.-H., Ooi, K.-B., Sim, J.-J., & Phusavat, K. (2012). Determinants of mobile learning adoption: An empirical analysis. *Journal of Computer Information Systems*, *52*(3), 82-91.

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information systems research*, *6*(2), 144-176. https://doi.org/10.1287/isre.6.2.144

Telekom Malaysia Corporate Profile. Telekom Malaysia Corporate Profile. www.tm.com.my

The European Qualifications Framework (EQF). (2008). *The European Qualifications Framework (EQF), Commission of the European Communities*. Retrieved from http://ec.europa.eu/education/policies/educ/eqf/rec08_en.pdf

Thong, J. Y., Hong, W., & Tam, K. Y. (2004). What leads to user acceptance of digital libraries? *Communications of the ACM*, *47*(11), 78-83.

Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *Journal of Information technology theory and application*, *11*(2), 5-40.

Vate-U-Lan, P. (2008). *Mobile learning: Major challenges for engineering education.* 2008 38th Annual Frontiers in Education Conference,

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information systems research*, *11*(4), 342-365. https://doi.org/10.1287/isre.11.4.342.11872

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46(2)*, 186-204. https://doi.org/doi:10.1287/mnsc.46.2.186.11926

Wagner, D. A., & Kozma, R. B. (2005). *New technologies for literacy and adult education: A global perspective.* Unesco.

Walsh, A. (2009). Text messaging (SMS) and libraries. *Library Hi Tech News*. https://doi.org/10.1108/07419050911000562

Wang, Y. S., Lin, H. H., & Luarn, P. (2006). Predicting consumer intention to use mobile service. *Information systems journal*, *16*(2), 157-179. https://doi.org/10.1111/j.1365-2575.2006.00213.x

Yadegaridehkordi, E., Iahad, N. A., & Baloch, H. Z. (2013). Success factors influencing the adoption of M-learning. *International Journal of Continuing Engineering Education and Life Long Learning*, *23*(2), 167-178. https://doi.org/10.1504/IJCEELL.2013.054290

Yoon, C., & Kim, S. (2007). Convenience and TAM in a ubiquitous computing environment: The case of wireless LAN. *Electronic Commerce Research and Applications*, *6*(1), 102-112. https://doi.org/10.1016/j.elerap.2006.06.009

Yusoff, Y. M., Muhammad, Z., Zahari, M. S. M., Pasah, E. S., & Robert, E. (2009). Individual differences, perceived ease of use, and perceived usefulness in the e-library usage. *Computer and Information Science*, *2*(1), 76-83. https://doi.org/10.5539/cis.v2n1p76

Zejno, B., & Islam, A. (2012). Development and validation of library ICT usage scale for the IIUM postgraduate students. *OIDA International Journal of Sustainable Development*, *3*(10), 11-18.