Journal of Theoretical and Applied Information Technology
15th September 2022. Vol.100. No 17

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

INVESTIGATING THE ADOPTION OF AN INNOVATION USING AN EXTENDED UTAUT MODEL: THE CASE OF MOBILE LEARNING TECHNOLOGY

KHALED M. S. FAQIH
Department of Information Systems, Al al-Bayt University, Jordan
km_faqih@aabu.edu.jo

ABSTRACT

Covid-19 pandemic is unleashing unprecedented digital revolution in educational systems, making mobile-enabled learning is unavoidable alternative option, especially in developing countries whereby university students have no option but to use smartphones for learning as desktop and laptop computers are becoming less popular at homes. To achieve the objectives of this study, this study extends the UTAUT model by incorporating three different mechanisms to enhance the UTAUT environment to investigate mobile learning adoption and enrich both theory and practice. The UTAUT theory was extended by incorporating three exogenous variables (perceived compatibility, perceived image, and perceived mobile anxiety), the endogenous variable of perceived innovativeness, and service quality as a moderator. The empirical data was collected using a survey questionnaire administered to higher education students in Jordan. The proposed research model was tested with the use of WarpPLS using 202 useable questionnaires. The results demonstrate that all hypotheses were found statistically significant, indicating that all variables included in this study play an important role in affecting the adoption process of mobile learning. The findings reveal that the research model explains 53% of the variance in the intention to adopt mobile learning. Theoretical contributions and practical implications are discussed.

Keywords: *Higher Education, Mobile Learning, UTAUT, Service Quality, Mobile Anxiety, Jordan*

1. INTRODUCTION

Mobile computing technology is becoming an increasingly relevant and prevalent trend in today's highly competitive world, indicating that organizations are required to take full advantage of the innovative mobile computing technologies to achieve and remain sustainably competitive [1]. The transformative power of mobile computing has dramatically revolutionized the entire landscape of daily living, especially learning environments. It is an observable phenomenon that the technology of mobile computing is growing in strength, scope, diversity, power, intelligence, innovativeness, resourcefulness, flexibility, collaboration, agility, effectiveness, and efficacy [2, 3, 4]. In the meantime, mobile computing is declining in cost and complexity. Mobile computing has ignited growing attention and interest in the use of mobile-based technologies in every human function. Most definitely, the world is witnessing an undergoing paradigm shift towards a portable and context-aware computation, implying that the world today is placing too much emphasis and expectations on mobile-based technologies in running day-to-day life. As a result, the mobile device has become the vehicle of choice for individuals to communicate and interact with the surrounding environment in a way that has exceeded all expectations. The development in mobile-based technologies has opened novel avenues in many aspects ranging from astronomy to medicine that facilitate the way people experience their environments in a fashion that renders efficiency, effectiveness, and productivity. The potentials of the mobile-based computing paradigm have unleashed the birth of a novel learning pattern named mobile learning. This new focus has attracted the attention of all stakeholders across the globe. One of the consequences unleashed by the Covid-19 pandemic is that the learning environment has been shifted from physical space to cyberspace at almost every corner of the world. Consequently, home-based learning via mobile-based technologies has become all of a sudden the savior to humans across the globe, especially in developing countries' perspectives where desktop and laptop computers are becoming less popular at homes. Therefore, a large number of educational institutions have already been forced to close to encourage social distancing to reduce social interaction and slow down the spread of the virus.

Many definitions have emerged for mobile-based learning in contemporary literature. Several of the proposed definitions place excessive emphasis on the technological attributes of m-learning (too techno-centric). The m-learning paradigm is too complex and revolutionary to define in simple terms. Yet, there is no scholarly agreement on the definition of m-learning technology because it is a technologically and pedagogically multifaceted learning format [5]. Nevertheless, mobile learning has not been given an agreed-upon definition that covers all its unique characteristics and aspects. Any definition developed should heavily rely on and within the perspective of the four pillars of m-learning: pedagogy, technological devices, context, and social interactions [6]. Thus, there is a necessity for re-definition and re-conceptualization of many terms and concepts associated with mobile learning systems before collectively embarking on finding a shared vision for the definition of mobile learning technology [5]. However, researchers seem to fall into many camps: each camp uses different lenses and perspectives to view the phenomenon of m-learning. For example, some define and conceptualize the phenomenon based on associated technologies and others view mobile learning in terms of the benefits provided to learning and learners. One of the most acceptable definitions of mobile learning proposed by Crompton [6], who defined m-learning as "learning across multiple contexts, through social and content interactions, using personal electronic devices". This multifaceted definition considers the characteristics and features of the four quality pillars of mobile learning. For instance, learning is not bounded to a specific context and crosses multiple contexts of different entities. Further, mobile technologies such as mobile devices provide portability and mobility for learning and learners, posing a technological shift in the learning environment.

Mobile technologies have transformed various learning processes with the perspective of having achieved the most important requirement of value maximization and waste minimization. Still, there have been many problematic issues challenging the successful implementation of m-learning systems in educational environments. One of the most controversial issues challenging researchers and practitioners is the need to form a new vision in addressing the process of mobile learning. As there are many conceptual and non-conceptual aspects related to the concept of mobile learning that are not fully matured and in great need of full comprehension and further elaboration before forming a new vision [7, 8, 9]. This study believes that the argument presented by Bannan et al. [7] is valid and sound as they identified new research design themes that have to be thoroughly investigated and reconceptualized before embarking on creating a new strategy or a new vision for mobile learning. Bannan and colleagues [7] argued that creating a more learner-centered environment as a vision for the future is simply favorable and imperative, implying that the learner is commanding entirely the learning process. To help achieve this aim, Bannan et al.'s key findings can be useful as guidelines to orchestrate and plan a new vision for launching mobile learning initiatives capable of delivering the intended learning objectives and realizing better learner outcomes. Conventionally, there have been many conceptually vague assumptions, unrealizable educational expectations, and design dilemmas surrounding mobile learning technology. For example, mobile learning has not been simplistic to contextualize due to the diversity of mobile-based technologies and the complex dynamics in mobile contexts that make the process of contextualization difficult to achieve [10]. Second, any future vision has to comply with the fact that m-learning is not only a combination of 'mobile' and 'learning'. There are other issues such as social, cultural, and environmental that have an important role in affecting the alignment and interplay between technology and learning. Still, the promised synergy on merging technology and the learning process is elusively unachievable. Pessimistically, digital technologies are sometimes seen as no more than tokenistic addition to learning contexts, indicating that doubts remain vibrant about the efficacy, suitability, and viability of digital technologies to improve learning and teaching outcomes. In addition, providing smooth integration between mobile technologies and the learning process is still a challenging task. Researchers have documented the complexity in achieving a smooth mobile-enabled learning environment to create an unparalleled mobile learning platform that leads to enhancing the teaching/learning process in a fashion that emulates socially and behaviorally the physical classroom [11].

Jordan is part of the Arab nation that shares common historical, cultural, social, and religious threads. Therefore, global regional analysis on the adoption and acceptance of ICT-based technologies considers the Arab nation as a separate region. The Arab world expands over a large geographical area. Mobile technologies are the proper vehicle to propagate digital initiatives into remote areas of

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Arab populations. The Arab stakeholders, policymakers, and researchers recognize that mobile-based technologies are shifting and expanding learning frontiers to a new era of excellence by allowing learners to access learning content anywhere and anytime. Surprisingly, even with the proliferation of smart mobile devices across the Arab world, the availability of the Internet, and the deployment of m-learning initiatives in some countries of the Arab world, mobile learning technology is still an emerging learning format in this part of the world and under-used in learning environments [12]. The slow uptake of this technology in the Arab region has been attributed to an array of issues. There are many outstanding issues that impede the proliferation and propagation of m-learning technology in the Arab world: First, the lack of research on what factors inspire learners to accept mobile learning. Second, lack of awareness of the benefits of m-learning to the learning landscape [12, 13, 14]. Thus, this study intends to reveal what factors influence the adoption of m-learning among university students in Jordan.

Walking through the contemporary IS literature, the adoption of m-learning has been investigated via the most popular adoption, acceptance, and diffusion theories/models. For example, the UTAUT theory has been extensively used as a framework to study the adoption and acceptance of mobile technologies in learning environments. Evidently, many research studies based on the UTAUT model have appeared in the literature in recent years examining the adoption of mobile learning patterns worldwide. Indeed, the UTAUT is a widely accepted theoretical model for examining the adoption of m-learning. In many cases, the boundary of the original UTAUT format has been either modified or extended with domain-specific variables to accommodate for the particular aspects of the technology undergoing investigation or blended with other adoption models to conform to the perspective of each particular context and also strengthen the empirical conclusions of each investigation [15, 16, 17, 18, 19]. In the meantime, the original message of the UTAUT has not always been delivered, particularly in cases of developing country-based studies. Indeed, the performance of the UTAUT model has been detected to be somehow different between developing-country and developed-country contexts [20]. According to published research, the harmony between the model (UTAUT) and the technology (mobile learning) is exceptionally unparalleled. As a result, more and more researchers are propelled to exploit the rich utility and proven superiority of the UTAUT model in the adoption and acceptance of m-learning as a new learning format for learners and educators [21]. In effect, it has been more than a decade since the first empirical investigation to apply UTAUT as a theoretical model to explore the adoption dynamics of mobile learning. However, this line of research is still gaining momentum, growing in attention and challenges, and maturing in different perspectives. Still, the use of this technology is far-off from mainstream at present [22]. And this has been attributed fundamentally to the low level of satisfaction and lack of motivation among learners from using mobile-based technologies for learning [23, 24] because learners' perceptions are perhaps unreasonably high and far exceeding normal expectations. The door is still open for further exploration in the context of m-learning and the key for improving empirical analysis is the use of the UTAUT with more appropriate extensions and expansions.

The rapid propagation of mobile-based technologies is remarkable and its competency in extending the reach of mobile learning is well-known and prevalent and becoming a very popular preference in promoting educational excellence and fostering better educational engagement. Lack of research on what factors inspire learners to adopt mobile learning has been responsible for slowing down the proliferation and propagation of m-learning in the Arab nation in general and Jordan in particular [12, 13, 14]. The current study intends to fill in the existing knowledge gap in contemporary research by focusing on more related variables leading to an improved under-standing of the mobile learning phenomenon. To achieve the intentions of this empirical investigation, this study aims to extend the UTAUT model to explore the mobile learning adoption process with more effective and more relevant variables that are capable of driving enhanced learners' adoption intention towards the technology. Probably this is the first study to enrich and extend the original UTAUT theory with three mechanisms in one single model. First, two exogenous variables (i.e., perceived compatibility and perceived image) were incorporated to investigate their impact on performance expectancy in the UTAUT model, and an exogenous variable of perceived mobile anxiety was also added to examine its impact on effort expectancy. In addition, facilitating conditions dimension was also used to examine its impact on effort expectancy. Second, the endogenous variable of perceived innovativeness was incorporated to investigate its predicting

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

impact on intention in the UTAUT theory. Third, the present study has included the service quality variable to investigate its moderating impact on three original UTAUT relationships connection performance expectancy, effort expectancy, and social influence with behavioral intention. The variables incorporated in this model to extend the UTAUT have been found relevant to mobile learning adoption research [25, 26, 27, 28, 29]. Finally, this study is suggesting a more versatile model by incorporating more prominent variables that could play an impactful role in influencing the adoption behavior of m-learning in developing nations.

2. THEORETICAL FOUNDATION

2.1 Mobile Learning

The powerful mobile-based technological trends are offering fascinating new perspectives and shaping every aspect of our lives across the globe. Today, insightful achievements are unleashed in a progressively more knowledge-intensive and technology-driven educational landscape, allowing for more knowledgeable evaluation of multifaceted, dynamically vibrant processes and mechanisms that underlying how we acquire knowledge and skills, and how environmental parameters impact learning and knowledge acquisition. Given the availability of these significant glimpses, the scene is set for stakeholders, policymakers, educationalists, practitioners, and academic researchers to work and collaborate to explore the implications of new findings of how humans learn innovatively, effectively, and efficiently, and set forth scientific actions to tackle the learning and educational challenges confronting today's learners and educators [30], particularly those issues influencing learning behavior associated with the deployment of mobile technologies and applications in learning and teaching processes. Indeed, any attempt to merge technologies such as mobile-based with teaching and learning processes should not overlook the complex nature of how humans learn, ignoring these perspectives frequently create unrealistic expectations, and the expected synergy between technology and the learning process remains intangible.

The enormous growth and successful integration of digital and mobile-based technologies as well as mobile devices into the education landscape have triggered the beginning of a mobile-based learning era. This new learning format has completely revolutionized and redefined the way learning is conducted, signifying the fact that this breakthrough of both ICT-enabled innovation and mobile-driven digital technologies for learning will undoubtedly become the mainstream learning environments for higher educational systems, particularly the urgent need for home-based learning systems in the wake of Coved-19. Indeed, the novelty of mobile-based technologies comes in its potential to offer opportunities for learning regardless of space and time constraints. Mobile learning is uniquely different from other digitally-based learning environments because it makes available certain specific affordances (quality pillars) that have been accountable for miraculously transforming the learning process to become portable, more imaginative, creative, interactive, and seamlessly delivering educational contents, and these favorable quality attributes have driven quality and transformational change to the learning landscape [31, 32]. The distinctively crafted quality pillars, therefore, distinguish mobile learning from other learning formats such as e-learning. Indeed, mobile learning has already become a primary catalyst for reforming the educational landscape, and fundamentally changing the way education is perceived, delivered, and shared. Indeed, the perception of what constitutes a classroom is in flux. In more optimistic terms, mobile learning is shifting the classroom to the learner's pocket, converting the learning environment to become fully student-oriented which underlines the fact that the student is driving exclusively the learning process. From a pedagogical perspective, mobile learning is a powerful technological tool as it offers incomparable platforms for efficient delivery of educational content in all digitized formats to students anyplace, anytime, and anywhere in a way that has never been imagined before.

Mobile learning is becoming more prevalent and relevant in educational systems, particularly at the higher education level. In addition to what has been said in the preceding paragraphs on the benefits of m-learning, the digital technology of mobile devices delivers numerous impactful benefits to learning. First, supporting bite-sized learning (also called micro-learning). It is an emerging learning trend that can be described as learning through the delivery of small learning units to learners, and it has been documented to significantly increase the level of knowledge retention and enhance learning performance [33]. Second, facilitating, promoting, and providing personalized learning ecologies leading to a greater level of engagement among learners and allowing learners to adopt the most optimum learning paths. To promote the concept of personalization in mobile-based learning systems, mobile learning technology utilizes an approach called dynamic content adaptation to facilitate the consumption of m-learning content in a way that fits learners' profiles. Studies highlighted that personalized learning can enhance learning motivation and encourage learners to put in greater efforts to acquire the desired knowledge [34]. Third, improving knowledge retention. Learning through mobile-based technologies, including both multimedia educational contents and Infographics emerging trend, has been recognized to help learners resourcefully maximize their learning outcomes leading to enhanced knowledge retention [35, 36].

Fourth, overcoming resistance to get new education opportunities. The collision between personal professional duties and the mandatory educational time constraints has been recognized to hamper the willingness of individuals to engage in a learning project, especially at an advanced age. However, mobile learning provides the silver bullet solution to overcome this challenge, helping in prevailing over the resistance manifested among some of the individuals since mobile learning technology has the capability to provide a flexible and convenient environment for learning anywhere and anytime. Utilizing m-learning in educational environments offer also the following importantly relevant benefits: Creating shared learning environments [37], creating a dynamic and engaging learning experience [38], increasing the effectiveness of teaching and learning [39], enhancing creativity and innovations by making the learning environment rich and immersive [40], and augmenting both learners and teachers with effective collaborative learning [41]. Despite the adoption of m-learning technology in a variety of educational applications, the technology has not received adequate embracement and acceptance as a medium of learning at various academic entities. Indeed, technology is still facing technical, social, cultural, and environmental challenges and implications. The majority of empirical and non-empirical studies conducted either qualitatively or quantitatively from different perspectives of educators and learners have pointed to several challenges, barriers, and limitations in the process of deploying mobile learning innovation throughout educational systems. A study was carried out by Benali and Ally [42] to examine the root causes accountable for mobile learning implementation barriers based on a literature review. Benali and Ally [42] utilized a qualitative content analysis approach identified 24 primary barriers that negatively impact the propagation of mobile devices in learning environments and that have been classified into four major categories including technological, learner, pedagogical, and facilitating conditions. Also, another study explored the limitations of mobile learning using the content analysis method to find out what are the primary factors largely responsible for causing a delay in embracing mobile learning as a learning tool in educational perspectives [43]. Based on articles published between 2008 and 2017, Sophonhiranrak and Sakonnak [43] spotted an array of limitations that have been essentially cited for lowering the confidence in considering mobile learning for leading successful learning development and transformations worldwide. The analysis highlighted that the characteristics of devices and networks are accountable for impeding the performance of mobile learning in achieving better learning outcomes. The attitude of educators and learners, the delivered learning contents, and distraction are also limiting factors in the adoption of deploying m-learning in educational domains. For more effective integration of mobile learning technologies into educational ecosystems, there is a pressing need to minimize the presence and effects of these challenges and barriers.

2.2 Mobile Learning in the Arab World

The Arab world shares similar historical, traditional, and cultural contexts and backgrounds, practicing the same religion and speaking the same language. Therefore, researchers consider the Arab countries as one entity. The Arab world is a populous (430 million in population) and resource-rich countries. Usually, the global regional analysis of technology trends such as the ICT adoption, acceptance, and diffusion regards the Arab world as a separate region. In the Arab world, there are some cultural and social variations within each country [44]. Certainly, it is essential to assess adoption theories such as the UTAUT model among Arab learners to examine their applicability, utilities, and adaptabilities in the m-learning context. Implementation of m-learning initiatives in learning environments for a particular culture necessitates that knowledge of the challenges and implications that affect their successful application, development, and growth is extremely imperative. Furthermore, knowledge of learners' perceptions, perspectives, and expectations is considered crucial for developing matured mobile learning system. Indeed, there is little evidence highlighting the existence of adequate research to investigate the attitude of learners towards acceptance of mobile

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

learning technology across the Arab world [45, 46, 47].

Many Arab countries are pursuing ways to promote learning practices and outcomes through the integration of educational digitized technologies in the learning environments. However, recent studies conducted in the Arab world have demonstrated that there is a lack of real evidence on the prospective potentials that can be leveraged through deploying mobile learning for promoting learners' outcomes. Evidence confirms that learning students excel when becoming fully engaged in the learning process. Further, research endeavor on m-learning in the Arab world is in its premature stages of development, whereas our understanding of the technology has not advanced beyond the basic concepts of existing theoretical foundations [48]. In the meantime, recent studies conducted in the Arab countries to investigate the learners' perceptions of m-learning adoption reported that the technological innovation of mobile learning has been highlighted to offer pleasurable learning experience and unique opportunities, enhance knowledge acquisition and increase collaboration within learning environments [49, 50, 51].

The most challenging issue facing the Arab world is the large and growing diversity in wealth and technological levels among Arab states, creating compositional heterogeneity among member states, especially in terms of e-readiness. There are certain countries, especially oil-rich countries, have a high level of digital infrastructure deployed across all business and non-business domains, making huge investments in digital technologies to achieve a digital economy status [49]. These countries have deployed mobile learning initiatives across some of their higher educational institutions for implementation within learning processes to increase the effectiveness and efficiency of the learning systems. Alternatively, other countries such as Sudan, Yemen, and Somalia are continually challenged with budgetary constraints, and economically unable to deliver an adequate level of digital infrastructure sufficient to make available the required ICT capabilities for usage in learning settings. These countries have a low presence of ICT infrastructures as well as a poor alignment between ICT technologies and academic entities, thus, incapable of powering an acceptable level of ICT technological capabilities in education. The third category is those countries that are economically stronger such as Egypt, Jordan, and Lebanon. These countries have heavily invested in acquiring cutting-edge information technologies to update, improve, and modernize their educational systems to a level comparable to that of well-advanced developing countries. However, management and technological barriers are still challenging the development and growth of m-learning systems in most Arab states. As a result, mobile learning has not adequately expanded and propagated among higher educational systems in many Arab countries.

Mobile learning initiatives have been proposed and put in action in some higher education systems across the Arab world to go along with global integrative trends of the latest educational mobile-based technologies [52]. However, some of these initiatives could not meet expectations because they were unable to make an impact and incapable of achieving concrete results. The underutilization of mobile learning initiatives for learning has been attributed to many causes including (1) the complexity of the learning environments and processes [46]. (2) Mobile learning initiatives are lacking proper alignments with learning objectives and outcomes and between context and the technology [53]. (3) Lack of adequate learning infrastructure in place for the appropriate deployment of mobile learning initiatives within educational environments [23]. (4) Resistance to change has posed implementation difficulties in deploying mobile learning encounters in the learning setting, and these implementation challenges have negatively impacted technology adoption, acceptance, and use among Arab learners [49]. (5) Inconsistent usage of the technology across the Gulf region was observed to obstruct full tapping of its potentials and opportunities [14]. (6) The absence of awareness, responsive and strong leadership, and adequate policy practices has been accountable for creating many potential barriers to the proliferation of m-learning in this part of the world [14]. Finally, a study investigated the main challenges hampering the proliferation and propagation of m-learning in the higher educational systems in Jordan [54]. The study concluded that four major challenges have been responsible for the slow acceptance of the technology among learners including the quality of service, quality of available learning materials, design and technology-related matters, and learners' demands and expectations [54]. These challenges should be addressed before any attempt to deploy mobile learning technologies. Conducting well-aligned research focusing on how to overcome major challenges is an imperative requirement. This could be the stepping stone to finally abolish or minimize the unfavorable negative influence of these challenges on the effectiveness of launching m-learning platforms within educational environments to improve learning processes and outcomes as well activating learner engagement.

Implementation of m-learning initiatives in learning environments for a particular culture necessitates that knowledge of the challenges and implications that affect their successful application, development, and growth is crucial. Furthermore, learners' perceptions, perspectives, and expectations are considered essential. Indeed, there is little evidence highlighting the existence of adequate research to study the attitude of learners towards acceptance of m-learning technology across the Arab world [45, 46, 47]. Many Arab countries are pursuing ways to promote learning practices and outcomes through the integration of educational digitized technologies in the learning environments. However, recent studies conducted in the Arab world have demonstrated that there is a lack of real evidence on the prospective potentials that can be leveraged through deploying mobile learning for promoting learners' engagement. Evidence confirms that students excel when becoming fully engaged in the learning process. Further, research endeavor on m-learning in the Arab world is in its premature stages of development, whereas our understanding of the technology has not advanced beyond the basic concepts of the existing theoretical foundation.

2.2 The UTAUT

One of the leading technology adoption and acceptance model is the Technology Acceptance Model (TAM). Despite the TAM's popularity in IT adoption research, it has been subjected to various criticisms for being sufficiently incapable of providing actionable guidance to help practitioners design effective interventions and strategies to enhance users' positive perceptions and motivations towards the adoption of the technology. At the same time, the complex context of some types of technologies necessitates that more elaborate and more comprehensive adoption model to handle such context than the technology-centric nature of the TAM model [55]. Consequently, the TAM model has undergone several revisions and refinements to improve its capability to address more complex adoption issues and scenarios for different IT fields, contexts, domains, and settings [56, 57, 58]. Insightfully synthesizing and interpreting the rich and extensive TAM-related literature has led to the development and formulation of TAM2 and TAM3. These re-engineered models have the strength to offer more appropriate theoretical frameworks that are competent in potentially providing better guidelines to improve the adoption dynamics of new technology.

In harmony with TAM's formulation, a new conceptual modeling framework emerged for handling the complexities and challenges associated with emerging technologies. One of the most prominent of these alternative specifications has been introduced by Venkatesh et al. [59] called UTAUT (Unified Theory of Acceptance and Use of Technology). Indeed, the UTAUT has been statistically well-established and adaptable, robust, reliable, and very effective in the adoption of varying IT domains. The success of UTAUT has been attributed due to its integrative perspective, whereby eight prominent technology adoption theoretical frameworks of individual acceptance of new technology have been synthesized and integrated to formulate and empirically validate a more comprehensive model [59]. A model that has been widely recognized as a powerful theoretical framework of IS/IT adoption and use. In addition, the UTAUT has been academically embraced across a wide array of IT and communication technologies and in diverse cultural settings, and in comparing with other adoption frameworks, the UTAUT offers a large amount of variance in intentional behavior to adopt a technology, and this exceeding the traditional TAM model by a minimum of 20-30%, which proves its robustness. By contrast, the UTAUT theory equipped with a strong theoretical foundation and comprehensiveness has enjoyed a high level of citations in scholarly research in comparison with other adoption, acceptance, and diffusion models [60]. In effect, many scholars have argued and questioned the reasons that make academic researchers too enthusiastic to heavily cite the UTAUT model, leading to gaining momentum and enhancing its use in studying the adoption dynamics of IT artifacts [58, 61]. Many possible explanations have come into view. One of the earliest studies addressing this issue was accomplished by Williams et al. [61], they concluded that citations and usage trends are not strongly correlated, indicating that citation counts do not predict the actual use of the UTAUT model. Besides, Venkatesh et al. [21] attributed the existence of this phenomenon partly as a consequence of the proliferation and diffusion of new Information Technology products and services from 2003 onwards. Abrahao et al. [58] concluded that this theoretical framework can be recognized as providing argument support rather than theory

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

testing. Finally, the UTAUT has brought about a unique argument and novel perspectives to adoption dominion, and accordingly researchers have strongly advocated its citation and usage in adoption-based studies.

Since its inception, the original theoretical UTAUT theory has been adopted in various IT domains. Despite the UTAUT model's overwhelming acceptance as a theoretical framework, there have been serious doubts casting over its capability to explain fully users' adoption of all newly introduced technological innovations. Therefore, the existing literature reveals that the UTAUT theory has been integrated, modified, and expanded to study the adoption dynamics of particular technologies and to comply with the type of technology domain under investigation, nature of participants studied, the cultural settings that influence the usage of the technology, and the challenging environmental situations that impact technology adoption behavior. Indeed, researchers and practitioners have identified many determinants that have been incorporated with the original UTAUT model, implying that the UTAUT model cannot be utilized standalone without adding specific external variables to account for the context specificity of the technology under investigation. Thus, various studies have been implemented for the benefit of understanding the adoption process of various IT domains utilizing the UTAUT model with certain enhancements on the original format [35, 62, 63, 64, 65].

3. RESEARCH MODEL AND HYPOTHESES

3.1 Effort Expectancy

The UTAUT theory theorizes that the concept of effort expectancy is a primary determinant of behavioral intention [59] (Venkatesh et al., 2003). The key assumption behind this concept that users may not be motivated to adopt a technology if they find it complex to handle with ease. Venkatesh et al. [59] defined effort expectancy as "the degree of ease of use associated with the use of technology". In connection to the context of the current study, effort expectancy may be regarded as learners' perceptions that mobile-based technologies are easy to use for learning. The complexity of the technology is a barrier to its adoption as it fosters anxiety and generates a negative attitude leading to a low level of adoption behavior. It is expected that the higher the perceptions of effort expectancy, the higher the intentional behavior will be [59], [60]. Several empirical studies conducted in the context of mobile learning have confirmed that effort expectancy has a positive effect on learners' intentional behavior to adopt the mobile technologies for learning [19], [20], [22], [66]. Jordan is still at the beginning of the mobile learning trajectory, it is therefore recommended to recognize the aspect of effort expectancy as an important variable affecting intention to adopt mobile learning technology. Therefore, incorporating the aspect of effort expectancy in the current study is a necessity for better understanding the dynamics of mobile learning adoption in Jordan. Consequently, the subsequent hypothesis is suggested.

H1: Effort expectancy will positively influence behavioral intention.

3.2 Performance Expectancy (PE)

In the UTAUT model, Venkatesh et al. [59] introduced the concept of performance expectancy (equivalent to perceived usefulness in the TAM model) that has been empirically recognized as one of the most influential determinants in driving behavioral intention to adopt an innovation. Indeed, among all technology adoption variables tested through the lenses of all adoption models and theories in various contexts and different cultural settings, performance expectancy has usually manifested to have the strongest correlation with behavioral intention to adopt, accept, and use new technology. Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" [59]. It is anticipated that if users find adopting and using a new technological innovation provides job performance enhancements and valuable elements of usefulness to help them carry out their job tasks more efficiently and more productively, they will be more likely motivated to adopt and use the technology. In the context of mobile learning, performance expectancy is perceived as the extent to which learners believe that mobile learning technology is valuable for learning processes as reflected in improving learning motivation, performance, quality, as well as enhancing knowledge retention and acquisition processes. Evidence of the considerable importance of performance expectancy in the perspective of technology adoption studies has been fundamentally highlighted by various empirical analysis emphasizing and establishing its empirical consequence in shaping individuals' behavior and perceptions in the context of the mobile learning adoption process [19],[20], [22], [23]. Thus, the subsequent hypothesis is suggested.

H2: Performance expectancy will positively influence behavioral intention.

3.3 Social Influence (SI)

The social influence perspective has been recognized as an important element in affecting individuals' behavior and in particular the technology adoption process. The concept of social influence came to existence via the social influence theory proposed by Kelman [67] who endorsed the effect of social influence in shaping human behavior and perception. The concept of social influence as an adoption variable was introduced by the theory of planned behavior in the domain of technology adoption research [68]. Since its introduction, empirical evidence has largely documented the importance of social influence in impacting individuals' orientation towards innovation adoption, and its impact on the adoption process of new technology is more crucial in developing cultures. Social influence has a magnetized effect in the sense that it attracts an individual's behavior in a specific orientation and remains rather unchanged. This effect has been attributed to the convention that individuals have the tendency to perform behaviors because others in the same social category desire these behaviors.

Social influence has been defined in many ways and perspectives. Indeed, the social influence paradigm has been recognized as one of the most complicated social phenomena to understand and conceptualize. However, the most acceptable classical definition was delivered by Venkatesh et al. [59] who defined the concept as "the degree to which an individual perceives that important others believe he or she should use the new system". A body of literature has investigated the phenomena of social influence and its influence in the adoption process of a new technological innovation in various contexts and perspectives. Researchers suggest that learning is a social process, especially those activities such as interaction, collaboration, and feedback. Thus, any attempt to quantify what factors affect the adoption of digital learning such as e-learning and mobile learning, the social influence dimension should be included in the analysis, especially for developing countries' cultures. Indeed, investigating the influence of social influence in the adoption of mobile learning in Jordan is a valid argument because Jordanians like most Arabs are influenced by the social system when making a decision to adopt a new technology [70], [95], [107], [112], [140].

Several studies have used the social influence construct in investigating mobile learning adoption and acceptance and revealed that the social influence was influential in predicting the behavioral intention to adopt the mobile-based technologies for learning [135], [136]. In contrast, empirical-based studies have also concluded that social influence had no effect on behavioral intention to adopt mobile learning [66], [69]. These inconsistent findings suggest that further investigations should be conducted to understand more deeply the function of social influence in shaping individual behavior towards the adoption of mobile learning. Still, however, researchers share a strong common perception that the aspects of social influence play a pivotal role in the adoption of new technologies in a developing country context. Consequently, the subsequent hypothesis is suggested.

H3: Social influence will positively influence behavioral intention.

3.4 Facilitating Conditions (FC)

Facilitating conditions is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" [60]. The concept of facilitating conditions was originally recognized as an important environmental criterion for facilitating task accomplishment by Triandis [71]. Over the years, the facilitating conditions construct has been utilized in technology adoption research for a number of contexts and in various forms and under varying labels. Definitely, using digital technological innovations requires skills, knowledge, training, resources, and adequate organizational infrastructure to support implementing tasks related to a specific behavior. The nature of these requirements varies according to each technology context and embedded tenets (ideology), signifying that each technology has its own compatibility and alignment features and therefore needs different sets of facilitating conditions.

The original UTAUT model theorizes that facilitating conditions determinant predicts usage behavior. However, the model has been applied to investigate the adoption behavior of various information technology domains, and in the process, the model was subjected to a number of extensions to augment its adoption impact. Indeed, many variables have been tested to assess their viability in enhancing the adoption and growth of digital technologies. Many of these studies tested the influence of facilitating conditions on behavioral intention in different IS/IT environments and platforms, underlining the importance of facilitating conditions in enhancing intentional behaviors towards the adoption of new technology [33], [72, 73,74]. New developments in technology adoption domains have led to the emergence of a new format called UTAUT2, a more comprehensive adoption theory than the original UTAUT format. Indeed, the UTAUT2 has consolidated the impact of facilitating conditions on the intention to adopt new technology. In the meantime, many studies have revealed that facilitating conditions had no impact on behavioral intention [19], [24], [141]. Facilitating conditions has been reported to be highly controversial across different cultures and different contexts in the sense that its role within the UTAUT research framework has been demonstrated to give inconsistent empirical evidence and outcomes, indicating that the impact of facilitating conditions on the adoption process of new innovation varies according to the context of the investigation [141].

In the perspective of technology adoption, Venkatesh et al. [59] initially proposed in their UTAUT framework that the aspect of facilitating conditions is an important determinant in affecting users' actual use behavior. However, Venkatesh et al. [59] utilized a set of psychometric measurement items to investigate the influence of facilitating conditions, and those were not developed and tailored to a particular type of technology or culture and it was rather fundamentally general. As a result, this determinant can be safely applied and implemented in the adoption of mobile learning technology from the perspective of learners. In the context of the technology-enabled educational systems, the determinant of facilitating conditions has figured out as an important technical requirement for successful implementation and effective delivery of digital-based educational services, especially for mobile-based technologies [19], [75]. Several studies have confirmed the positive influence of facilitating conditions on behavioral intention to adopt mobile learning technology [67]-[78]. Based on the argument presented here, consequently, the subsequent hypothesis is suggested.

H4: Facilitating conditions will positively influence behavioral intention.

It is widely acknowledged that facilitating conditions construct can strengthen the perceptions of ease-of-use (effort expectancy), indicating that the availability of facilitating conditions provide users with positive expectations such as infrastructure, capabilities, information, and technical resources that could, to some extent, overcome the complexity of system usage and therefore reinforce its ease of use and flexibility [71]. Indeed, many empirical investigations have established the influential role of facilitating conditions in enhancing the level of ease-of-use of TAM needed to facilitate the adoption and use of various information technology domains, mainly mobile-based technologies [79], [80]. However, little knowledge exists about the impact of facilitating conditions on effort expectancy to adopt mobile learning technology. This study will take on this important relationship regarding the adoption process of mobile learning in a developing country environment. Consequently, the subsequent hypothesis is suggested.

H5: Facilitating conditions will positively influence effort expectancy.

3.5 Perceived Innovativeness (PI)

The concept of innovativeness is commonly associated with the phenomenon of the new product adoption process. This trendy concept has been over the years the subject of ongoing scientific discussion with emphasis on attempting to utilize innovativeness for a greater understanding of the dynamics of innovation adoption and diffusion processes [80], [81]. However, no technological innovation springs straightforwardly from production to immediate usage [83]. Indeed, accepting innovation has always been recognized as a critical consequence and a challenging behavioral issue. Therefore, there is a need to investigate and understand what impacts individuals' resistance to adopting innovation. The resistance to adopting and use innovation is attributed to a number of aspects that normally shape a technological innovation such as functional considerations, social expectations, cultural and political forces and imperatives, economical needs, psychological traits, and situational and environmental factors [83], [84]. Fundamentally, the implications of these aspects need to be fully comprehended to help combat resistance to adopt and use innovation.

The concept of perceived innovativeness was defined by Rogers [85] as "the degree of speed of an individual to adopt new ideas in relation to other members of the system". Also, Agarwal and Prasad [68] provided another widely popular and academically accepted definition, whereas perceived innovativeness is defined as "the degree to which an individual is responsive to new ideas and adopts innovative decisions freely and earlier than others". Further, Lowe and Alpert [87] defined perceived innovativeness as "the perceived degree of newness and improvement over existing alternatives". Many conceptual definitions have emerged regarding the concept of innovativeness in literature. All definitions have common themes, indicating the predominance of innovativeness as being the switching gear and the trigger for innovative use behavior. Among all different definitions proposed by researchers and practitioners depending on the type of technology under investigation, still, the definition proposed by Agarwal and Prasad [86] is the most acceptable definition in the technology adoption-related research.

The aspect of innovativeness was initially introduced as perceived innovativeness (PI) construct to information technology adoption behavior research by Agarwal and Prasad [86]. Their intention was to determine the influence of this construct on the dynamics of the adoption process of a particular technology. Agarwal and Prasad [95] argued that perceived innovativeness should be incorporated in all models of technology adoption on the assumption that innovative users would be more inclined to take the risk, experiment, and adopt new technological innovation. Indeed, the innovative user tends to perceive technologies highly positively and therefore embraces its adoption and usage [88]. The reasons for accepting and rejecting of innovation have become a research focus, attracting both academicians and practitioners to identify the factors affecting the acceptance motives. Various studies conducted on the adoption behavior of IT products and services have highlighted that perceived innovativeness affects the behavioral intention to adopt an innovation [89]-[91]. In the meantime, the concept of innovativeness has been investigated in the context of mobile learning and found to have a positive impact on the adoption process of mobile learning [92]-[94]. Consequently, the subsequent hypothesis is suggested.

H6: Perceived innovativeness will positively influence behavioral intention.

3.6 Perceived Mobile Anxiety

The use of IT/IS products and services has been labeled to involve some degree of anxiety, fear, and stress, this state of mind is referred to as technophobia, meaning fear of technological innovation. Technophobia leads to the formation of resistance to change which diminishes usage intentions, especially in the context of technology adoption, acceptance, and use. The formation of anxiety in the adoption process of emerging technologies has been attributed to a variety of factors, primarily environmental, cultural, and social factors. Research studies have demonstrated that the impact of anxiety-related issues on users' acceptance of technology is more pronounced, influential, and dominant in developing country culture. Technology-related anxiety has been the subject of many academic studies, attempting to understand its negative role in process of technology adoption and use in order to be able to put in place appropriate intervention mechanisms to combat and reduce challenging behaviors resulting from anxiety arousal for the benefit of enhancing the adoption of a technology [94, 95, 96, 97].

There are clear manifestations that anxiety is induced in response to perceived threats from using technological innovation [97], leading to the formation of a negative attitude towards the technology or total refusal to accept the technology. The first technology-induced anxiety was observed to arise at the beginning of the computer era. Gribbin [98] was the first to coin, diagnose, and describe the concept of computer phobia, it is defined as a negative impact on people's willingness and motivation to use computers [99]. On the arrival of personal computers at the beginning of the 1980s, the concept was unexpectedly everywhere and started to emerge as a global challenge [100]. Also, on the introduction of the Internet, Internet-related anxiety emerged as a powerful barrier and major obstacle to the adoption of Internet-based technologies [99]. Internet anxiety has been highlighted to be accountable for motivating avoidance behavior and resulting in low propagation and growth of Internet-enabled technologies [96], [101].

Mobile computing technologies have been accelerating beyond expectations. Mobile-based technologies have emerged with strong potentials to provide support to an array of domains such as education and learning practices. In effect, it has been observed that home-based learning relies heavily on mobile technologies rather than computer technologies because the majority of students own smartphones and tend to access the Internet through smartphones. Still, applying these technologies in various domains has led to the emergence of a new construct called perceived mobile anxiety and is defined in the context of this study as the fear and apprehension of using mobile technologies in the learning environment [102], [103]. This construct has not been widely applied in mobile learning technology in proportion to other adoption constructs such as mobile self-efficacy. Indeed, mobile-induced anxiety can have a negative role in the proliferation and growth of mobile technologies in supporting successful learning outcomes. Indeed, it is imperative to investigate the impact of perceived mobile anxiety on the adoption of mobile learning technology. However, this study believes that perceived mobile anxiety may have a prominent influence on the adoption process of mobile learning, especially its negative impact on the perceptions of effort expectancy. For example, a study conducted by Callum et al. [101] concluded that the aspect of anxiety negatively influenced the perceived ease-of-use (effort expectancy) to adopt mobile learning from the perspective of educators. Research analysis regarding the influence of perceived mobile anxiety on the adoption of learning technology is scarce. Consequently, the need to address the anxiety issue in the context of mobile learning is imperative because, in the wake of the Covid-19, home-based learning via mobile-based technologies are the most commonly used learning tools. Therefore, this study proposes the subsequent hypothesis.

H7: Perceived mobile anxiety will negatively influence effort expectancy.

The current study also aims to explore the empirical relationship between perceived mobile anxiety and perceived innovativeness. In other words, the intention of this study to test if perceived mobile anxiety generates a negative impact on the formation of innovativeness towards the adoption of mobile learning technology. The current study recognizes the importance of unveiling such a hidden relationship between the two constructs for the benefit of enhancing the knowledge base encompassing the adoption dynamics of mobile learning technology in a developing country context. Also, it is extremely valuable to understand the dimensions, patterns, or threads that make perceived mobile anxiety play the role of deterring the processes of innovativeness development in favor of mobile learning adoption and acceptance as a learning tool. To this end, the subsequent hypothesis is suggested.

H8: Perceived mobile anxiety will negatively influence perceived innovativeness.

3.6 Perceived Image (PIM)

Perceived image has been recognized as an important determinant in affecting users' perceptions and intentions towards acceptance and use of Internet and non-Internet delivered technologies and services in different domains of life, particularly those services that heavily influence users' social status and wellbeing. Indeed, learner's subjective perception of image has been demonstrated to have a significant influence in establishing stronger intentional behaviors that drive the adoption of digital technologies within learning environments to enhance learning practices and outcomes [104], [105]. To develop an effective and successful mobile learning technology, it is imperative to consider the influencing impact of perceived image on the adoption behavior of mobile learning technological format.

Perceived image refers to which an individual perceives that the use of innovation will boost his or her image and will achieve a higher social status in society [106], which is a decisive factor in driving a strong behavioral attitude to adopt new technology. Alternatively, it is well-acknowledged that a negative perception of image can badly distract behaviors. This distraction in behaviors may generate negative perceptions towards the technology and may also cause a lack of individuals' trust in the technology, and these unfavorable feelings may hold back learners' intentions from adopting and using mobile learning technology as a tool for learning and engagement.

This study follows the theoretical conventions of TAM2 and TAM3 models regarding the influence of perceived image on the adoption process of innovation, perceived image may mediate the relationship linking learner's PE with their intentions to adopt mobile learning. Some evidence from prior research supports this assumption. Maintaining a good image augments the perceptions of learners to adopt a new learning technology. At the same time, several studies conducted in Jordan have confirmed the importance of PIM on the adoption process of mobile-based technologies [107], [108], these studies revealed that the perceptions of image positively enhanced behavioral intention through the mediation of perceived usefulness (performance expectancy) to adopt mobile-based technologies. Based on the above arguments, the current study suggests the following hypothesis.

H9: Perceived image will positively affect performance expectancy.

This study intends to explore if there exists a relationship between PIM and PI. In other words, does the aspect of perceived image trigger the personal innovation perceptions of learners towards the adoption of mobile learning? This study believes that enhanced perceptions of image that learners may gain as a result of the adoption of innovation would potentially lead to an increased level of perceived personal innovativeness. A study conducted by Hao et al. [69] revealed that PIM influenced positively the

PI studying the adoption of mobile learning. Therefore, the subsequent hypothesis is proposed.

H10: Perceived image will positively influence perceived innovativeness.

3.7 Perceived Compatibility

The concept of perceived compatibility was first theorized and popularized by the innovation adoption and diffusion theory [85]. Since its inception, the perceived compatibility construct was fundamentally utilized in the perspective of diffusion research. Recently, perceived compatibility has been widely utilized in the adoption and acceptance research of many digital-based technologies and systems. The majority of these investigations have reported that perceived compatibility has been very influential in affecting individuals' perceptions in the decision-making process to adopt various types of digital innovations [108]-[110]. In the meantime, researchers have constantly embraced the use of perceived compatibility construct as a highly dominant variable in affecting individual behavior in the process of examining the adoption of innovation, especially in investigating various digital-based learning technologies in its varying formats, such as e-learning, mobile learning, and distance learning [108], [111]-[113].

Perceived compatibility has been defined in many ways. For example, Rogers [83] provided one of the earlier conceptualizations of compatibility and defined it as " the degree to which using an innovation is perceived as consistent with the existing socio-cultural values and beliefs, past and present experiences, and needs of potential adopters". A new focus on compatibility conceptualizations emerged, Agarwal and Karahanna [84] redefined the concept on the belief that it has a much broader connotation than previously conceptualized, leading to a much comprehensive definition by adding new dimensions such as present work practices and preferred work style. Still, the definition of compatibility expands and grows as new technological contexts are emerging and calling for new conceptualizations, emphasis, and reflections. In the context of this study, perceived compatibility measures the degree of harmony and suitability between mobile learning innovation and learner's values, beliefs, experiences, perspectives, lifestyles, and habits. Learning is a lengthy and challenging process and having a technology aligned and compatible with learners' perspectives, preferences, expectations, varying interests, and learning needs is highly desirable and meaningful that could lead to motivationally enhanced learning environments.

Contemporary adoption and acceptance literature provide evidence that perceived compatibility has been examined as an indicator of attitude, behavioral intention, perceived value/benefits, as well as a mediating construct in the original TAM and UTAUT models, and moderating construct in various contexts and perspectives [106], [107], [114]. These studies have fundamentally demonstrated the prominent role of perceived compatibility in positively driving motivational intentions through enhancements of perceived fit between the technology and the tasks related to performing the behavior. This study further extends the original UTAUT format by incorporating the concept of perceived compatibility in investigating the adoption process of mobile learning technology in Jordan. Consequently, the subsequent hypothesis is suggested.

H11: Perceived compatibility will positively influence performance expectancy.

This study will explore if perceptions of compatibility could have correlation with perceived innovativeness in the context of mobile learning adoption. It is expected, however, that enhanced compatibility features may trigger innovativeness development and stimulate innovative behavior which is nowadays the primary driver of development and growth. An innovation consistent with learners' values, and needs, and experiences is highly recommendable for acceptance and adoption. Thus, the subsequent hypothesis is suggested.

H12: Perceived compatibility will positively influence perceived innovativeness.

3.8 Service Quality (SQ)

The importance of service quality dimension has been widely recognized in the adoption processes of various information technologies products, services, and applications. Indeed, delivering the quality of service to individual users that meet their expectations, needs, and requirements will drive positive behaviors and perceptions towards the adoption and acceptance of these technological innovations [116], whereby mobile-enabled learning is no exception. The inclusion of service quality perspectives and aspects in investigating the adoption dynamics of mobile-based technologies has been a common practice in literature, especially in the adoption and acceptance of mobile-delivered technologies such as mobile-based commerce, mobile banking, and mobile payment services

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[117]-[119]. The need for including a service quality perspective stems from the fact that transactional activities are vulnerable to poor quality since superior service quality drives trustworthy behavior in the transactional process and enhances its acceptance and use [117]. However, in the context of non-transactional technologies such as mobile learning behavior, the service quality perspective has not been given its due in contemporary literature by the research community. However, this study believes that greater emphasis should be placed on service quality in relation to the adoption of mobile learning technology. Also, this study believes that the functional aspect of service quality is of prevailing importance in developing a deeper understanding of the m-learning adoption mechanisms and achieving greater knowledge of what drives mobile learning adoption behavior.

In the context of this study, service quality intends to guarantee that services delivered to learners must be of superior quality to facilitate mobile learning processes to drive dynamically best practices in learning environments as well as emphasize and endorse effective, robust, reliable, and flexible qualities in learning functionalities that might foster engagement, motivation, creativity, and interaction. Indeed, the excellence of service quality delivered to learners can affect positively their attitude to embrace and build favorable perceptions and inclinations to adopt and accept mobile-based learning systems. In the development stage of mobile learning systems, service quality perceptions must be reflected in the design of mobile-learning system to capture the attention of the learners and educators by making available specific visual cues, signifiers, perceived affordances, and indicators throughout the system design to promote a highly interactive, engaging and communicative mobile learning environment.

Mobile learning service quality encompasses a wide array of various technical aspects and attributes, making the concept problematical to fully understand and conceptualize in simple terms. In effect, there is no academic conformance on how the concept of service quality can be conceptualized, operationalized, and measured, causing a confusion among academics and practitioners as to how the concept can be comprehensively defined. For example, a model was developed by Sarrab et al. [16] to capture most abstract and generic technical elements, perspectives, and attributes pertinent to mobile learning service quality that leading to learners' satisfaction such as flexibility, usability, functionality, performance, and availability. The study identified twelve service quality dimensions relating to mobile learning [16], implicating and highlighting the complexity of the service quality concept and its attributes.

The majority of empirical studies conducted to investigate the adoption process of mobile learning have placed heavy emphasis on the impact of service quality on learners' and educators' satisfaction and loyalty [16], [121], [122]. In the meantime, several studies have explored the effect of service quality on mobile learning adoption and acceptance in the learning environment [122]-[125]. These studies have concluded that service quality is a fundamentally multifaceted concept, a predominantly influential parameter in driving positive intentional and attitudinal behavior towards embracing the mobile technology as a learning tool, promoting satisfaction among learners and educators, and highly relevant to achieving favorable learning outcomes. However, a good percentage of empirical analysis involving service quality construct implemented to examine the adoption process of varying technology domains for both digital and non-digital technologies have utilized service quality as a moderating variable in their models [121], [127]. The outcomes of these studies have potentially highlighted that service quality played an important role as a moderator. This study will extend research outside the conventional research focus by exploring the moderating effect of service quality on primary UTAUT relationships. Thus, the subsequent hypotheses are suggested.

H13: Service quality will positively moderate the relationships between performance expectancy and intention to adopt mobile learning technology.

H14: Service quality will positively moderate the relationships between effort expectancy and intention to adopt mobile learning technology.

H15: Service quality will positively moderate the relationships between social influence and intention to adopt mobile learning technology.

As discussed above, the research model is shown in Figure 1.

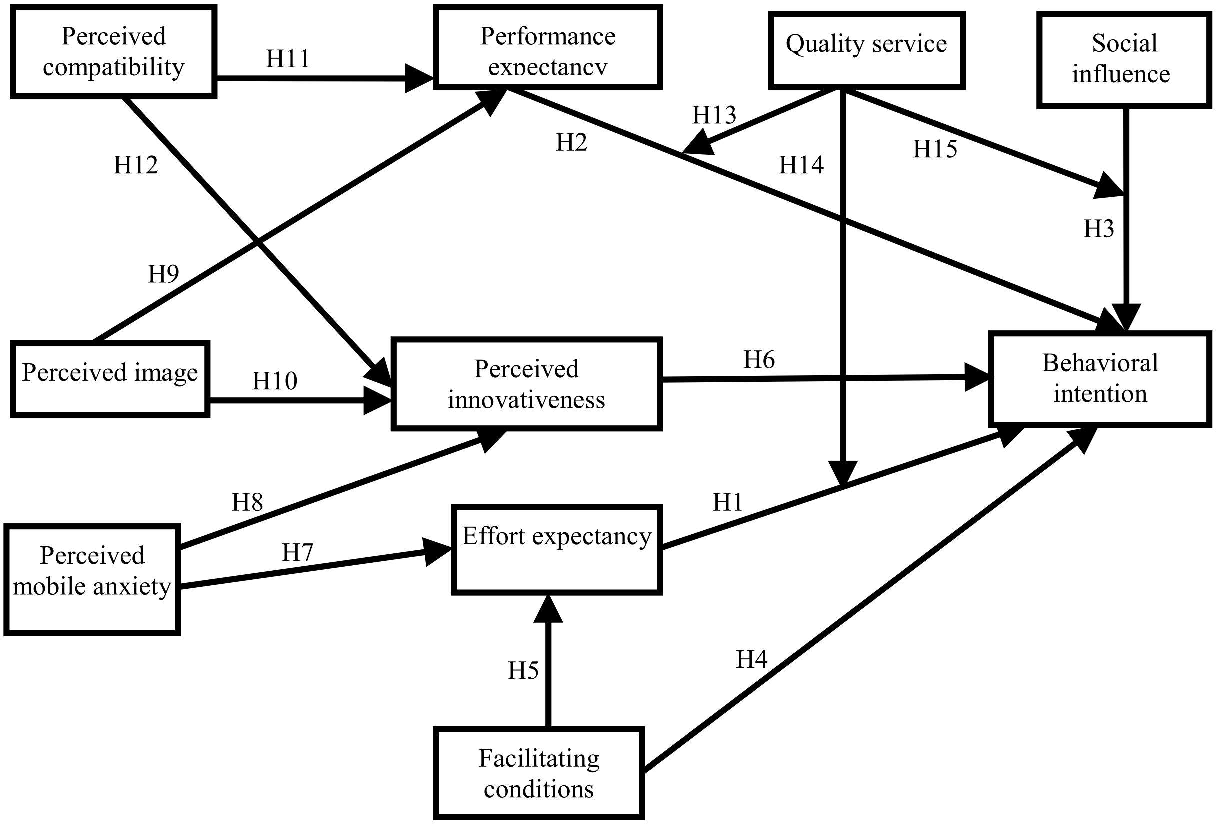

Figure 1: The research model and hypotheses

4. RESEARCH METHODOLOGY

The present study intends to examine the adoption behavior of mobile learning from a developing country perspective using an extended UTAUT model. To achieve the aim of this study, a quantitative research approach was selected. This research approach requires relevant data to be gathered for testing the study hypotheses as displayed in Figure 1. The most frequently and preferred data collection method used in this type of empirical analysis is the survey questionnaire. Therefore, this study will develop a questionnaire for collecting the data that fits the requirements of this study.

4.1 Questionnaire Design

It is a highly challenging issue to design and develop the survey instruments that serve accurately the established research objectives of any empirical investigation. To reduce the possibility of errors in measurement and maintain the content validity of the instrument, it is advisable for the current study to adopt the survey items used in measuring the UTAUT variables (performance expectancy, effort expectancy, social influence, and facilitating conditions) [59]. The rest of the survey items for other variables (PI, PMA, PC, PIM and SQ) were borrowed from prior studies to ensure that the measurement items are reliable and valid (Appendix A lists the survey items used in the current study). The questionnaire was initially developed in English language using previously validated measures as already mentioned and certain rewordings were conducted to suit the context of the current study. The survey questionnaire was translated from the original language into Arabic by the author and verified to guarantee that the translation effectively communicates the exact meaning of the original message without ambiguity. In accordance with the experts' recommendations and comments, necessary changes and corrections in the measurement items were performed. The popular Likert scale was applied for the current research. Seven items were utilized to operationalize each construct (1 represents "strongly disagree" and 7 represents "strongly agree").

4.2 Data Collection and Respondents

Quantitative data was collected through paper-based and online questionnaires to test the research

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

model. All participants were university students, studying information technology courses at both graduate and postgraduate levels at Al al-Bayt University (Jordan). A valid 202 questionnaires (109 males, 93 females) were obtained and considered adequate for carrying out the hypothesis test procedure.

5. RESULTS AND ANALSIS

5.1 Evaluation of the Measurement Model

The proposed model was tested using WarpPLS 7.0 software. Before embarking on the analysis of the hypothesis testing, there is a need to provide an assessment of the adequacy of the model's fit to the empirical data. To validate this requirement, a number of quality criteria (Cronbach's alpha, average variance extracted (AVE), composite reliability (CR), and factor loading) were analyzed to evaluate the reliability and validity of each construct in the proposed model. The construct reliability is referred to as "the ability of an instrument to measure consistently" and construct validity is referred to as "the extent to which an instrument measures what it is intended to measure" [128]. The outcomes of this assessment are presented in Table 1.

Cronbach's Alpha is one of the most commonly used index of reliability estimate for assessing the internal consistency reliability of the survey items, or in other words, the extent to which survey items correlate with each other in measuring the same theoretical construct. A reliability Alpha coefficient of 0.70 or higher has been recommended to be acceptable by [129]. In the current study, the alpha coefficient has been calculated to vary between 0.772 and 0.895 (Table 1), this provides clear evidence that all constructs demonstrate adequate reliability index. The composite reliability (CR) is another important reliability measure that is more comprehensive than alpha coefficient [131]. The calculated values for composite reliability found to vary between 0.869 and 0.923 (Table 1), indicating that the composite reliability estimates for all constructs are exceeding the recommended minimum threshold of 0.7 [130]. Moreover, two criteria need to be investigated to provide evidence of construct validity, these are the factor loading of each survey item and the average variance explained (AVE) of each construct. The established empirical literature suggests that construct validity is confirmed if the loading factor of each survey item and the average variance explained (AVE) for each construct measure above the recommended cut-off values of 0.7 and 0.5 respectively [131]. The findings of this study (Table 1) provide strong evidence that construct validity is confirmed.

Discriminant validity refers to the extent to which a particular construct truly differs from other constructs. To establish that the proposed model exhibits an adequate level of discriminant validity, Fornell and Larcker's [132] criterion is applied, which requires that assessment of discriminant validity has to be implemented at both item level and construct level. The discriminant validity at the item level can be verified if each survey item correlates more strongly with its associated construct than it correlates with other constructs [132]. Appendix B shows clearly that each survey item correlates more strongly with the respective construct than with other constructs, indicating that the model exhibits a satisfactory level of discriminant validity at the item level. Furthermore, to establish the existence of discriminant validity at the construct level, there is a need to compare the square root of the average variance explained (AVE) of each construct and its correlations with other constructs. Table 2 reveals that the square root of AVE for all constructs are greater than the amount of its correlation with other constructs, indicating that the discriminant validity at the construct level is confirmed. In conclusion, the findings of the current study provide strong statistical evidence that the model can be carried forward for further analysis.

5.2 Evaluation of the Structural Model

In the previous section, the proposed model was validated for reliability and validity. The model needs to be evaluated in terms of suitability for carrying out the hypothesis testing. The model has to be assessed according to multiple criteria. First, there is a need to assess the model for multicollinearity problem by means of estimating variance inflation factor (VIF) for each construct. The multicollinearity problem arises if strong correlations among different constructs (>0.7) [131] exist which may lead to spurious results. The multicollinearity becomes a serious problem if VIF exceeding 5.0. As shown in Table 2, the results reported by this study for all constructs that VIFs vary from 3.120 to 1.631, confirming the absence of multicollinearity problem. Second, we need to check the quality of the proposed model to guarantee that the data fit the model well. The WarpPLS 7.0 offers a set of model fit and quality indices proposed by Kock [133]. Table 3 shows the estimated values for these indices, it can be demonstrated that all model fit indices are in

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

conformity with the requirements which provides clear evidence that the model fits the data. Finally, we have to test the global validity of the proposed model by assessing the goodness-of-fit (GoF) criterion for the research model [134]. The calculated GoF index is 0.545 (Table 3), which exceeds the cut-off point of 0.36 recommended level for large GoF statistics [134], providing strong evidence that the proposed model has sufficient global validity. The reported results have firmly emphasized that the model qualifies for further statistical analysis such as hypothesis testing. The WarpPLS 7.0 was used to perform the hypothesis testing process. The results of hypothesis testing are shown in Table 4 and Figure 2, and all hypotheses are statistically significant and supported as proposed with the exception of service quality and it was found to negatively (as opposed to what has been hypothesized in the model) moderate the relationship between social influence and intention.

Table 1: Quality criterion (Cronbach's Alpha, CR, AVE, and Factor Loading) and VIFs

Construct	Item Code	Factor Loading	Cronbach's Alpha	CR	AVE	VIFs
Behavioral intention (BI)	BI1	0.821	0.878	0.917	0.733	2.803
	BI2	0.855				
	BI3	0.888				
	BI4	0.860				
Effort expectancy (EE)	EE1	0.828	0.843	0.895	0.681	2.645
	EE2	0.851				
	EE3	0.840				
	EE4	0.779				
Performance expectancy (PE)	PE1	0.840	0.895	0.923	0.705	2.688
	PE2	0.817				
	PE3	0.836				
	PE4	0.861				
	PE5	0.843				
Social influence (SI)	SI1	0.715	0.792	0.857	0.546	2.003
	SI2	0.744				
	SI3	0.777				
	SI4	0.713				
	SI5	0.745				
Facilitating conditions (FC)	FC1	0.873	0.813	0.890	0.729	2.143
	FC2	0.870				
	FC3	0.817				
Perceived innovativeness (PI)	PI1	0.843	0.772	0.869	0.688	2.192
	PI2	0.778				
	PI3	0.865				
Perceived mobile anxiety (PMA)	PMA1	0.868	0.837	0.902	0.755	1.631
	PMA2	0.898				
	PMA3	0.839				
Perceived compatibility (PC)	PC1	0.876	0.853	0.901	0.695	3.210
	PC2	0.845				
	PC3	0.822				
	PC4	0.788				
Perceived image (PIM)	PIM1	0.812	0.787	0.876	0.703	1.965
	PIM2	0.895				
	PIM3	0.804				
Service quality (SQ)	SQ1	0.836	0.855	0.903	0.699	3.080
	SQ2	0.872				
	SQ3	0.880				
	SQ4	0.750				

Journal of Theoretical and Applied Information Technology
15th September 2022. Vol.100. No 17

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 2: Discriminant validity of the constructs

	1	2	3	4	5	6	7	8	9	10
1. BI	**0.856**									
2. EE	0.632	**0.825**								
3. PE	0.700	0.633	**0.840**							
4. SI	0.555	0.417	0.484	**0.739**						
5. FC	0.594	0.576	0.539	0.492	**0.854**					
6. PI	0.548	0.597	0.497	0.437	0.537	**0.830**				
7. PMA	-0.140	-0.104	-0.031	0.008	0.006	-0.127	**0.869**			
8. PC	0.677	0.620	0.630	0.592	0.609	0.598	-0.220	**0.834**		
9. PIM	0.399	0.597	0.497	0.437	0.435	0.387	0.348	0.335	**0.838**	
10. SQ	0.625	0.534	0.557	0.594	0.593	0.632	-0.219	0.723	0.262	**0.836**
Note: The Diagonal elements (bold) are the square root of AVE. Off-diagonal elements are the correlations among constructs.										

Table 3: Model Fit and Quality Indices

Measure	Value	Criteria Fit
Average path coefficient (APC) (<0.05)	0.256	P= 0.001
Average R-squared (ARS) (<0.05)	0.455	p< 0.001
Average adjusted R-squared (AARS)	0.445	p< 0.001
Average block VIF (AVIF)	1.869	Good if <= 5, ideally <= 3.3
Average full collinearity VIF (AFVIF)	2.476	Acceptable if <= 5, ideally <= 3.3
Tenenhaus GoF (GoF)	0.545	Small >= 0.1, medium >= 0.25, large >= 0.36
Sympson's paradox ratio (SPR)	0.867	Acceptable if >= 0.7, ideally = 1
R-squared contribution ratio (RSCR)	0.935	Acceptable if >= 0.9, ideally = 1
Statistical suppression ratio (SSR)	1.000	Acceptable if >= 0.7
Nonlinear bivariate causality direction ratio (NLBCDR)	0.933	Acceptable if >= 0.7

Table 4: Hypothesis testing results

Hypothesis	Path	Path coefficient	p-value	Supported
H1	EE → BI	0.163	0.009	yes
H2	PE → BI	0.412	<0.001	yes
H3	SI → BI	0.137	0.023	yes
H4	FC → BI	0.140	0.021	yes
H5	FC→ EE	0.521	<0.001	yes
H6	PI → BI	0.126	0.034	yes
H7	PMA→ EE	-0.146	0.017	yes
H8	PMA→ PI	-0.147	0.017	yes
H9	PIM→ PE	0.349	<0.001	yes
H10	PIM→ PI	0.230	<0.001	yes
H11	PC→ PE	0.517	<0.001	yes
H12	PC→ PI	0.478	<0.001	yes
H13	PE×SQ→ BI	0.217	<0.001	yes
H14	EE×SQ→ BI	0.137	0.024	yes
H15	SI×SQ→ BI	-0.119	0.042	yes

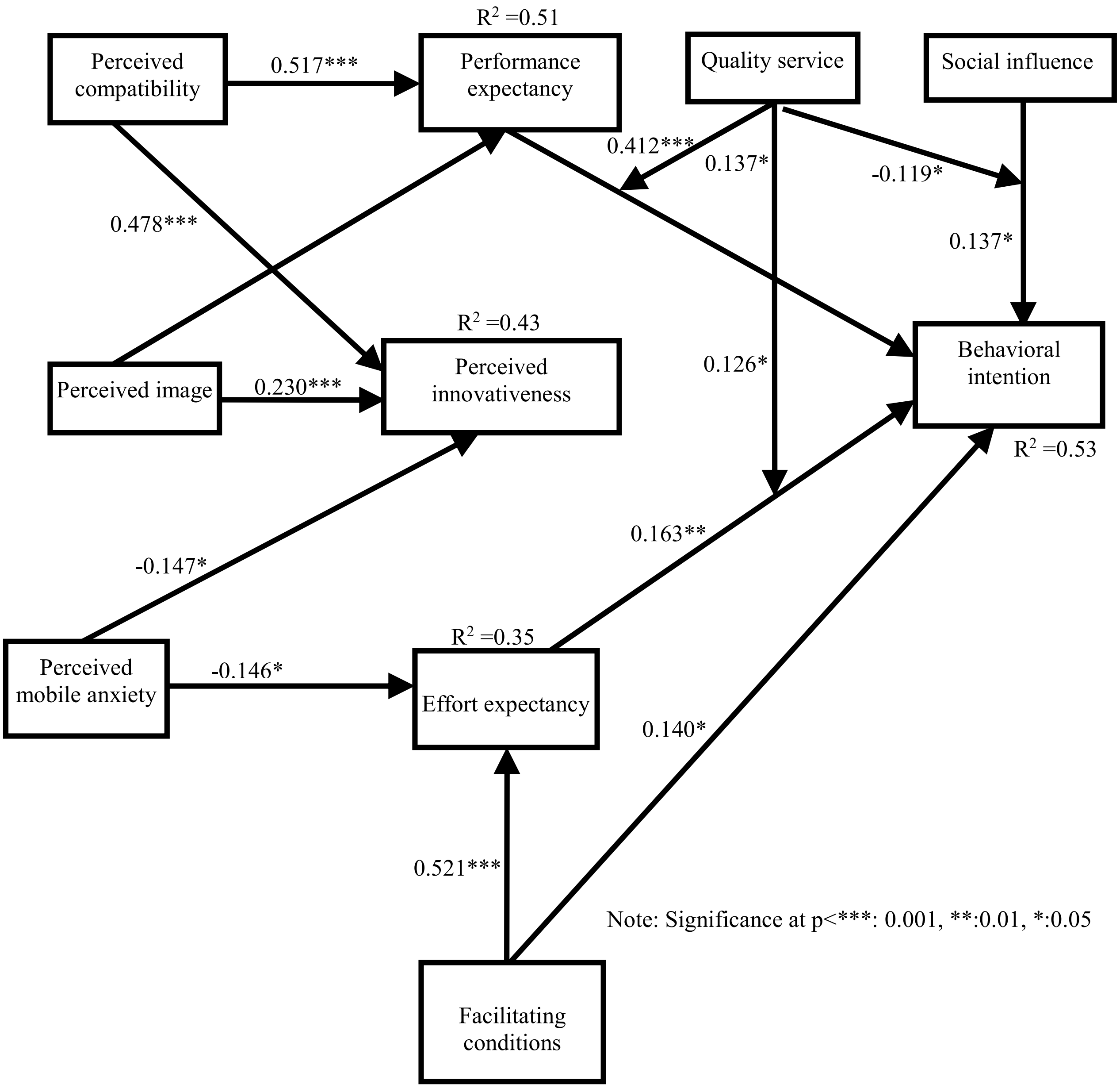

Figure 2: Results of Testing Hypotheses

6. DISCUSSION OF FINDINGS

The current study proposed a model to the investigate adoption of m-learning. The current study extends the UTAUT framework by including three different mechanisms to enhance the UTAUT environment with constructs that prove consequentially influential for mobile learning adoption dynamics and enriching both theory and practice. However, to my knowledge, the UTAUT framework has not been extended in the context of mobile-based adoption research in a similar fashion to the current investigation.

The findings obtained in the current study highlight that effort expectancy has a positive impact on intention to adopt m-learning technology (**H1**). These findings are compatible with prior

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

studies [15, 16, 17]. Furthermore, comparable conclusions were reported by prior studies conducted in a similar cultural environment [95, 107, 108, 112, 142]. This conclusion indicates that students would only adopt mobile-based technology for learning if they find it easy to use and apply in the learning environment. The aspect of performance expectancy has been found to have a substantial influence on the intention to adopt mobile learning technology (**H2**). In compliance with current findings, comparable findings were reported from earlier studies [15, 16, 17, 18]. Consequently, the findings obtained in this study provide empirical support that students would be more motivated to adopt a mobile learning system if they perceive it useful and beneficial in improving their performance in achieving learning outcomes. The findings of this investigation offer empirical evidence that performance expectancy is more influential than effort expectancy in predicting behavioral intention in the context of this study. The prominence of performance expectancy is justifiable from a conceptual perspective because users intrinsically adopt and use new technology for functional motives and the benefits gained. Performance expectancy and effort expectancy are critical factors in positively influencing mobile technology adoption because the technology will not be favorable for adoption if it does not support users' learning objectives or it requires unnecessarily too much effort to use and apply in the learning environment. The current findings demonstrated the significance of social influence in influencing positively the behavioral intention to adopt a mobile learning system (**H3**). These conclusions are in agreement with many studies conducted in a similar context [135, 137]. The results of this study confirmed that Jordanians are exposed to social influence which implies that social pressures can be exploited for motivating students to adopt m-learning.

This study provides empirical evidence that facilitating conditions has a direct influence on the intention to adopt m-learning in Jordan (**H4**). The findings obtained by this study are in agreement with previous studies conducted in the context of mobile learning adoption [19, 138]. Moreover, the empirical investigation reveals that facilitating conditions has an important positive impact on effort expectancy that indirectly leads to enhancement in intention to adopt (**H5**). A similar conclusion was reported in the context of the mobile payment system [139]. The present finding shows that the availability of facilitating conditions must be emphasized and strengthened in order to overcome the difficulties allied with the implementation of mobile-based technologies in the learning process. The current study provides empirical support that perceived innovativeness influences the intention to adopt m-learning (**H6**). In effect, the current finding corresponds to previous findings obtained by studies conducted in the context of m-learning adoption [90]. The result obtained in this study implies that if learners exhibit an adequate level of innovativeness behavior towards mobile learning technology, it is expected that they will be more enthusiastic for technology adoption.

The present study added three variables (perceived mobile anxiety, perceived compatibility, perceived image) to test their influence on effort expectancy, performance expectancy, and perceived innovativeness as proposed in the current model (see Figure 1). These variables have been labeled to have a prominent role in the adoption of IT products and services. This study has concluded that perceived mobile anxiety has a negative effect on effort expectancy and perceived innovativeness (**H7**, **H8**). With regard to the context of the present study, these types of findings are absent from the literature and therefore comparable findings are not available to make any comparison with current findings. The current results imply that the higher the perceptions of mobile anxiety the lower the perceptions of effort expectancy and innovativeness. Consequently, any suggested strategy to enhance the adoption of m-learning must be built on the convention that reduction of perceived mobile anxiety is one of its leading distinguishing aspects. The findings achieved in the current study demonstrate that perceived image has a considerable positive impact on performance expectancy and perceived innovativeness (**H9**, **H10**). This implies that the higher the perceived image, the higher the level of performance expectancy and perceived innovativeness that leads to enhance students' intention to adopt m-learning in Jordan. Similar findings were reached by Hao et al. [69]. This effectively implies that students in Jordan are more willing to adopt new learning technology like mobile learning if that technology promotes their social status and reputation. Perceived compatibility has been underlined to be an important variable in affecting the adoption behavior of information technologies. The current findings have revealed that perceived compatibility significantly affects performance expectancy and perceived innovativeness (**H11**, **H12**), indicating that the higher the level of perceived compatibility, the greater the level of performance expectancy and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

perceived innovativeness students would perceive in the adoption of m-learning. Indeed, if the technology is observed to align with learner personal, profiles needs, habits, preferences, interests, and lifestyles, therefore this will enhance students' perceptions of performance expectancy and innovativeness to adopt m-learning technology in Jordan. However, the literature is lacking comparable outcomes in the context of the mobile learning adoption process. In conclusion, the findings of the present study provide increasing emphasis on the significance of both perceived compatibility and perceived image as exogenous variables regarding the adoption dynamics of mobile learning in a developing country perspective.

Finally, current literature acknowledges that service quality plays a pivotal role in influencing the adoption behavior of IT products and services [29, 116,117]. The current analysis offers empirical evidence of the importance of the service quality dimension in moderating the primary UTAUT relationships that link effort expectancy and performance expectancy with the intention to adopt a mobile learning system (**H13**, **H14**). According to this study findings, an enhancement in service quality perceptions leads to strengthening the relationships linking effort expectancy and performance expectancy with behavioral intention. However, unlike what has been proposed in the current study, service quality was found to have a negative moderating effect on the relationship between social influence and the intentional behavior to adopt m-learning (**H15**). This indicates that the effect of social influence on intention to adopt m-learning is sensitive to the variation in the level of service quality of mobile learning technology such that the greater the degree of service quality the lesser the effect of social influence dimension on intention to adopt. However, the literature review carried out in the current analysis points out that there have been no studies to investigate the moderating effect of service quality on mobile learning adoption in developing country perspective using the theoretical framework of the UTAUT. As a result, a comparison between contemporary findings with previous analysis cannot be made.

7. CONTRIBUTIONS AND CONCLUSIONS

7.1 Theoretical Contributions

This study provides significant contributions to contemporary IS adoption literature. First, crafting and proposing a theoretical framework to study the adoption dynamics of a technological context such as mobile learning is a tough undertaking to ensure that the model has the very characteristics of comprehensiveness and parsimony, or in other words, only relevant influential variables are included and variables with little value are excluded. As a result, this study has proposed a paradigm shift in UTAUT extensions, whereas the current study has extended the boundary of the original UTAUT model with three mechanisms. (1) The study proposed three exogenous variables (perceived compatibility, perceived image, and perceived mobile anxiety) to examine their effects on behavioral intention through the mediation of the primary variables of the UTAUT (i.e., performance expectancy, effort expectancy). The present study also proposed the relationship between facilitating conditions of the UTAUT model as an exogenous variable to examine its impact on effort expectancy of UTAUT. (2) This study suggested the incorporation of perceived innovativeness to the UTAUT model as an endogenous variable to investigate its impact on behavioral intention. (3) The current study added the service quality determinant to explore its moderating effect on three primary UTAUT relationships connection (i.e., performance expectancy, effort expectancy, and social influence) with behavioral intention. This type of extensions of the UTAUT model is not a common practice in IS research. To the best of our knowledge, not many similar investigations have been conducted in this part of the world regarding mobile learning adoption process. Indeed, this rich combination of various important adoption variables covering theoretically acceptable forms of extensions on the UTAUT model has the potential to be synergistic. As already mentioned, the theoretical framework of the UTAUT was suggested with specific extensions to consolidate different theoretical perspectives to realize the objective of the study. The current study has tested successfully the applicability and adaptability of the extended UTAUT in the context of mobile learning within a developing country environment. Definitely, this study has diverted away from how IS researchers normally use the UTAUT model in technology adoption domain by proposing three mechanisms of extensions in one single model that proved to be conducive, relevant, and influential. This is by itself an important theoretical contribution to contemporary IS adoption literature.

Second, this study has reinforced the importance of mediation effect in the UTAUT environment, whereby mediation approach is not a popular option when IS researchers attempt to extend the UTAUT model [26]. The current study has demonstrated the utility and viability of the mediation role on applying the UTAUT environment in the adoption process of mobile learning in a developing country context, whereby perceived compatibility and perceived image constructs significantly and positively impacted the performance expectancy. This implies that these constructs are indirectly influencing the behavioral intention to adopt mobile learning. In addition, the current study provides empirical evidence of the existence of a negative correlation between perceived mobile anxiety and effort expectancy and perceived innovativeness. Indeed, these findings have not been reported elsewhere in the context of this study. Third, this study has reinforced the significance of the perceived innovativeness as an endogenous variable in determining behavioral intention to adopt mobile learning technology in developing country environment. Perhaps, this is the first study to provide empirical evidence demonstrating the effect of perceived innovativeness on intentional behavior to adopt mobile-based technologies in learning process from a developing country perspective. Moreover, the current study has concluded that innovativeness behavior can be inspired and motivated positively by enhancing the perceptions of compatibility and image in the process of mobile learning adoption. In the meantime, high perceived mobile anxiety leads to reduction in innovativeness behavior.

Fourth, the current study examines the moderating role of service quality on three primary UTAUT relationships, extending research on UTAUT outside the conventional research focus. The outcomes of this study provide empirical support for the influential moderating role the service quality can play in the adoption of mobile learning technology. Extending the UTAUT model with the aspect of service quality has not been widely popular research practice, especially in mobile-based learning systems. Indeed, this study has emphasized the importance of service quality in mobile learning adoption process as already manifested in various industries and disciplines as a key determinant in enhancing the acceptance of product and service innovations. Finally, this study hypothesizes new theoretical relationship that connects facilitating conditions with effort expectancy in the context of mobile-based learning adoption, and attempting to provide empirical evidence that the availability of adequate facilitating conditions at the students' disposal may positively enhance their perceptions of effort expectancy that leading to higher intentional behavior to adopt mobile learning technology in the Jordanian context. It has been confirmed that there is a lack of knowledge on the relation linking facilitating conditions with effort expectancy. This study provides empirical evidence on the significant impact of facilitating conditions on effort expectancy, and highlighting the importance of this determinant in augmenting the perceptions of effort expectancy, and therefore enhancing the level of behavioral intention to adopt mobile learning technology. The theoretical relationship proposed can provide practical utility in reducing students' resistance by facilitating the use of mobile learning system through making sure that adequate level of facilitating conditions is in place.

7.2 Conclusions and Practical Implications

Mobile technology has caused a dramatic spin in learning experience. However, understanding what factors encouraging individuals to adopt and use mobile-based technologies in learning settings is an imperative underpinning that enables putting in place appropriate, effective, and motivational strategies. The findings of this study provide many valuable implications for researchers, practitioners, developers, and academic institutions for the benefits of enhancing the perspectives of mobile learning technology to encourage its adoption. The findings of this study provide empirical evidence that the following factors are important in influencing positively the intentional behavior of mobile learning technology adoption in a developing country perspective: effort expectancy, performance expectancy, social influence, and perceived innovativeness. Therefore, it is extremely important from practical perspective to design and develop mobile learning system that enhances the perceptions of these factors to enhance the intention to adopt mobile learning technology.

The aspect of effort expectancy in the context of mobile learning has a different meaning in comparison with other contexts. For example, fitting learning materials in a small screen in multiple formats requires careful design to facilitate variations in the data consumption patterns to keep learners engaged and interested. To use the system with little agonizing training and experimentation, the system must be designed in a way that provides friendly user-interface, flexible features, easy-to-use learning environment, and liability for searchable contents. The aspects of performance expectancy must be strengthened to improve the likelihood of learners' acceptance of mobile technologies in learning process. From practical perspective, the mobile learning technology must be equipped with functionalities and tools that improve learning effectiveness, achievement, productivity, and knowledge retention. Enhancing the effectiveness of mobile learning system can be accomplished by placing greater emphasis on learner-centered approach. Mobile learning design strategy must focus on enhancing job performance so that learners would easily perceive the benefits and the usefulness of accepting the technology. In addition, achieving smooth delivery of individualized educational contents in various formats to learners may enhance learning deliverables and outcomes.

This study provides empirical evidence that learners in Jordan are exposed to social influence. From practical viewpoint, the aspects of social influence can be exploited for the benefit of improving the adoption of mobile learning by attempting to change and modify learners' behavior positively towards mobile learning adoption. For example, pressures and expectations of social environment can shape learners' behavior to enhance their motivations to accept new learning pathways such as mobile learning. Effectively, behavioral change can be reinforced by educators, friends, and parents. In addition, advertising and social media platforms are recognized as powerful tools for inspiring learners to accept and use mobile technologies in learning environments. The current findings highlighted that facilitating conditions positively impacts effort expectancy in the adoption of mobile technology in learning process. Therefore, academic institutions must play a central role in the provision of managerial, organizational, and technical learning infrastructure and resources as a prerequisite for learners to easily and conveniently implement mobile-based technologies in the learning environment. The present study demonstrates that perceived innovativeness positively impacts mobile learning adoption in Jordan. From practical perspective, proposed strategies must be able to identify aspects that stimulate and create high sense of innovativeness among learners in the context of mobile learning adoption. Indeed, having a high level of innovativeness helps individuals to have adequate courage, initiative, and confidence to adopt a new innovative technology such as mobile learning.

The current findings provide empirical support that perceived anxiety negatively influences effort expectancy and perceived innovativeness. However, if mobile learning system is perceived as less anxiety-prone by learners the perceptions of effort expectancy and perceived innovativeness will be largely enhanced. Consequently, system developers must provide less anxiety-provoking mobile learning system to reduce the negative effects of perceived mobile anxiety that hampers the development of motivating behavior towards the adoption of mobile learning technology. In addition, the current study demonstrates that perceived compatibility strongly augments the aspects of performance expectancy and perceived innovativeness in the adoption process of mobile learning. Therefore, it is highly preferable from practical implementation view to develop a mobile-assisted learning system compatible with learners' style preferences, educational orientation, experiences, needs, values, and expectations. In the meantime, the system of mobile learning should deliver a separate individualized learning path compliant with preferred learner's learning format and modality. This study reveals that perceived image positively affects performance expectancy and perceived innovativeness as hypothesized in the current model. Hence, from practical considerations, the suggested approaches to enhance perceived image should focus on ways and aspects that promote the adoption of mobile technologies for learning in a way that it will be tailored to enhance favorably learner's social image and prestige and contribute to achieving individuals' high-profile in their own social circle.

Finally, the service quality of mobile-based technologies in learning landscape has been underlined in this study to moderate positively the effect of effort expectancy and performance expectancy on behavioral intention. Consequently, academic institutions and developers need to place greater emphases on the aspects of service quality in relation to mobile learning technology. The service quality is a second-order construct which is composed of various aspects, and quality aspects are context-dependent. It is therefore essential to identify the quality aspects related to mobile learning technologies in a developing country environment to take them into consideration.

8. LIMITATIONS AND FUTURE STUDIES

Although this study has important contributions to theory and practice, it also has some limitations that offer perspectives for future studies. First, the sample was drawn from one university limiting the generalizations of the findings. Second, additional mediating and moderating variables can be considered to enhance the capability of the study to

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

drive further insights into the adoption dynamics of mobile learning process. Third, conducting a longitudinal study could prove useful for providing further evidence and valuable information of how to amplify the uptake of the technology. Fourth, the present study is limited to investigating behavioral intention. Therefore future studies may need to investigate the actual behavior of mobile learning adoption.

REFERENCES

[1] Nazir, S., Ali, Y., Ullah, N., & García-Magariño, I. (2019). Internet of Things for Healthcare using effects of mobile computing: A systematic literature review. *Wireless Communications and Mobile Computing*, *2019*.W.-K. Chen, *Linear Networks and Systems*. Belmont, CA, USA: Wadsworth, 1993, pp. 123–135.

[2] Tout, H., Kara, N., Talhi, C., & Mourad, A. (2019). Proactive machine learning-based solution for advanced manageability of multi-persona mobile computing. *Computers & Electrical Engineering*, *80*, 106497.

[3] Imran, A., Quimno, V., & Hussain, M. (2016). Current landscape and potential of mobile computing research in the least developed countries. *The Electronic Journal of Information Systems in Developing Countries*, *74*(1), 1-25.

[4] Law, R., Chan, I. C. C., & Wang, L. (2018). A comprehensive review of mobile technology use in hospitality and tourism. *Journal of Hospitality Marketing & Management*, *27*(6), 626-648.

[5] Ahmad, A., Malik, A. W., Alreshidi, A., Khan, W., & Sajjad, M. (2019). Adaptive Security for Self-Protection of Mobile Computing Devices. *Mobile Networks and Applications*, 1-20.

[6] Koo, B. M., & Vizer, L. M. (2019). Examining Mobile Technologies to Support Older Adults With Dementia Through the Lens of Personhood and Human Needs: Scoping Review. *JMIR mHealth and uHealth*, *7*(11), e15122

[7] Danish, J., & Hmelo-Silver, C. E. (2020). On activities and affordances for mobile learning. *Contemporary Educational Psychology*, *60*, 101829.

[8] Crompton, H. (2013). Mobile learning: New approach, new theory. *Handbook of mobile learning*, *1*, 47-58.

[9] Bannan, B., Cook, J., & Pachler, N. (2016). Reconceptualizing design research in the age of mobile learning. *Interactive Learning Environments*, *24*(5), 938-953.

[10] Ismail, I., Azizan, S. N., & Gunasegaran, T. (2016). Mobile learning in **M**alaysian universities: are students ready?. *International Journal of Interactive Mobile Technologies (iJIM)*, *10*(3), 17-23.

[11] Demir, K., & Akpinar, E. (2018). The Effect of Mobile Learning Applications on Students' Academic Achievement and Attitudes toward Mobile Learning. *Malaysian Online Journal of Educational Technology*, *6*(2), 48-59.

[12] Elkhateeb, M., Shehab, A., & El-Bakry, H. (2019). Mobile Learning System for Egyptian Higher Education Using Agile-Based Approach. *Education Research International*, *2019*.

[13] Baccari, S., & Neji, M. (2016). Design for a context-aware and collaborative mobile learning system. In *2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)* (pp. 1-6). IEEE.

[14] France, D., Lee, R., Maclachlan, J., & McPhee, S. R. (2020). Should you be using mobile technologies in teaching? Applying a pedagogical framework. *Journal of Geography in Higher Education*, 1-17.

[15] Al-Adwan, A. S., Al-Madadha, A., & Zvirzdinaite, Z. (2018). Modeling students' readiness to adopt mobile learning in higher education: An empirical study. *International Review of Research in Open and Distributed Learning*, *19*(1).

[16] Sarrab, M., Al Shibli, I., & Badursha, N. (2016). An empirical study of factors driving the adoption of mobile learning in Omani higher education. *International Review of Research in Open and Distributed Learning*, *17*(4), 331-349.

[17] Alawani, A. S., & Singh, A. D. (2017). A Smart Mobile Learning Conceptual Framework for Professional Development of UAE In-Service Teachers. *International journal of management and applied research*, *4*(3), 146-165.

[18] Alsswey, A., Al-Samarraie, H., El-Qirem, F. A., & Zaqout, F. (2020). M-learning technology in Arab Gulf countries: A systematic review of progress and recommendations. *Education and Information Technologies*, *25*(4), 2919-2931.

[19] Thomas, T., Singh, L., & Gaffar, K. (2013). The utility of the UTAUT model in explaining mobile learning adoption in higher education in Guyana. *International Journal of Education and Development using ICT*, *9*(3).

[20] Jawad, H. H. M., & Hassan, Z. B. (2015). Applying UTAUT to evaluate the acceptance of

mobile learning in higher education in Iraq. *International Journal of Science and Research (IJSR)*, *4*(5), 952-954.

[21] Mosunmola, A., Mayowa, A., Okuboyejo, S., & Adeniji, C. (2018). Adoption and use of mobile learning in higher education: the UTAUT model. In *Proceedings of the 9th International Conference on E-Education, E-Business, E-Management and E-Learning* (pp. 20-25).

[22] Thongsri, N., Shen, L., Bao, Y., & Alharbi, I. M. (2018). Integrating UTAUT and UGT to explain behavioural intention to use M-learning: A developing country's perspective. *Journal of Systems and Information Technology*, *20*(3), 278–297.

[23] Chao, C. M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in psychology*, *10*, 1652.

[24] Israel, D. J., & Velu, R. (2019). The partial test of UTAUT model to explain the influence of variables on the intention to adopt the mobile learning in higher education. *IJITEE*, *8*(8), 1076-1082.

[25] Simeonova, B., Bogolyubov, P., Blagov, E., & Kharabsheh, R. (2014). Cross-cultural validation of UTAUT: The case of University VLEs in Jordan, Russia and the UK. *Electronic Journal of Knowledge Management*, *12*(1), 25-34.

[26] Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the association for Information Systems*, *17*(5), 328-376.

[27] Camilleri, M. A., & Camilleri, A. C. (2020). The Use of Mobile Learning Technologies in Primary Education. In *Cognitive and Affective Perspectives on Immersive Technology in Education* (pp. 250-266). IGI Global.

[28] Khan, A. I., Al-Shihi, H., Al-Khanjari, Z. A., & Sarrab, M. (2015). Mobile Learning (M-Learning) adoption in the Middle East: Lessons learned from the educationally advanced countries. *Telematics and Informatics*, *32*(4), 909-920.

[29] Miller, H. B., & Cuevas, J. A. (2017). Mobile learning and its effects on academic achievement and student motivation in middle grades students. *International Journal for the Scholarship of Technology Enhanced Learning*, *1*(2), 91-110.

[30] Kuhl, P. K., Lim, S. S., Guerriero, S., & Van Damme, D. (2019). *Developing Minds in the Digital Age*. OECD Publishing.

[31] Lindsay, L. (2016). Transformation of teacher practice using mobile technology with one-to-one classes: M-learning pedagogical approaches. *British Journal of Educational Technology*, *47*(5), 883-892.

[32] Bernacki, M. L., Crompton, H., & Greene, J. A. (2020). Towards convergence of mobile and psychological theories of learning. *Contemporary Educational Psychology*, *60*, 101828.

[33] Giurgiu, L. (2017). Microlearning an evolving elearning trend. *Scientific Bulletin*, *22*(1), 18-23.

[34] Chung, C. J., Hwang, G. J., & Lai, C. L. (2019). A review of experimental mobile learning research in 2010–2016 based on the activity theory framework. *Computers & education*, *129*, 1-13.

[35] Kohnke, L., Zhang, R., & Zou, D. (2019). Using mobile vocabulary learning apps as aids to knowledge retention: Business vocabulary acquisition. *Journal of Asia TEFL*, *16*(2), 683.

[36] Wang, H., Tao, D., Yu, N., & Qu, X. (2020). Understanding consumer acceptance of healthcare wearable devices: An integrated model of UTAUT and TTF. *International journal of medical informatics*, *139*, 104156.

[37] Bere, A., & Rambe, P. (2019). Understanding Mobile Learning Using a Social Embeddedness Approach: A Case of Instant Messaging. *International Journal of Education and Development using Information and Communication Technology*, *15*(2), 132-153.

[38] Yong, K. H., Katuk, N., & Zakaria, N. H. (2018). A user preference study of authentication mechanisms for mobile learning applications. In *AIP Conference Proceedings* (Vol. 2016, No. 1, p. 020153). AIP Publishing LLC.

[39] Abidin, N. Z., & Tho, S. (2018). The development of an innovative resonance experiment using smartphones with free mobile software applications for tertiary education. *International Journal of Education and Development using ICT*, *14*(1).

[40] Jahnke, I., & Liebscher, J. (2020). Three types of integrated course designs for using mobile technologies to support creativity in higher education. *Computers & Education*, *146*, 103782.

[41] Kaliisa, R., & Picard, M. (2017). A systematic review on mobile learning in higher education: The African perspective. *TOJET: The Turkish Online Journal of Educational Technology*, *16*(1).

[42] Benali, M., & Ally, M. (2020). Towards a conceptual framework highlighting mobile learning challenges. *International Journal of Mobile and Blended Learning (IJMBL)*, *12*(1), 51-63.

[43] Sophonhiranrak, S., & Sakonnak, S. P. N. (2017). Limitations of Mobile Learning: A Systematic Review. In *E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education* (pp. 965-971). Association for the Advancement of Computing in Education (AACE).

[44] Rose, G., & Straub, D. (1998). Predicting general IT use: Applying TAM to the Arabic world. *Journal of Global Information Management (JGIM)*, *6*(3), 39- 46.

[45] Al-Emran, M., Elsherif, H. M., & Shaalan, K. (2016). Investigating attitudes towards the use of mobile learning in higher education. *Computers in Human behavior*, *56*, 93-102.

[46] Al-Hunaiyyan, A., Al-Sharhan, S., & Alhajri, R. (2017). A New Mobile Learning Model in the Context of Smart Classroom Environment: A Holistic Approach. *International journal of interactive mobile technologies*, *11*(3).

[47] Alsswey, A., & Al-Samarraie, H. (2019). M-learning adoption in the Arab gulf countries: A systematic review of factors and challenges. *Education and Information Technologies*, *24*(5), 3163-3176.

[48] Almasri, A. K. M. (2018). New mobile learning process model for higher education students in Jordanian universities. *International Journal of Information, Business and Management*, *10*(1), 201-213.

[49] Alfarani, L., 2015. Influences on the Adoption of Mobile Learning in Saudi Women Teachers in Higher Education. International Journal of Interactive Mobile Technologies. iJIM, 9(2), pp. 58-62.

[50] Almutairy, S., Davies, T. & Dimitriadi, W., 2015. The Readiness of Applying M-Learning among Saudi Arabian Students at Higher Education. International Journal of Interactive Mobile Technologies iJIM, 9(3), pp. 33- 36.

[51] Dashti, F. & Aldashti, A., 2015. EFL College Students' Attitudes towards Mobile Learning. International Education Studies, 8(8), pp. 13-20.

[52] Al-Shehri, S. (2014). Mobile learning in the Arab world: Contemporary and future implications. In *Interdisciplinary mobile media and communications: Social, political, and economic implications* (pp. 48-62). IGI Global.

[53] Khlaif, Z. N. (2018). Factors influencing teachers' attitudes toward mobile technology integration in K-12. *Technology, Knowledge and Learning*, *23*(1), 161-175.

[54] Almaiah, M. A., Jalil, M. A., & Man, M. (2016). Preliminary study for exploring the major problems and activities of mobile learning system: A case study of Jordan. *J. Theor. Appl. Inf. Technol.*, *93*(2), 580–594**.**

[55] Chuttur, M. Y. (2009). Overview of the technology acceptance model: Origins, developments and future directions. *Working Papers on Information Systems*, *9*(37), 9-37.

[56] Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management*, *34*(1), 1-13.

[57] Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior*, *50*, 418-430.

[58] de Sena Abrahão, R., Moriguchi, S. N., & Andrade, D. F. (2016). Intention of adoption of mobile payment: An analysis in the light of the Unified Theory of Acceptance and Use of Technology (UTAUT). *RAI Revista de Administração e Inovação*, *13*(3), 221-230.

[59] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

[60] Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178.

[61] Williams, M.D., Rana, N.P., Dwivedi, Y.K. and Lal, B. (2011) "Is UTAUT really used or just cited for the sake of it? A systematic review of citations of UTAUT's originating article", *ECIS 2011 Proceedings*. Paper 231.

[62] Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. *International journal of medical informatics*, *101*, 75-84.

[63] Alam, M. Z., Hu, W., & Barua, Z. (2018). Using the UTAUT model to determine factors affecting acceptance and use of mobile health (mHealth) services in Bangladesh. *Journal of Studies in Social Sciences*, *17*(2).

[64] Rahi, S., Ghani, M., Alnaser, F., & Ngah, A. (2018). Investigating the role of unified theory of acceptance and use of technology (UTAUT) in internet banking adoption context. *Management Science Letters*, *8*(3), 173-186.

[65] Al-Saedi, K., Al-Emran, M., Ramayah, T., & Abusham, E. (2020). Developing a general extended UTAUT model for M-payment adoption. *Technology in Society*, *62*, 101293.

[66] Nassuora, A. B. (2012). Students acceptance of mobile learning for higher education in Saudi Arabia. *American Academic & Scholarly Research Journal*, *4*(2), 24-30.

[67] Kelman, H. C. (1958). Compliance, identification, and internalization three processes of attitude change. *Journal of conflict resolution*, *2*(1), 51-60.

[68] Fishbein and Ajzen. "A Bayesian analysis of attribution processes." *Psychological bulletin* 82, no. 2 (1975): 261.

[69] Hao, S., Dennen, V. P., & Mei, L. (2017). Influential factors for mobile learning acceptance among Chinese users. *Educational Technology Research and Development*, *65*(1), 101-123.

[70] Wan Hamzah, W. M. A. F., Yusoff, H., Ismail, I., & Yacob, A. (2020). The Behavioral Intentions of Secondary School Students to Use Tablet as a Mobile Learning Device. *International Journal of Interactive Mobile Technologies*, *14*(13).

[71] Triandis, H. C. (1979). Values, attitudes, and interpersonal behavior. In *Nebraska symposium on motivation*. University of Nebraska Press.

[72] Mtebe, J., & Raisamo, R. (2014). Investigating students' behavioral intention to adopt and use mobile learning in higher education in East Africa. *International Journal of Education and Development using ICT*, *10*(3).

[73] Faqih, K. M., & Jaradat, M. I. R. M. (2021). Integrating TTF and UTAUT2 theories to investigate the adoption of augmented reality technology in education: Perspective from a developing country. *Technology in Society*, *67*, 101787.

[74] Jewer, J. (2018). Patients' intention to use online postings of ED wait times: A modified UTAUT model. *International journal of medical informatics*, *112*, 34-39.

[75] Molina-Castillo, F. J., Lopez-Nicolas, C., & de Reuver, M. (2020). Mobile payment: The hiding impact of learning costs on user intentions. *Journal of theoretical and applied electronic commerce research*, *15*(1), 1-12.

[76] Uğur, N. G., Koç, T., & Koç, M. (2016). An analysis of mobile learning acceptance by college students. *Journal of Educational & Instructional Studies in the World*, *6*(2).

[77] Onaolapo, S., & Oyewole, O. (2018). Performance expectancy, effort expectancy, and facilitating conditions as factors influencing smart phones use for mobile learning by postgraduate students of the University of Ibadan, Nigeria. *Interdisciplinary Journal of e-Skills and Lifelong Learning*, *14*(1), 95-115.

[78] Al-Adwan, A. S., Al-Madadha, A., & Zvirzdinaite, Z. (2018). Modeling students' readiness to adopt mobile learning in higher education: An empirical study. *International Review of Research in Open and Distributed Learning*, *19*(1).

[79] Huang, Y. M. (2017). Exploring the intention to use cloud services in collaboration contexts among Taiwan's private vocational students. *Information Development*, *33*(1), 29-42.

[80] Mostafa, A. A., & Eneizan, B. (2018). Factors affecting acceptance of mobile banking in developing countries. *International Journal of Academic Research in Business and Social Sciences*, *8*(1), 340-351.

[81] Faqih, K. M. (2022). Factors influencing the behavioral intention to adopt a technological innovation from a developing country context: The case of mobile augmented reality games. *Technology in Society*, 69, 101958.

[82] Vargo, S. L., Akaka, M. A., & Wieland, H. (2020). Rethinking the process of diffusion in innovation: A service-ecosystems and institutional perspective. *Journal of Business Research*, *116*, 526-534.

[83] Rogers, E. (1995). Diffusion of innovations. (4th ed.) New York: The Free Press.

[84] Ma, L., & Lee, C. S. (2019). Understanding the barriers to the use of MOOCs in a developing country: An innovation resistance perspective. *Journal of Educational Computing Research*, *57*(3), 571-590.

[85] Rogers, E. (1983). Diffusion of innovations. (3rd ed.) New York: The Free Press.

[86] Agarwal, R., & Prasad, J. (1998). A Conceptual and Operational Definition of Personal Innovativeness in the Domain of Information Technology. *Information Systems Research*, *9*(2), 204-215. INFORMS: Institute for Operations Research.

[87] Lowe, B., & Alpert, F. (2015). Forecasting consumer perception of innovativeness. *Technovation*, *45*, 1-14.

[88] Hussain, S., Qazi, S., Ahmed, R. R., Vveinhardt, J., & Streimikiene, D. (2019). Innovative user engagement and playfulness on adoption intentions of technological products: evidence from SEM-based multivariate approach. *Economic research-Ekonomska istraživanja*, *32*(1), 555-577.

[89] Makki, A. M., Ozturk, A. B., & Singh, D. (2016). Role of risk, self-efficacy, and innovativeness on behavioral intentions for mobile payment systems in the restaurant industry. *Journal of Foodservice Business Research*, *19*(5), 454-473.

[90] Chauhan, V., Yadav, R., & Choudhary, V. (2019). Analyzing the impact of consumer innovativeness and perceived risk in internet banking adoption. *International Journal of Bank Marketing*, *7*(1), 67-102.

[91] Simarmata, M. T., & Hia, I. J. (2020). THE ROLE OF PERSONAL INNOVATIVENESS ON BEHAVIORAL INTENTION OF INFORMATION TECHNOLOGY. *Journal of Economics and Business*, *1*(2), 18-29.

[92] Abu-Al-Aish, A., & Love, S. (2013). Factors influencing students' acceptance of m-learning: An investigation in higher education. *International Review of Research in Open and Distributed Learning*, *14*(5), 82-107.

[93] Huang, F., Sánchez-Prieto, J. C., Teo, T., García-Peñalvo, F. J., Sánchez, E. M. T., & Zhao, C. (2020). The influence of university students' learning beliefs on their intentions to use mobile technologies in learning: a study in China and Spain. *Educational Technology Research and Development*, *68*(6), 3547-3565.

[94] Nagar, K. (2016). Drivers of E-store patronage intentions: Choice overload, Internet shopping anxiety, and impulse purchase tendency. *Journal of Internet Commerce*, *15*(2), 97-124.

[95] Faqih, K. M., & Jaradat, M. I. R. M. (2015). Assessing the moderating effect of gender differences and individualism-collectivism at individual-level on the adoption of mobile commerce technology: TAM3 perspective. Journal of *Retailing and Consumer Services*, *22*, 37-52.

[96] Faqih, K. M. (2016a). An empirical analysis of factors predicting the behavioral intention to adopt Internet shopping technology among non-shoppers in a developing country context: Does gender matter?. *Journal of Retailing and Consumer Services*, *30*, 140-164.

[97] Faqih, K. M. (2022). Internet shopping in the Covid-19 era: Investigating the role of perceived risk, anxiety, gender, culture, and trust in the consumers' purchasing behavior from a developing country context. *Technology in Society*, 101992.

[98] Gribbin, J. H. (1970). Cornputerphobia and other problems: user reactions to an automated circulation operation in the library of Tulane university. Southeastern Librarian 20, 78-82.

[99] Parayitam, S., Desai, K. J., Desai, M. S., & Eason, M. K. (2010). Computer attitude as a moderator in the relationship between computer anxiety, satisfaction, and stress. *Computers in Human Behavior*, *26*(3), 345-352.

[100] Bloom, A. J. (1985). An Anxiety Management Approach to Computerphobia. *Training & Development Journal*, *39*(1), 90-95.

[101] Callum, K., Jeffrey, L., & Kinshuk, I. (2014). Factors impacting teachers' adoption of mobile learning. *Journal of Information Technology Education*: *Research*, *13*(1), 141-162.

[102] Chen, C. P. (2018). Understanding mobile English-learning gaming adopters in the self-learning market: The Uses and Gratification Expectancy Model. *Computers & Education*, *126*, 217-230.

[103] Pulla, S. (2020). Mobile learning and indigenous education in Canada: A synthesis of new ways of learning. In *Indigenous Studies: Breakthroughs in Research and Practice* (pp. 175-199). IGI Global

[104] Mohammadi, H. (2015). Social and individual antecedents of m-learning adoption in Iran. *Computers in Human Behavior*, *49*, 191-207.

[105] Nie, J., Zheng, C., Zeng, P., Zhou, B., Lei, L., & Wang, P. (2020). Using the theory of planned behavior and the role of social image to understand mobile English learning check-in behavior. *Computers & Education*, 103942.

[106] Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information systems research*, *2*(3), 192-222.

[107] Jaradat, M. I. R. M., & Faqih, K. M. (2014). Investigating the moderating effects of gender and self-efficacy in the context of mobile payment adoption: A developing country perspective. *International Journal of Business and Management*, *9*(11), 147.

[108] Faqih, K. M. (2016b). Which is more important in e-learning adoption, perceived value or perceived usefulness? Examining the moderating influence of perceived compatibility. In *4th Global Summit on*

Education GSE. Kuala Lumpur. World Conferences.

[109] Hsu, C. L., & Lin, J. C. C. (2016). An empirical examination of consumer adoption of Internet of Things services: Network externalities and concern for information privacy perspectives. *Computers in Human Behavior*, *62*, 516-527.

[110] NGUYEN, A. H., NGUYEN, T. P., & DANG, G. T. T. (2020). Determinants of E-invoice Adoption: Empirical Evidence from Vietnam. *The Journal of Asian Finance, Economics, and Business*, *7*(7), 311-321.

[111] Cheng, Y. M. (2015). Towards an understanding of the factors affecting m-learning acceptance: Roles of technological characteristics and compatibility. *Asia Pacific Management Review*, *20*(3), 109-119.

[112] Faqih, K. M. (2020). The influence of perceived usefulness, social influence, internet self-efficacy and compatibility on users' intentions to adopt e-learning: investigating the moderating effects of culture. *International E-Journal of Advances in Education*, *5*(15), 300-320.

[113] Huang, F., Sánchez-Prieto, J. C., Teo, T., García-Peñalvo, F. J., Sánchez, E. M. T., & Zhao, C. (2020). The influence of university students' learning beliefs on their intentions to use mobile technologies in learning: a study in China and Spain. *Educational Technology Research and Development*, 1-19.

[114] Ifinedo, P. (2018). Determinants of students' continuance intention to use blogs to learn: An empirical investigation. *Behavior & Information Technology*, *37*(4), 381-392.

[115] Agag, G. M., Khashan, M. A., & ElGayaar, M. H. (2019). Understanding online gamers' intentions to play games online and effects on their loyalty: An integration of IDT, TAM and TPB. *Journal of Customer Behaviour*, *18*(2), 101-130.

[116] Zeithaml, V. A., Parasuraman, A., Berry, L. L., & Berry, L. L. (1990). *Delivering quality service: Balancing customer perceptions and expectations*. Simon and Schuster.

[117] Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. *Decision support systems*, *54*(2), 1085-1091.

[118] Jun, M., & Palacios, S. (2016). Examining the key dimensions of mobile banking service quality: an exploratory study. *International Journal of Bank Marketing*, *34*(3), pp.307-326.

[119] Kaatz, C. (2020). Retail in my pocket–replicating and extending the construct of service quality into the mobile commerce context. *Journal of Retailing and Consumer Services*, *53*, 101983.

[120] Sarrab, M., Al Shibli, I., & Badursha, N. (2016). An empirical study of factors driving the adoption of mobile learning in Omani higher education. *International Review of Research in Open and Distributed Learning*, *17*(4), 331-349.

[121] Akter, S., D'Ambra, J., Ray, P., & Hani, U. (2013). Modelling the impact of mHealth service quality on satisfaction, continuance and quality of life. *Behaviour & Information Technology*, *32*(12), 1225-1241.

[122] Almaiah, M. A., & Alismaiel, O. A. (2019). Examination of factors influencing the use of mobile learning system: An empirical study. *Education and Information Technologies*, *24*(1), 885-909.

[123] Sarrab, M., Al-Shihi, H., & Al-Manthari, B. (2015). System Quality Characteristics for Selecting Mobile Learning Applications. *Turkish Online Journal of Distance Education*, *16*(4), 18-27.

[124] Budiman, E., Hairah, U., Haeruddin, H., & Saudek, A. (2018). Mobile networks for mobile learning tools. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, *10*(1-4), 47-52.

[125] Al-nassar, B. A. Y. (2020). Effect of information quality and system quality in information system success model as an antecedent of mobile learning in education institutions: case study in Jordan. *International Journal of Mobile Learning and Organization*, *14*(3), 277-306.

[126] Asharari, Y. S., & Alshmrani, A. S. (2017). The moderating effect commitment to service quality On the relationship between Attitudes and Organizational Performance: Evidence from the Saudi Arabia. *Asian Journal of Multidisciplinary Studies*, *5*, 11.

[127] Prentice, C., Wang, X., & Loureiro, S. M. C. (2019). The influence of brand experience and service quality on customer engagement. *Journal of Retailing and Consumer Services*, *50*, 50-59.

[128] Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International journal of medical education*, *2*, 53.

[129] Nunnally, J. C. (1978). *Psychometric Theory: 2d Ed*. McGraw-Hill.

[130] Chin, W. W., & Gopal, A. (1995). Adoption intention in GSS: relative importance of beliefs. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, *26*(2-3), 42-64.

[131] Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM). *European business review*.

[132] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

[133] Kock, N. (2010). Using WarpPLS in e-collaboration studies: An overview of five main analysis steps. *International Journal of e-Collaboration (IJeC)*, *6*(4), 1-11.

[134] Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y. M., & Lauro, C. (2005). PLS Path Modeling Computational Statistics & Data Analysis, 48, 159-205.

[135] Kang, M., Liew, B. Y. T., Lim, H., Jang, J., & Lee, S. (2015). Investigating the determinants of mobile learning acceptance in Korea using UTAUT2. In *Emerging issues in smart learning* (pp. 209-216). Springer, Berlin, Heidelberg.

[136] Yang, S. (2013). Understanding undergraduate students' adoption of mobile learning model: A perspective of the extended UTAUT2. *Journal of convergence information technology*, *8*(10), 969.

[137] Alasmari, T., & Zhang, K. (2019). Mobile learning technology acceptance in Saudi Arabian higher education: an extended framework and A mixed-method study. *Education and Information Technologies*, *24*(3), 2127-2144.

[138] Al-Hujran, O., Al-Lozi, E., & Al-Debei, M. M. (2014). Get ready to mobile learning: examining factors affecting college students' behavioral intentions to use m-learning in saudi arabia. *Jordan Journal of Business Administration*, *10*(1), 111-128.

[139] Patil, P., Tamilmani, K., Rana, N. P., & Raghavan, V. (2020). Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal. *International Journal of Information Management*, *54*, 102144.

[140] Jaradat, M. I. R. M., Ababneh, H. T., Faqih, K. M., & Nusairat, N. M. (2020). Exploring Cloud Computing Adoption in Higher Educational Environment: An Extension of the UTAUT Model with Trust. *International Journal of Advanced Science and Technology*, *29*(05), 8282-8306.

[141] Jahanbakhsh, M., Peikari, H. R., Hazhir, F., & Saghaeiannejad-Isfahani, S. (2018). An investigation into the effective factors on the acceptance and use of integrated health system in the primary health-care centers. *Journal of Education and Health Promotion*, *7*:128.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Appendix A: Survey questionnaire

Construct	Item code	Items
Behavioral intention (BI)	BI1	"I intend to use mobile learning."
	BI2	"I plan to use mobile learning in the future."
	BI3	"I would recommend others to use mobile learning."
	BI4	"If I had the chance, I would use mobile learning as much as possible."
Effort Expectancy (EE)	EE1	"Learning how to use mobile learning is easy for me."
	EE2	"I think that it would be easy for me to become skillful using mobile learning."
	EE3	"I think that using mobile learning is easy for me."
	EE4	I find it easy to use mobile learning to do what I want to do."
Performance Expectancy (PE)	PE1	"I think that using mobile learning improves my learning performance."
	PE2	"I think that using mobile learning improves my work effectiveness."
	PE3	"I would find mobile learning useful in learning activities."
	PE4	"I think that using mobile learning enhances my ability to learn."
	PE5	"In general, learning via mobile devices is useful."
Social Influence (SI)	SI1	"People who are important to me (my family) think that I should use mobile learning."
	SI2	"I think that university senior management thinks that I should use mobile learning."
	SI3	"People whose opinions that I value (friends and colleagues) prefer that I should use mobile learning."
	SI4	I will use mobile learning if the technology is widely used by people in my community.
	SI5	I would consider using mobile learning if someone personally recommended it.
Facilitating Conditions (FC)	FC1	"I think that I have the necessary resources to use mobile learning."
	FC2	"I think that I have the necessary knowledge to use mobile learning."
	FC3	"I think that the use of mobile is compatible with all aspects of learning activities."
Perceived innovativeness (PIN)	PIN1	"I like to experiment with new information technologies."
	PIN2	"Among my peers, I am usually the first to try out new information technologies."
	PIN3	"In general, I am not hesitant to try out new information technologies."
Perceived mobile anxiety (PMA)	PMA1	"I feel apprehensive about using mobile learning technology."
	PMA2	"I hesitate to use mobile learning technology for fear of making mistakes I cannot correct."
	PMA3	"I have avoided mobile learning technology because it is unfamiliar to me."
Perceived compatibility (PC)	PC1	"Using mobile learning fits well with my lifestyle."
	PC2	"Using mobile learning fits well with my learning style."
	PC3	"Using mobile learning will be unavoidable technological phenomenon in the future."
	PC4	"Using mobile learning fits well into my work style."
Perceived image (PIM)	PIN1	"People who use mobile learning have more prestige than those who do not."
	PIN2	"People who use mobile learning have a high profile in their social system."
	PIN3	"Using mobile learning is a symbol of social status."
Service quality (SQ)	SQ1	"It is important for mobile learning services to increase the quality of learning."
	SQ2	"I would prefer mobile learning services to be accurate and reliable."
	SQ3	"It is important for mobile learning services to be highly secure to use."
	SQ4	"It is preferable that mobile learning services are easy to navigate and download."

Appendix B: Cross-Loadings Matrix

	BI	EE	PE	SI	FC	PI	PMA	PC	PIM	QS
BI1	**0.821**	0.574	0.589	0.452	0.520	0.452	-0.116	0.628	0.341	0.499
BI2	**0.855**	0.543	0.552	0.476	0.485	0.520	-0.092	0.525	0.332	0.580
BI3	**0.888**	0.528	0.651	0.466	0.500	0.412	-0.083	0.549	0.409	0.486
BI4	**0.860**	0.523	0.604	0.506	0.533	0.496	-0.189	0.622	0.283	0.576
EE1	0.540	**0.828**	0.574	0.404	0.456	0.482	-0.095	0.529	0.344	0.437
EE2	0.500	**0.851**	0.433	0.315	0.443	0.501	-0.101	0.476	0.295	0.411
EE3	0.511	**0.840**	0.505	0.342	0.503	0.556	-0.095	0.555	0.371	0.489
EE4	0.539	**0.779**	0.586	0.314	0.504	0.430	-0.048	0.487	0.355	0.426
PE1	0.596	0.532	**0.840**	0.421	0.464	0.463	0.025	0.560	0.521	0.517
PE2	0.597	0.508	**0.817**	0.425	0.448	0.378	0.053	0.489	0.496	0.424
PE3	0.561	0.572	**0.836**	0.396	0.485	0.404	-0.068	0.529	0.410	0.411
PE4	0.536	0.494	**0.861**	0.346	0.413	0.389	-0.039	0.486	0.370	0.455
PE5	0.651	0.553	**0.843**	0.446	0.456	0.452	-0.100	0.581	0.364	0.530
SN1	0.415	0.267	0.306	**0.715**	0.369	0.218	0.218	0.362	0.315	0.325
SN2	0.399	0.321	0.307	**0.744**	0.352	0.267	0.074	0.397	0.253	0.385
SN3	0.333	0.308	0.371	**0.777**	0.399	0.309	-0.074	0.447	0.26	0.426
SN4	0.529	0.372	0.461	**0.713**	0.432	0.508	-0.170	0.621	0.193	0.652
SN5	0.386	0.274	0.346	**0.745**	0.268	0.320	-0.012	0.367	0.29	0.415
FC1	0.538	0.448	0.456	0.488	**0.873**	0.529	-0.017	0.534	0.405	0.543
FC2	0.501	0.512	0.500	0.415	**0.870**	0.493	0.013	0.580	0.336	0.601
FC3	0.482	0.519	0.424	0.353	**0.817**	0.347	0.022	0.441	0.373	0.366
PI1	0.508	0.513	0.447	0.430	0.493	**0.843**	-0.144	0.608	0.299	0.654
PI2	0.344	0.376	0.268	0.242	0.359	**0.778**	0.039	0.330	0.305	0.346
PI3	0.504	0.587	0.509	0.406	0.477	**0.865**	-0.198	0.538	0.357	0.559
PMA1	-0.041	-0.045	0.025	0.081	0.111	-0.015	**0.868**	-0.099	0.336	-0.065
PMA2	-0.172	-0.134	-0.058	-0.007	-0.016	-0.162	**0.898**	-0.207	0.274	-0.189
PMA3	-0.151	-0.089	-0.048	-0.053	-0.081	-0.153	**0.839**	-0.270	0.299	-0.321
PC1	0.529	0.520	0.498	0.485	0.432	0.463	-0.196	**0.876**	0.242	0.623
PC2	0.581	0.508	0.565	0.539	0.499	0.471	-0.176	**0.845**	0.335	0.618
PC3	0.575	0.516	0.488	0.477	0.511	0.602	-0.225	**0.822**	0.205	0.701
PC4	0.577	0.525	0.551	0.474	0.598	0.461	-0.136	**0.788**	0.339	0.464
PIM1	0.422	0.451	0.530	0.367	0.518	0.528	0.178	0.432	**0.812**	0.365
PIM2	0.343	0.341	0.472	0.319	0.347	0.330	0.317	0.287	**0.895**	0.258
PIM3	0.237	0.247	0.286	0.204	0.230	0.114	0.381	0.122	**0.804**	0.031
SQ1	0.583	0.508	0.533	0.515	0.557	0.614	-0.163	0.681	0.305	**0.836**
SQ2	0.511	0.357	0.438	0.539	0.546	0.470	-0.157	0.579	0.191	**0.872**
SQ3	0.486	0.426	0.420	0.485	0.475	0.550	-0.209	0.595	0.167	**0.880**
SQ4	0.514	0.510	0.482	0.447	0.397	0.479	-0.206	0.566	0.219	**0.750**