The Impact of Usability, Social and Organisational Factors on Students' Use of Learning Management Systems in Saudi Tertiary Education

A thesis submitted in partial fulfilment of the requirements of Edinburgh Napier University, for the award of Doctor of Philosophy

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ABSTRACT

Advances in e-learning have reshaped universities worldwide. Universities place great emphasis on technology-enhanced learning development and are investing significantly in information technology infrastructure. However, in spite of this effort and investment, it seems that instructors and students do not fully benefit from learning technology, and more often Learning Management Systems (LMSs) remain underutilized. This is evident in Saudi higher education where LMSs have recently been introduced. Understanding the factors affecting the use of LMSs and prompting their engagement are therefore crucial to the success of such platforms. This study aims to fill this gap by examining usability, and organisational and social factors affecting the students' intentions and use of LMSs in Saudi tertiary education. To this end, a theoretical framework was proposed that combined perceived usability attributes with the Unified Theory of Acceptance and Use of Technology (UTAUT) variables to identify the impact on students' intention and use of the LMS. Furthermore, the study examined the moderating effect of demographic characteristics (gender, age, experience, and training) on the model's proposed relationships.

This study used a quantitative approach to validate the proposed model and test the research hypotheses. A cross-sectional survey method was adopted to collect the data. Using the probability multi-stage cluster-sampling technique, the empirical data were collected from five state universities in different regions of Saudi Arabia. The data were coded, cleaned, and preliminarily analysed using the Statistical Package for Social Science (SPSS) package. In total, 605 responses were usable for testing the measurement and structural model, employing partial least squares structural equation modelling (PLS-SEM) technique and SmartPLS software. The results reveal the significant drivers of student use of LMS and the moderating effect of demographics on the proposed relationships. The results confirm that the study model is valid and reliable to indicate the key factors that influence the use of LMS. The dimension of social influence emerged to significantly influence the students' usage behaviour. The performance expectancy was affected by information quality and the system interactivity whereas the effort expectancy was influenced by system navigation, system learnability and instructional assessment. The statistical analysis reveals that six associations were moderated by the four proposed personal characteristics. In the light of the findings of this study, recommendations were put forward to universities to gain insights into the best way to promote e-learning system popularity and acceptance among students.

DEDICATION

To my mother, wife, and children.

إلى والدتي فاطمة
إلى زوجتي أميرة
إلى بناتي ألما وسما

DECLARATION

I hereby declare that the work presented in this thesis has not been submitted for any other degree or professional qualification, and that it is the result of my own independent work.

Ahmed Ali M Alshehri

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ABBREVIATIONS

Acronym	Definition
UTAUT	Unified Theory of Acceptance and Use of Technology
SaaS	Software as a Service
OSS	Open Source Software
LMS	Learning Management System
VLE	Virtual Learning Environment
CMS	Course Management System
ICT	Information Communication Technology
NCeDL	National Center for e-learning and Distance Learning
KSA	Kingdom of Saudi Arabia
CITC	Communications and Information Technology Commission
IT	Information Technology
IS	Information System
HCI	Human Computer Interaction
UE	User Experience
UEM	Usability Evaluation Method
UI	User Interface
DPA	Data Protection Act
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behaviour
SCT	Social Cognitive Theory
MM	Motivational Model
IDT	Innovation Diffusion Theory
HTML	Hypertext Markup Language
SEM	Structural Equation Modelling
VIF	Variance Inflation Factor
AVE	Average Variance Extracted
CA	Cronbach's Alpha
Df	Degree of Freedom
DOI	Diffusion of Innovation
HTMT	Heterotrait-Monotrait Ratio

NFI	Normed Fit Index.
CR	Composite Reliability
D^2	Mahalanobis Distance
R^2	Coefficient of Determination
Q^2	Cross-validated Redundancy
GoF	Goodness-of-fit
MGA	Multi-group Analysis
MICOM	Measurement Invariance of Composite Models
SRMR	Standardised Root Mean Square Residual
CB-SEM	Covariance-based Structural Equation Modelling
PLS-SEM	Partial Least Squares Structural Equation Modelling
ERP	Enterprise Resource Planning
PE	Performance Expectancy
EE	Effort Expectancy
SI	Social Influence
FC	Facilitating Condition
BI	Behavioural Intention
AU	Actual Use
SN	System Navigation
VD	Visual Design
SL	System Learnability
IQ	Information Quality
IA	Instructional Assessment
ESI	E-learning System Interactivity
SPSS	The Statistical Package for the Social Sciences

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CHAPTER 1: INTRODUCTION

1.1 Introduction

In recent years, expansion of higher education in Saudi Arabia has resulted in increased interest in the introduction, management and use of Learning Management Systems (LMSs). This study was designed to increase understanding of the factors influencing the use of LMSs through a consideration of theoretical models and in-context data gathering and analysis with a view to improving the use of LMSs throughout Saudi Arabia. This chapter presents an overview of the relevant research background, summarising the current understanding of LMSs in Saudi Arabia. This is followed by an articulation of the research problem and supported by the study's rationale. The next section of this chapter deals with the research questions, aims and objectives, and outlines the research scope and boundaries. Then, the context of this study is introduced: the Kingdom of Saudi Arabia. This section presents information about Saudi Arabian education, e-learning and the National Centre for e-learning and Distance Learning. The rationale underlying this section is to understand the current status and importance of e-learning in Saudi higher education. The last part describes the main structure of the thesis through a consideration of each chapter.

1.2 Background to the Study

Technological advancements have progressed substantially in recent decades. The rapid improvement in information and communication technologies has shaped opportunities in many fields. The inception of IT services is no longer limited to back-office functions but has expanded to include core processes in finance, education, healthcare and tourism and many other fields (AL-Sabawy, 2013). While the progress of technological innovation is continuing, the transfer and integration of these advances into education has become a current topic of debate (Al-Gahtani, 2016). The successful experience of e-services around the world has led to a redefinition of the role of educational institutions, through the adoption of e-learning services and techniques. This transformation has had a substantial influence on the need and opportunity to learn (Garrison, 2011). Thus, many educational institutions have made considerable investments in terms of finance and other resources in the implementation and use of e-learning systems (Alsabawy et al., 2016). The goal is to create a lifelong learning environment through cost-efficient, flexible and accessible education, regardless of geographic and time boundaries. Enrichment of communication, accessibility, mobility, learning and teaching enhancement have been evident. Therefore, the trend towards the use of e-learning systems in education has increased, and has attracted global attention (Liaw et al., 2007).

Nonetheless, despite the proliferation of IT artefacts, the transformative impact on education is intriguing and merits further exploration. At the core of this transition is the notion that students should be actively engaged in the learning environment (Garrison, 2011). The students' engagement with technology may not always be effective nor efficient (Garrison, 2011). Since the ultimate goal of using an e-learning system is the improvement of effective learning, its benefits cannot be achieved if the students' adoption rate is low (Alshehri et al., 2019a). Although higher education is investing heavily in e-learning system development, to stay competitive, educational officials have requested an assessment of the students' perceptions of e-learning systems and whether a system is effective and efficient in facilitating students' learning (Halawi & McCarthy, 2008). The content of the e-learning system alone will not define the quality of learning but the context is also important; how students experience the e-learning system (Garrison, 2011). Thus, the focus of students' acceptance and utilization of LMSs has come to prominence.

Decisions about the integration of LMSs into universities are frequently taken at the higher management level. Yet, it is the individual adoption patterns that illustrate successful implementation (Straub, 2009). Therefore, understanding why students decide to use or reject an e-learning system can create a more favourable environment for greater adoption, as well as helping to design strategies to promote acceptance (Alshehri et al., 2019a).

The focus of this research is primarily oriented towards Saudi Arabian society. Saudi social and cultural mores are fundamentally different from those of the West. E-learning systems and strategies have been implemented and are well-established in developed countries. However, the replication of Western theories and models in the Saudi environment is considered problematic without certain refinements (Baker et al., 2010). Furthermore, the influential factors for adopting and using e-learning systems might be different from those of the West, especially in terms of significance and intensity. Learners may adopt different attitudes towards e-learning systems, especially those with different cultural and computational experience (Tarhini et al., 2014b). Hofstede (1997) examined the cultural dimensions of 117,000 employees from 40 different countries. The analysis showed significant pattern differences between eastern and western cultures: western cultures were classified as being individualistic, masculine, with low power distance, and low uncertainty avoidance; while eastern cultures were categorized as being collectivistic, feminine, with high power distance, and high uncertainty avoidance. It is evident that different technology usage patterns differ among cultures and the application of western theories in the eastern context might not be fully effective (Straub et al., 1997).

In an online learning scenario, students and instructors are dependent on LMS functionalities, so understanding the relationship between learners and technology is crucial, especially in developing countries (Šumak et al., 2010). Several systematic reviews have been undertaken to understand the association between cultures and users' specific preferences for usability qualities. Callahan (2006) explored groups' preferences towards website visual design from different countries and found that Japanese and Malaysian participants prefer vertical layout, whereas Danish and Austrian users favour horizontal page design. Barber and Badre (1998) explored the link between usability and culture and attested that cultural differences can directly influence users' performance and perceptions of a given website design. Complementary to this, users from different cultures place different weight on usability parameters especially with efficiency and satisfaction elements (Wallace et al., 2013). Bhuasiri, Xaymoungkhoun, Zo, Rho, and Ciganek (2012) explored the critical success factors of e-learning systems in developing countries and found that different factors vary in weight among various groups of users from different emerging countries. It was reported that the factors of system and information qualities emerged to be the most significant parameters that influence the students' learning performance. Thus, it can be concluded that usability factors are perceived differently across cultures. As such, variation in the importance of usability metrics as well as a variation of the strength of relationships between variables is anticipated in the current study.

The issue might be exacerbated when implementing a learning technology without an adequate understanding of the target audience. Various e-learning systems have been deployed in educational settings; some create a pleasurable and informative experience; others inflict frustration and unfavourable interaction. An LMS supports or hinders active engagement, easy communication and formative feedback for all educational stakeholders (Rubin et al., 2010). If the e-learning system is difficult to use, the learners might: find themselves disoriented, skip vital content, be reluctant to engage in the module, or be unwilling to communicate with a module coordinator and other peers using the e-learning system (Koohang & Paliszkiewicz, 2016). Thus, it becomes imperative to examine the students' experience of an e-learning system, with much emphasis on the factors that influence the use of these applications. This is relevant to e-learning solutions in which further enhancements might be needed to suit individuals in unique settings such as the Saudi environment. An integral step in filling this knowledge gap is to conduct a quantitative evaluation of the e-learning system and identify the drivers for effective utilization of the software (Decman, 2015; Koohang & Paliszkiewicz, 2016).

Difficulties can arise when an attempt is made to implement learning technologies in an academic setting. Many forms of LMS have been developed and deployed in educational contexts. However, having access to an LMS does not necessarily mean that effective learning will occur (Chaw & Tang, 2018). Despite the apparent usefulness, the issue of effective use of an LMS is an intriguing one which could be usefully explored in further research (Chaw & Tang, 2018). This exploration would be of great benefit to many stakeholders such as module providers, LMS vendors, and learners, especially in developing countries. Salloum and Shaalan (2019) reported that developing countries have failed, fully or partially, to implement learning management systems effectively. A lack of utilization of these systems has been observed and the need to explore this challenge is evident (Ameen et al., 2019; Salloum & Shaalan, 2019).

Several studies have postulated that educational stakeholders appear to lack full understanding of e-learning skills, e-learning techniques and the best practices needed to apply in learning applications and module design (Seel, 2012). Many scholars hold the view that students play an indispensable role in determining the effectiveness, efficiency and adoption of an LMS. Therefore, the learners' behavioural intention to make use of the proposed system is fundamental to its adoption (Šumak et al., 2010). It has become important for academic institutions to assess students' intention towards, and actual usage of e-learning applications (Lwoga & Komba, 2015). Understanding of learners' cognitive processes in their adaptation to learning behaviour is becoming an important factor in improving educational inputs and outcomes. According to Davis (1993), behavioural intention is a significant element for evaluating the use of information systems. Thus, assessing students' acceptance would potentially predict individuals' actual use of these technologies. Taken together, these studies support the theory that it is wise to examine the relationship between students' experiences, perception, behavioural intention and usage of educational technologies to enhance the learning and teaching process.

1.3 Research Problem

Students might experience significant difficulties in learning if they are not prepared to use the information systems available to them (Davis, 1993). The integration of information systems into educational environments has triggered policymakers to explore best practices for teaching and learning using technology (Allen & Seaman, 2013). Educational institutions place great emphasis on technology-enhanced learning development and invest significantly in information technology infrastructure. However, in spite of this effort and investment, it seems that instructors and students do not fully benefit from the learning technology and often learning management systems remain underutilized (Binyamin et al., 2017; Dahlstrom et al., 2014; Salloum & Shaalan, 2019). E-learning systems have no value without students using them. Recent evidence shows that students and instructors are less satisfied with LMS functionalities, especially those intended to foster collaboration and engagement (Dahlstrom et al., 2014). Furthermore, concerns have been expressed as to whether the utilization of an LMS is as an effective learning system or merely as a container for document repositories (Badge et al., 2005). Still, reluctance to adopt LMSs among students, academics and executives is a common problem (Chaw & Tang, 2018; Dahlstrom et al., 2014). In Saudi universities, the majority of students are still unwilling to use e-learning systems (Alenezi et al., 2011). Furthermore, recent studies have examined the use of e-learning systems in a Saudi higher institution and found that more than half of university students only use an LMS either rarely or occasionally (Binyamin et al., 2017, 2016). Thus, academic institutions would benefit more from these technologies if they could examine the factors that encourage effective use of LMS in Saudi Arabia (Alenezi et al., 2011; Binyamin et al., 2017).

To overcome these challenges and enhance user acceptance, it is important to recognise the underlying reasons for people accepting or rejecting technology. Furthermore, the transition from traditional face-to-face instruction to online and distance education can be difficult for students and lecturers (Garrison & Kanuka, 2004). As a result, learning processes and outcomes might be affected. Given the continuous demand for LMSs in education, it is imperative to investigate the factors that may encourage the use of LMSs among learners (Chaw & Tang, 2018). It is important to periodically survey university students about the use of LMSs that has been made (Al-Fraihat et al., 2019). This should result in continuous improvement of these systems to address any concerns and shortcomings (Al-Fraihat et al., 2019).

There is a growing body of literature that recognizes the importance of conducting technology acceptance and usability research to explore the specific factors that may influence an end user's decision to accept an LMS (Buchanan et al., 2013; Islam, 2013; Liu et al., 2010). It has been reported that the success of an IS depends on the level of user acceptance (Khechine et al., 2016), in our case the student's acceptance. Much of the current literature on technology acceptance research pays particular attention to the psychological characteristics that could affect the implementation of an LMS. These include students' and lecturers' perceptions and beliefs about psychological qualities and organizational infrastructure. However, it has been established that there is a link between user acceptance and usability metrics, and success in utilizing technology (Scholtz et al., 2016; Thongsri et al., 2019). Such approaches, however, have failed to address the usability qualities which could be a factor in the success of online learning (Thongsri et al., 2019). Moreover, no consensus has emerged among researchers and practitioners about the antecedents and conditions affecting the students' LMS usage, especially in developing countries (Ameen et al., 2019; Moreno et al., 2017; Salloum & Shaalan, 2019; Thongsri et al., 2019).

Although many studies have attempted to examine students' intentions to use e-learning systems, few quantitative analyses have focused on the correlation between perceived usability attributes and technology acceptance factors, particularly in developing countries (Moreno et al., 2017). In the Saudi context, the technological factors appeared to significantly influence the e-learning system usefulness, functionality, interactivity and ease of use (Alenezi, 2012b). Al-Youssef (2015) stressed the importance of incorporating the Unified Theory of Acceptance and Use of Technology (UTAUT) model with usability attributes to investigate the acceptance and use of e-learning systems in the Saudi context. Therefore, an exploration of the factors that may influence the use of an e-learning system could act as a catalyst to enhance students' acceptance and utilization of e-learning tools in Saudi tertiary education (Alenezi, 2012b). The incorporation of usability attributes into the acceptance model is required to study the elements that drive the adoption of LMSs specifically in Saudi Arabian higher education (Bouznif, 2018).

This research attempts to bridge the gap between system acceptance and usability research by developing a unified framework that combines both concepts. Some Saudi universities have used blended learning and distance learning approaches as the teaching strategy for materials delivery. However, a critical analysis of the learners' experiences and perceptions of the used LMS has not been performed. Asarbakhsh and Sandars (2013) highlighted the importance of the learner's requirements for effective learning with technology. Many researchers and practitioners employ traditional usability criteria for e-learning system evaluation in which specific heuristics for e-learning system environments are overlooked (Zaharias & Koutsabasis, 2011). Nowadays, it is felt that usability should be evaluated in the specific fields of the application, such as the e-learning context (Zaharias & Koutsabasis, 2011).

This study investigates the learners' perceived usability criteria of the e-learning system and their impact on students' intentions to use and actual use. This research is focused on an e-learning system (Blackboard) which uses a web-based learning technology and is accessible through an Internet connection and a web browser. Most Saudi state universities have shifted to the use of the Blackboard system. Nonetheless, this migration has resulted in some resistance among students to using the system (Bouznif, 2018). Overall, the adoption of LMSs is not only limited to academic institutions and schools. Enterprises and governmental bodies have implemented such platforms for employees' training and personal development (Oztekin et al., 2010). The scope of this research is oriented towards Saudi universities to improve the quality of the learning and teaching process. It is important to note that in this research, a module represents an academic unit of teaching that focuses on a particular topic and often has its own examination.

This area of research is still in its infancy in developing countries such as Saudi Arabia (Bhuasiri et al., 2012). The evidence presented thus far supports the idea that, as yet, Saudi education is still influenced by traditional pedagogy and the new proposed innovations such as LMSs lack acceptance and utilization (Alshammari et al., 2016). Prior studies have shown that there is a dearth of academic research on Saudi higher education to examine the effects of usability factors on students' use of LMSs, so significant issues have not yet been examined (Al-Asmari & Khan, 2014; Al-Gahtani et al., 2007; Al-Harbi, 2011b; Al-Qahtani & Higgins, 2013; Al-Shehri, 2010; Alhareth, 2014; Alshammari et al., 2016; Binyamin et al., 2019a; Salloum & Shaalan, 2019; Yamani, 2014). The present research aims to fill the gap by determining empirically the effects of usability, social and organisational factors on the use of LMS in Saudi universities from students' standpoints through the development of a new model that combines usability factors with UTAUT constructs. In particular, developing countries such as Saudi Arabia still lack this kind of research. The next section discusses the motivations driving the research.

1.4 Study Motivation

The main driver of the research is the current education and e-learning status in Saudi Arabia. Due to the significant increase in the Saudi population, many potential students miss out on a place at university (Aldiab et al., 2017). To add to this, the solutions created by e-learning enable those in full-time employment to pursue a university qualification to fulfil their career aspirations. Thus, the Ministry of Education has demanded that all public and private higher education institutions establish a Deanship of e-Learning and Distance Learning in order to meet the current demand (Aldiab et al., 2017). To this end, the establishment of the National Center for e-Learning and Distance Learning (NCeDL) assists in compliance with the high e-learning standards and quality requirements, providing guidance for these new deans (NCeDL, 2017). Furthermore, Vision 2030 has focused on national plans to provide e-learning resources in higher education (*KSA Vision 2030*, 2016). Based on evident support for e-learning, the Ministry of Education has begun to introduce LMSs in all public universities (Aldiab et al., 2017). The government has made considerable investment in LMS implementation infrastructure, learning centres, training, licencing, operation and maintenance. This study thus attempts to shed light on the factors that affect the students' use of LMS in Saudi Arabia. The findings of the study findings may assist with authorities' decision-making process on the effective use of LMS in Saudi universities. This is the primary motivation for undertaking this research.

The study was also motivated by the inauguration of Saudi Vision 2030, in April 2016 (KSA Vision 2030, 2016). This initiative was based on three essential pillars: being the heart of the Middle East, becoming a global investment powerhouse, and being a hub that links the continents of Asia, Europe and Africa (KSA Vision 2030, 2016). The vision is built around three themes, a vibrant society, a thriving economy, and an ambitious nation (KSA Vision 2030, 2016). A primary objective of the plan is to diversify the economy including income sources and reduce oil-dependency by developing non-oil exports, making the private sector the engine for growth. One of the principle calls is to link education with economic growth. In the light of the need to focus on education, the vision concentrated on four essential areas: equality of access to education, curriculum development, higher education advancement and producing graduates with critical skills aligned with the labour market. The demand and focus is on providing a quality of education that ensures that students are equipped with the required skills and knowledge to compete in the globalised society, while preserving the values underpinning Saudi culture (Allmnakrah & Evers, 2019). To this end, Saudi Arabia requires an educated citizenry – students who possess the necessary skills to progress toward a knowledge-based economy (Allmnakrah & Evers, 2019). To put that into practice, the educational system comprising policy, goals, curricula and systems has to be reformed (Allmnakrah & Evers, 2019). The education sector is considered a vital sector that has a close connection with society for developing the national economy. The transition to a more digitised education (e.g. e-learning) has been stressed in the current plan, particularly in rural areas where e-learning infrastructure is evolving. The assessment of e-learning services might assist in improving blended and distance learning modalities, thus supporting the accomplishment of the initiative objectives. Hence, the identification of the driving factors that influence the use of an LMS in Saudi tertiary education can be seen as a means by which the goal of improving distance learning is to be fostered.

The current shortage of female lecturers in gender-segregated colleges has motivated the Saudi government to incorporate e-learning systems into teaching and learning at universities. In fact, face-to-face classes are very large, especially in the newly-established universities. This places extra pressure on the government to propose e-learning technologies in universities to compensate for this inadequacy. This is evident in the cases where a small campus serves more than its normal capacity because, for example, students need to travel long distances every day to reach universities. E-learning programs will make it possible for students to enjoy the delivery of materials and knowledge that has not been possible without an e-learning system. Not only this, but the problem is exacerbated by the scarcity of academics, both in terms of quality and quantity (Al-Asmari & Khan, 2014). The e-learning system ensures the delivery of services for both male and female students irrespective of time and geographic boundaries (Yamani, 2014). The Saudi Ministry of Education strives to make high-quality education available to all students especially those for whom distance education may be an alternative (Al-youssef, 2015).

There is a dearth of theory-driven research that investigates the determinants of system characteristics on the students' use of e-learning systems (Pituch & Lee, 2006). System characteristics are known to influence the use of an e-learning system (Chaw & Tang, 2018; Cho et al., 2009; Pituch & Lee, 2006; Thongsri et al., 2019). This is consistent with Dringus and Cohen's (2005) conclusion that usability attributes such as navigability, usefulness, utility, ease of learning, ease of use, must be evaluated to ensure the effectiveness and efficiency of the e-learning solutions. In fact, specific system usability features such as navigation, interface design and interactivity were found to lack detailed investigation, especially regarding their effect on system ease of use and usefulness (Jeong, 2011; Thong et al., 2004). This deficiency might be attributed to the idiosyncrasies of different system interfaces and the challenge of acquiring common characteristics that can be applied to many systems (Thong et al., 2004).

A survey of prior literature reveals that usability and acceptance of e-learning along with moderators have not been addressed in existing studies of e-learning in Saudi Arabia. Dwivedi et al. (2011) in their meta-analysis confirmed that the studies utilising the UTAUT model generally ignore the moderating effects. In particular, organizational, technological and social barriers have been recognized as the main inhibitors in the utilization and adoption of e-learning systems in Saudi universities (Asiri et al., 2012). The study also examined the effects of four moderators (gender, age, system experience and training) on the model relationships. The effect of a moderating variable is characterized statistically as an interaction. The moderating variable affects the direction and/or strength of the relation between input and outcome variables (Hair et al., 2014). For instance, the moderators of gender, e-learning system use experience, and also training, have been critical in the use of the system in Saudi (Asiri et al., 2012). It has been established that moderating factors have profound effects on user technology acceptance (Sun & Zhang, 2006). In particular, users' individual differences, such as age, experience, training, can have an influence on the users beliefs in using the system (Burton-Jones & Hubona, 2006). It is evident that earlier research lacks the examination of moderating effects in the use of LMS, so the present research explores, for the first time, the effects of four moderating effects: age, gender, experience and training in the use of LMS in Saudi tertiary education, and this prior lack of examination can be seen as motivation to conduct this study.

Different theories exist in the wider literature regarding users' acceptance and usability, yet the culture of usability and acceptance in the e-learning field is deficient and most of the academic literature is only at an initial stage or in need of further empirical investigations (Granić & Ćukušić, 2011; Nakamura et al., 2017). Up until now, from the review of the literature (Chapter 3), there has been little exploration of the extent, nature and significance of the relationship between usability variables and intention and use behaviour in the e-learning context, especially in Saudi higher education. There seem to be a lack of focus regarding an integrative framework that combines usability variables, instructional design parameters and the acceptance and use of technology. The predictors of behavioural changes can be examined through individual, cognitive and contextual constructs. Personal factors, characteristics of the system, and the context will all shape the ultimate decision to persist with a technology (Straub, 2009). Yet existing models deal independently with these factors, and no previous theory accounts for all three concerns.

1.5 Research Questions

This research will seek to address the following questions.

1. To what extent do psychological, social and organisational variables influence a student's acceptance and use of learning management systems in Saudi state universities?
2. To what extent do usability attributes influence the students' acceptance and use of learning management systems in Saudi state universities?
3. To what extent do the demographic variables of gender, age, experience and training moderate the relationships of the model?

These questions will guide how the research will be conducted. This research is important since there is a general move towards digital technologies, and Saudi should not be left behind. The research will seek to find out the factors that affect the implementation and adoption of the main LMS, the Blackboard system, in Saudi Arabia, from the students' perspective. The results will be essential in coming up with concrete recommendations on how to improve the use of the system.

1.6 Research Aim and Objectives

The primary **aim** of this research is:

To identify the significant usability, social and organisational factors, along the demographics characteristics, that influence students' use of learning management systems in Saudi state universities.

To realize this aim, this research develops an integrated conceptual framework that amalgamates the technology acceptance model variables and usability principles to predict students' use of an e-learning system in a Saudi Arabian environment. The effects of age, gender, experience and training moderators have been examined on the model relationships.

The main focus is to explore how usability factors along with social components and university facilitating conditions influence the students' acceptance of an e-learning system in a Saudi Arabian context. In considering the gender segregation in Saudi higher education, the research will compare the perceptions of male and female students of the usability variables that impact their use of an e-learning system. The study adopts UTAUT as a well-understood baseline theoretical model and extends it to include usability requirements and then tests its application in a Saudi context. The reasons for the choice of UTAUT were due to its comprehensiveness of different components (social and organisational support) and its powerful predictive power (Venkatesh et al., 2003) compared with other technology acceptance theories.

The integrated model provided evidence of the association between usability metrics and the students' behavioural intention and their actual use of e-learning applications. The findings contribute to a deeper understanding of a learner's behavioural intention to use e-learning services and evaluate the actual use of LMSs in developing countries such as Saudi Arabia. This improved model will help us to understand the factors that influence students' use of the LMS deployed in Saudi universities.

The following **objectives** will assist in meeting the overall aim and address the aforementioned research questions:

1- To review the literature related to Saudi e-learning, technology acceptance models and the usability evaluation of e-learning systems;

2- To understand and explore the usability of e-learning systems and their influence on students' intention to use and actual use;

3- To identify the most relevant usability design attributes of e-learning systems in the Saudi environment;

4- To develop an integrated theoretical framework that combines UTAUT and usability variables;

5- To examine and validate empirically the proposed theoretical model and research hypotheses in Saudi universities;

6- To examine the effect of moderators (gender, age, experience and training) on the key determinants of the model;

7- To examine and evaluate the viability of the UTAUT model and accumulate further evidence about the validity, reliability and the relationship between the model variables for the assessment of user acceptance of an LMS in a non-Western context (Saudi Arabia);

8- To examine and evaluate the viability of the usability metrics and explore their effects on the students' use of an LMS in non-Western context (e.g., Saudi Arabia).

This chapter (see section 1.3) shows that there is a gap in the research regarding technology acceptance and usability studies in a Saudi Arabian environment. The ultimate goal of this research is to extend prior studies by generating a theoretical framework that combines technology acceptance theories with usability attributes pertaining to learning management systems and test the proposed model in a Saudi Arabian environment. The UTAUT model's constructs will be applied to a different environment than was tested initially. The construct testing will, therefore, be against new collected data from Saudi universities' students. It will also attempt to determine the role of usability attributes in the usage of the LMS, so it is hoped to achieve a richer understanding of technology adoption and usage. Hence, and as Venkatesh et al. (2003) stated, it is important to revalidate and extend the proposed research to further contexts. Venkatesh et al. (2003) also asserted that the future direction of research should focus on identifying factors that clarify the link between intention and behaviour. Thus, the extension of UTAUT theory will include usability variables which enable us to understand the suitability of the proposed model in a Saudi environment. Due to the large sample of students from different universities in Saudi Arabia in different provinces, the generalizability of the findings can be extended to the total population. Also, the generalizability could be expanded to similar regions of the Arab world such as Gulf countries that share similar characteristics to Saudi Arabia.

1.7 Research Scope

The scope of research is a fundamental aspect of a research process. It involves a consideration of the main aim and objectives of the study as well as the resources and time available that determine the depth and breadth of the study. This study essentially extends the UTAUT theory by adding usability attributes to find factors that influence an individual's behaviour towards the adoption of an LMS in Saudi higher education. Thus, the scope of research is as follows.

- The Blackboard system will be the subject of the investigation, as 90% of Saudi Arabian higher public universities have adopted it (Aldiab & Kootsookos, 2017). Nevertheless, the results could be extended to other learning environments such as Moodle, Desire2Learn and Jusur, that share similar functionalities.
- This research will essentially be based within a Saudi Arabian geographical context. More specifically, only university students of Saudi Arabia will be considered in this research. However, the generalizability could possibly be extended to other areas that have similar characteristics to the Saudi culture, such as Gulf countries.

- The target population sample for the study will be university students who use the LMS and the final conceptual framework will be tested and analysed against students' usage of the Blackboard LMS.

1.8 Research Context

This section provides a brief profile of the Kingdom of Saudi Arabia. Dedicating a section to the context of the study is essential because it assists in understanding the environment where the LMS is implemented. The section begins with a description of key aspects of Saudi Arabia such as location, population, economy and culture. This is followed by a discussion of the availability of ICT infrastructure, focusing on the urban and rural deployment of ICT. The section has also a discussion of governmental support demonstrated by the establishment of NCeDL. Furthermore, since the gender split has a significant effect in Saudi Arabia, the impact of gender-segregated colleges on education is assessed. The section ends with a brief overview of Saudi Arabian support for e-learning in the higher education sector.

1.8.1 Kingdom of Saudi Arabia: Location, Population, Economy

There are various factors and characteristics that make Saudi Arabia a distinct country. Saudi Arabia is located in Western Asia and, geographically, is the second-largest country in the Arab world with approximately 865,000 square miles of land area (General Authority of Statistics, 2018). Administratively, the kingdoms' five regions are subdivided into thirteen provinces (General Authority of Statistics, 2018) (refer to Figure 1.1). The Saudi economy is the largest in the Middle East and the 18th largest in the global economy (Abir, 2019). It is the world's largest oil exporter, categorising it as a high-income economy (Abir, 2019). Saudi population growth must be addressed to understand the potential of online learning in higher education. The latest statistics disclosed that the population growth rate is high and reached more than 33.4 million (General Authority of Statistics, 2018), expanding from just 23.98 million in 2007 to 34.14 million in 2019, the population boom is evident (Abir, 2019). The Saudi population is growing considerably and almost two-thirds of the total population live in three major provinces, Riyadh, Makkah, and Eastern Province (General Authority of Statistics, 2018). It is important to mention that young people constitute the overwhelming majority of the Saudi population. In fact, a recent statistical analysis shows that the Saudi population under 20 grew by 52.88% over the last ten years (General Authority of Statistics, 2018). A surge in the number of Saudi students has been observed in the latest statistics. Universities face difficulties accommodating this growth. In fact, the need to leverage the scalability of online learning in Saudi higher education is inevitable. There is a need to expand access to educational services and training in Saudi academic institutions (KSA Vision 2030, 2016). To alleviate the capacity constraint, there is thus greater demand for educational authorities to initiate viable alternatives such as online education. This also has to be linked to the challenge of advancing internet-based instructional delivery. Furthermore, this involves transforming physical content into Web-based educational materials to meet the fast-growing global demand for online learning. In all cases, the promise is that e-learning will enable the distribution of online materials and activities to other remote areas that lack colleges and universities. It will also offer the opportunity of lifelong learning to all regions (Aldiab et al., 2017). There is also a proposed plan to invigorate the Saudi educational system infrastructure to launch and develop open digital modules at all educational levels (Ministry of Education Saudi Arabia, 2017).

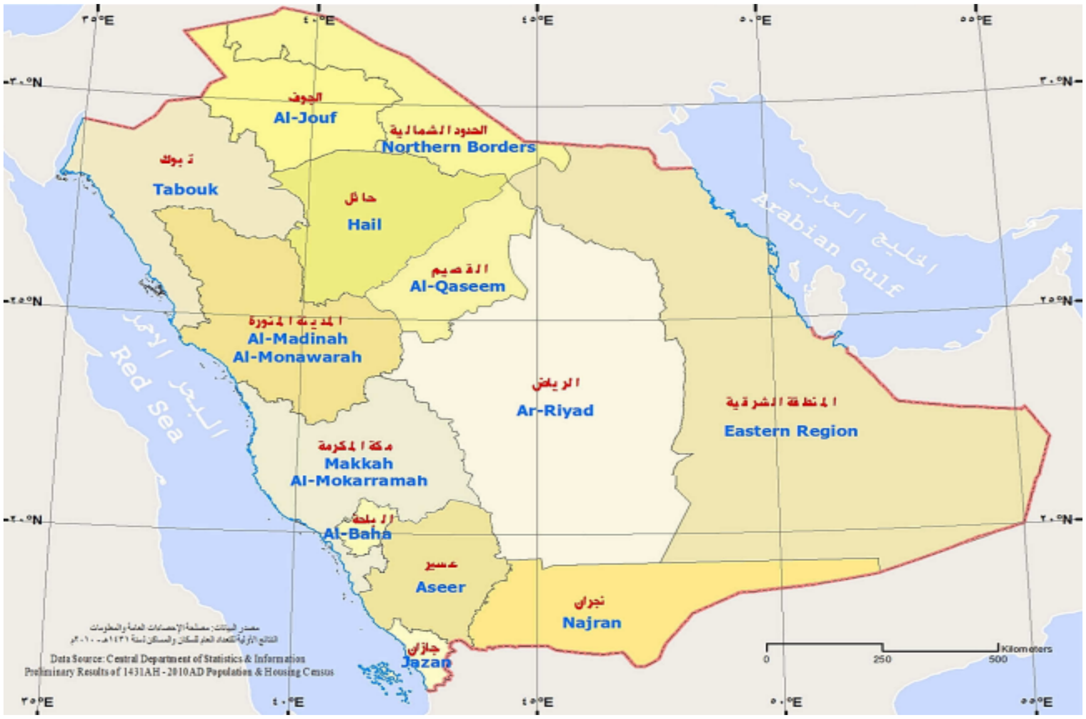

Figure 1.1 Map of Saudi Arabia
(General Authority of Statistics, 2018)

1.8.2 Information and Communication Technology Infrastructure

Another significant factor is the available ICT infrastructure in Saudi Arabia. According to the Saudi Communications and Information Technology Commission report, the number of Internet users has increased from 7.7 million in 2008 to 21.6 million in 2015 with more than 53 million online mobile services subscribers (CITC, 2015). Among the general population, Mobile Internet usage was 80% and more importantly 91% among the group aged between 20-29 years old (CITC, 2015). A recent survey of 3000 participants has revealed that 91% of Saudis use the Internet for various reasons including, website browsing (87%), social networking (67%), communication (55%), and looking for information (54%) (CITC, 2015). A recent report has shown that the use of the Internet for learning and educational purposes came at 45%, either using portable devices or at home (CITC, 2015). 77% of participants used a laptop, desktop or tablet device for accessing the Internet and 55% of the younger population (aged between 20 and 29) accessed the network from an educational institution, and 83% from the same group access it from home (CITC, 2015). A further study has revealed that although the use of technology is high among Saudi undergraduate students, it seems that the increase in use is not harnessed to educational and learning purposes (Alothman et al., 2017).

1.8.3 National Centre for E-learning and Distance Learning

The Saudi Arabian government has launched a comprehensive initiative for the use of information technology. The initiative is supported by the National Center for e-learning and Distance Learning (NCeDL), established by the Ministry of Higher Education in 2005 (NCeDL, 2017). It emphasizes the employment of e-learning and distance learning systems in Saudi academic institutions that comply with the e-learning high standards and quality requirements (NCeDL, 2017). The Saudi government has taken significant steps in developing initiatives not only to fund research in e-learning and distance learning but also to establish projects that enhance and improve the existing e-learning provision (Al-Khalifa, 2010; Alhabeeb & Rowley, 2018; NCeDL, 2017). These initiatives make it compulsory for Saudi universities to appoint a dedicated dean for e-learning and distance learning. The responsibilities of the deanship include the transformation of conventional curricula and programs into online resources to be delivered via distance learning or blended learning modes of study. This requirement also ensures adequate IT and e-learning infrastructure for the delivery of state-of-the-art online programs. In fact, the universities responded positively to NCeDL initiatives and many are proactively using e-learning services in the educational processes. In fact, some have even started offering entire degree programs using distance learning modality (Alhabeeb & Rowley, 2018). However, despite the massive financial resources and support given to Saudi Arabian higher education, the underutilization of computing and technological capacity in learning is still evident (Baker et al., 2010). Therefore, and in order to address this gap, the research explores the factors that affect the use of e-learning in Saudi higher education.

1.8.4 Higher Education in Saudi Arabia

In Saudi Arabia, the number of students in higher education has grown almost exponentially in the last ten years; from 850,000 in 2009 and 636,000 in 2006 to 1.7 million students 2017 (General Authority of Statistics, 2018). In fact, the Saudi Arabian government has spent between a quarter and a third of its annual budget on higher education over the last ten years. Specifically, over the last nine years, there has been a substantial increase in educational budget from US $23.41 billion in 2008 to US $57.3 billion in 2016 (General Authority of Statistics, 2018). The Saudi Arabian government is deemed to be the major sponsor for the development of the higher education e-learning scheme. The government has also invested considerably in information and communication technology infrastructure specifically for higher education. This expansion has created not only incentives for universities to develop module delivery programs that meet such a rise but also urged them to assess and improve the e-learning systems in which those programs are implemented.

However, although this initiative towards e-learning is continually moving forward, the students' acceptance of an e-learning system now needs to be considered. It is believed that transition has put extra pressure on educational stakeholders to optimise LMSs at universities from the students' standpoint. Therefore, it has become imperative for universities to assess the e-learning system's effectiveness from the students' standpoint. The effectiveness is closely related to the quality of the learning experience. That is, the students' perceptions of and interaction with the e-learning systems. Some researchers argue that some important factors have to be considered in order to offer a quality experience for learners including usability elements, support and social influence (Lin et al., 2013; Sandars, 2010). Therefore, the incorporation of technology acceptance model variables and usability metrics in a Saudi context is expected to reveal the drivers of e-learning system adoption. As a result, further improvements to the current e-learning system will be proposed in which system acceptance and spread would be promoted. The relevant literature will be reviewed to identify the main variables influencing the use of an LMS from the students' perspective with a particular focus on the Saudi Arabian context.

1.9 Thesis Structure

This thesis is composed of eight themed chapters as follows:

Chapter 1 Introduction: The first chapter introduces the current PhD thesis. This part of the document presents the background to the research. This is followed by the research problem, the research motivation and the research aim and objectives. The next element of this chapter deals with research questions, outlining the research scope and boundaries. The section also offers insights into the context of this study: the Kingdom of Saudi Arabia. The rationale underlying this section is to understand the current status and necessity of e-learning in Saudi higher education. It presents information about Saudi Arabian education, e-learning, and the national centre for e-learning and distance learning.

Chapter 2 Research Background: The aim of this chapter is to is to provide an overview of the published literature on the three areas that underpin this study; e-learning, technology acceptance theories and usability. The chapter is intended to articulate what others have examined in the topic, critiquing scholarly undertaken studies and building a bridge between different theories and concepts to build on in this research. So it begins by introducing e-learning – providing an overview of e-learning, its definitions, characteristics, advantages and disadvantages. It then goes on to define learning management systems and the system under investigation (i.e., Blackboard). Also, the chapter presents a literature review of the most relevant technology acceptance models, focusing primarily on UTAUT and its empirical research. The last section introduces the term "usability". It emphasises the need for the usability evaluation of e-learning systems and then presents the different types of usability evaluation methods.

Chapter 3 Theoretical Framework: This chapter begins by laying out the theoretical dimensions of the research and looks at the usability attributes and UTAUT variables together with the hypotheses. In total, the theoretical model postulates ten factors that are hypothesized to influence behavioural intention and use of e-learning systems in Saudi. The input parameters are those which (probably) influence outcomes. The chapter also provides the theoretical foundation for the moderating effects.

Chapter 4 Research Design and Methodology: As the goal of this research is to examine and validate the conceptual framework, data were collected from Saudi higher education institutions. This chapter explains in detail the research design, paradigm, population, sampling size and technique, instrumentation as well as the justification for using a questionnaire-based method for data collection.

Chapter 5 Data Analysis: Since empirical data were collected, this chapter begins with presenting the issues concerned with the preliminary data analysis including data screening, missing data, outliers, and normality for UTAUT and usability variables. The chapter also reports the descriptive statistics of the main study, including frequencies and percentages related to respondents' profiles as well as the Blackboard experience, frequency of use and the training received.

Chapter 6 Model Analysis: This section describes the analysis of the data. The SEM technique connects multi-item scales to constructs and estimates the relationship between the constructs, resulting in two models: a reflective measurement model and a structural model. Thus, the analysis was conducted in two phases. In phase one, and as with reflective measurement models, the estimations of internal consistency, convergent validity and discriminant validity are established to prove the validity and reliability of the constructs and the measurement items. The second phase involves structural model analysis and hypothesis-testing using SEM techniques. A PLS-SEM examination of the structural model is then presented.

Chapter 7 Discussion: This chapter describes and interprets the significance of the posed hypotheses and explains insights emerging from the analysis. The effect of UTAUT and usability variables on the student's intention and use of the e-learning system is discussed. To begin with, the results of the analysis of the UTAUT model relationships, predictors and outcomes, are discussed which aims to answer the question of how psychological, social and organisational factors influence a student's intention to use the e-learning system in Saudi higher education. The next section presents a discussion of the findings of the usability effects on a student's intention to use the LMS in Saudi higher education. This is followed by the effect of demographic characteristics on the model relationships, which explains how the moderators (age, gender, experience and training) influence the model relationships. The last section provides a comprehensive summary of the research findings.

Chapter 8 Conclusion: This chapter deals with the overall conclusion of the research, reiterating the research overview and key findings, research questions and the methods used to address them. This is followed by the research results' implications and recommendations that are important for different stakeholders (e.g., educational decision-makers). The chapter also presents the contribution to the body of knowledge from three different perspectives: theoretical, practical and methodological. It ends up with a discussion of the study's limitations along with suggestions for the directions of future research.

1.10 Summary

This chapter presented the background of the study, the rationale, the research problem, aim and objectives, questions and scope. A glimpse of the context of the study was provided, focusing on the key aspects of the Saudi economy, population and culture. Furthermore, the Saudi national e-learning initiative was discussed, focusing on its role in the Saudi educational environment. The next chapter will explore the e-learning, technology acceptance theories and usability. In particular, it will review the UTAUT model and it will also provide a brief overview of recent research and published works on the acceptance of diverse e-learning technologies both in Saudi Arabia and globally.

CHAPTER 2: RESEARCH BACKGROUND

2.1 Introduction

This literature review determines whether the proposed topic is worth investigating by capturing and summarizing the studies about it. It also helps to outline the research scope and boundary and explain the research problem by discussing the ongoing dialogue in the literature. This chapter is intended to articulate what others have examined in the topic, critiquing scholarly undertaken studies and building a bridge between different theories and concepts to build on in this research. In this research, the purpose is to discover the central issues in the topic and from that build a novel theoretical framework. Considerable weight is given to a quantitative approach rather than qualitative as most of the studies in technology acceptance have used deductive reasoning which is a fundamental element in the quantitative approach (Straub et al., 2004; Straub, 2009).

The aim of this chapter is to provide an overview of the published literature on the three areas that underpin this study; e-learning, usability, and technology acceptance theories and models. The chapter begins by introducing e-learning, its definitions, types and characteristics. It will then go on to define learning management systems, their benefits, and drawbacks as well as the system under investigation (i.e., Blackboard). The Blackboard system used in Saudi Arabia higher education is presented, stressing its significant features in education and highlighting its importance to the learning success. Then, the chapter presents a literature review of the most relevant technology acceptance models, focusing primarily on UTAUT theory and its empirical research. It also contains a brief overview of recent research and published works into the acceptance of diverse e-learning technologies; in particular, LMSs. The chapter ends with usability, focusing on its definition, methods, as well as the importance of usability in an LMS. The aim of the study is to explore the acceptance and use of the new LMS in Saudi tertiary education.

2.2 E-learning Definition

E-learning has emerged as a new paradigm in education to meet the rapid revolutions in information and communication technology. In fact, the influence of technological advancements on higher education is still ongoing, and it needs to be explored further to reveal new approaches for pushing educational capabilities to new levels for more effective collaborative and productive learning environment (Al-youssef, 2015; Chaw & Tang, 2018).

The effect of digital technologies on learning and teaching is evident, especially since the mid-1990s when the term e-learning was established (Lee et al., 2009). The concept of e-learning has also been discussed extensively in prior studies, whereby learning is facilitated by electronic media, utilizing various technologies for the delivery of educational and learning materials (Moore et al., 2011). However, the term e-learning (electronic learning) was first coined by Cross in 1998 (Cross, 2004). While the literature has disclosed extensive e-learning definitions, there is still no consensus about the definition of the term (Abaidoo & Arkorful, 2015; Al-Harbi, 2011a; Dublin, 2003; Haythornthwaite & Andrews, 2011; Lee et al., 2009; Moore et al., 2011). However, some researchers have attempted a number of different definitions, based on the domain and the interest of the scientists (Abaidoo & Arkorful, 2015). In its broadest sense, e-learning is defined as the use of ICT to enable access to online learning and teaching materials (Abaidoo & Arkorful, 2015). In the view of Lee et al. (2009), e-learning is defined as web-based learning which utilizes web-based communication, collaboration, multimedia, knowledge transfer, and training to support learners' active learning without the time and space barriers. A similar description was presented by Sun et al. (2008) in which e-learning is a web-based system that makes information or knowledge available to learners irrespective of time and geographic proximity. According to Clark and Mayer (2016) e-learning is defined as instruction delivered through any form of electronic media, whether they be computers, applications, smart phone or any objects to support learning. The term covers diverse features related to education, including 1) storing content in a medium relevant to learning goals, 2) using a wide range of media to deliver the content, 3) utilising instructional and educational methods to enhance the learning process, 4) synchronous or asynchronous e-learning based on individual and institutional goals, 5) providing assistance for learners to build new knowledge and skills suited for their goals to improve educational performance (Clark & Mayer, 2016). The term e-learning has been variously viewed as synonymous with online learning, distance learning, blended learning, distributed learning, Internet-based training, and web-based learning (Khan, 2005). Drawn from these expressions, it can be concluded that the e-learning definition varies greatly based on the purpose, form, and technology involved.

While there has been some recent uncertainty about terminology, the delivery of learning materials increasingly relies on web-based information systems. An LMS is a variant of an e-learning system which specifically focuses on the management and delivery of educational modules. The LMS helps both students and instructors to acquire knowledge and develop essential skills through synchronous and asynchronous learning applications, irrespective of time and geographic boundaries (Allen & Seaman, 2013; Moore et al., 2011).

2.2.1 Forms of E-learning

E-learning can include synchronous or asynchronous forms of interaction (Clark & Mayer, 2016). Synchronous communication involves learning in real-time between students and instructors (Johnson, 2006). This approach allows students and lectures to communicate instantly through live messaging and video conferencing or similar means using the Internet (Abaidoo & Arkorful, 2015). The online modules and training materials are available in the e-learning software so students can easily interact with their fellows and teachers in a more interactive manner during the module (Hrastinski, 2008). Immediate feedback features a synchronous communication strategy, in which the bond is heightened between instructor and students (Abaidoo & Arkorful, 2015). Another key advantage of synchronous communication is that of increased social presence especially in a simultaneous chat facility (Johnson, 2006). Research has found that a synchronous approach helps to understand the students' learning attitudes and also increases learners' satisfaction, especially in distance education (Cao et al., 2009; Hwang & Yang, 2008). However, it can be inconvenient for some participants, and the time for discussion can be limited.

Asynchronous e-learning, on the other hand, enables students to work and study at the same time, download materials and send messages to instructors and peers at different times (Abaidoo & Arkorful, 2015; Johnson, 2006). It also helps participants to post more thoughtful and planned responses and contributions in their communication with other participants in the online module. Moreover, participants appreciate the enthusiasm of the collaborative learning (Hrastinski, 2008). Learning skills such as critical thinking and independent education are enhanced in this mode of the study. The asynchronous mode enables participants to interact with each other in online and offline channels at different times, so it does not depend on the simultaneous access of educational outcomes (Johnson, 2006). This mode is typically facilitated by media such as emails and discussion board. It also offers flexibility for learners to complete the module at their own pace and convenience (Abaidoo & Arkorful, 2015; Hrastinski, 2008). In this form of communication, not only is the level of peer interaction enhanced, but also the time-on-task reflection and the opportunity to participate in the discussion is heightened (Johnson, 2006). However, the time between posts can drag out the discussion. Furthermore, the lack of interactivity and the instructor-student connection are considered to be major drawbacks, due to the sense of physical separation (Huang & Hsiao, 2012). Also the absence of instant feedback from lecturers can be considered another disadvantage of this form of interaction. Overall, despite the ongoing debate about the effectiveness of each e-learning technique, organisations and academic institutions should address the benefits and limitations, respecting their requirements and strategic priorities (Hrastinski, 2008).

From a different angle, there are also two main forms of instruction in e-learning. The first is blended learning where computers are employed to aid in the delivery of pedagogical resources (Garrison & Kanuka, 2004). This format enhances the traditional teaching and learning process by providing a supplemental online environment for lesson delivery and interactions (Abaidoo & Arkorful, 2015; Sharpe et al., 2006). The balance between online and face-to-face human interaction differs for every offered module. The aim is to find the appropriate amount of each type to reach a harmony based on the nature of the module and the instructional goals (Osguthorpe & Graham, 2003). Data from several studies suggest that students' learning outcomes and instructors' teaching practices have improved considerably when incorporating an LMS into a blended delivery (Garrison & Kanuka, 2004; Sharpe et al., 2006).

Another mode is that of distance learning, which uses innovative technologies to distribute module content and instruction to remote learners (Moore et al., 2011). The educational materials are delivered online at various times. A feature associated with distance learning is the maximum independence of the learners (Abaidoo & Arkorful, 2015). Some argue that the term online learning is a more recent expression to mean distance learning (Moore et al., 2011). Yet, what is common between the terminologies is the access to learning content, using technology (Moore et al., 2011).

2.2.2 Learning Management System (LMS)

Advances in technological innovation have revolutionised teaching delivery not only in educational sectors but also in corporate settings. Indeed, educational trends have been changing rapidly to adopt web-based learning, especially in educational settings. The shift from traditional face-to-face teaching to online education has created a demand for digital resources and educational innovations to be deployed in the educational sector. This has led to the development of LMSs as a delivery mechanism for educational content in universities and the corporate sector.

The key to understanding the distinction between an LMS and other computer education is to understand the nature of an LMS. The LMS term was introduced in the 1990s (Coates et al., 2005). Since then, these systems have matured and been adopted in many academic institutions (Coates et al., 2005; Dahlstrom et al., 2014). In the literature, a Learning Management System (LMS), also called Virtual Learning

Environment (VLE) or Course Management System (CMS), are used interchangeably to provide learning and content management. Even though there might be a slight difference between the terms (Hariri, 2013), they all refer to the technology that delivers e-learning. The way they are used distinguishes them (Pinner, 2011). Some authors have attempted to distinguish between the naming schemas. It seems that LMS is predominantly used in North America while VLE is widely used in Europe and Asia (Martindale & Dowdy, 2010). Pinner (2011) argued that while LMS and VLE are used interchangeably, there are some differences between two concepts. VLE is often characterised by constructivist approaches, and often aims to provide an online environment to collaborate and extend discussions while LMS aims to track learning materials (Pinner, 2011). Although there might be a confusion between Learning Management Systems and Course Management Systems, the systematic nature of LMS functionalities seems to represent a broader span and is not limited to instructional content delivery and administration (Watson & Watson, 2007). Similarly, CMSs support classroom settings, develop module materials, link students to modules, track students' performance, and offer a communication facility among students and between students and instructors (Kabassi et al., 2016; Watson & Watson, 2007). Conversely, an LMS is an infrastructure to register and administer students and modules, manage and deliver educational contents as well as identify and assess educational goals for online learning (Watson & Watson, 2007). In the same vein, Black et al. (2007) offer the distinction that an LMS emphasises learning management whereas a CMS focuses on module management. Generally, LMSs are scalable and focus on all aspects of the learning process and a CMS is viewed as a subcomponent of an LMS (Watson & Watson, 2007). This divergence, nonetheless, does not alter the fact that all these systems share common characteristics and features.

LMSs are software for the management, tracking, reporting and the delivery of e-learning materials (Solomon, 2013). The LMSs are designed specifically to provide a means of designing, managing and delivering an online learning environment (Coates et al., 2005). An LMS is software designed with the particular goal of assisting lecturers in meeting their learning objectives of delivering learning content to students (Machado & Tao, 2007). It is a framework that manages all aspects of the learning process (Watson & Watson, 2007). It embodies a multitude of services such the placement of module materials online, online communication and collaboration between students and students, students and instructors and instructors-and-instructors, also the monitoring of student participation and assessing students' performance (Watson & Watson, 2007). In fact, there is a plethora of LMSs in the market with many features and functionalities. Blackboard, Moodle, and Sakai are examples of LMS. It is recognised to be a challenge to evaluate an LMS due its complexities and intricate nature and it requires great competency, time and effort to perform this process.

There are many generic features that are associated with LMSs. In the literature, an LMS consists of three main elements: asynchronous and synchronous communication, content development and delivery, and assessment (Coates et al., 2005; Kabassi et al., 2016). Communication tools may involve a discussion board, announcements, e-mail and instant messaging, and forums (Kabassi et al., 2016). The communication is categorised as student-content, student-student, and student-instructor interaction. Discussion boards and instant messaging can occur synchronously as opposed to asynchronously, as with emails and announcements (Hariri, 2013). The utilization of different communication tools may enhance students' engagement, participation and contribution to the subject of the modules (Hariri, 2013). Meanwhile, the content development and delivery may involve learning resources, learning materials, files and links to internet resources (Kabassi et al., 2016). According to Ellis (2010) the development of content comprises authoring, maintaining and storing learning content. Online content delivery involves medium (classroom, online), methods (e.g., teacher-led and self-paced), the language of delivery and the target stakeholders (Ellis, 2010; Watson & Watson, 2007). Formative and summative assessment involves tools for evaluation such as tests, quizzes, assignment submission, exams, and grading (Kabassi et al., 2016). Formative assessment monitors student learning to provide ongoing feedback, whereas summative assessment evaluates student learning at the end of a module (Taras, 2005). Assessment is an essential part of an LMS, not only to provide students with feedback about their strengths and weaknesses but also to enable instructors to create strategies for students' learning difficulties (Hariri, 2013).

LMSs are growing at a compound annual rate of 24.7% from 2016, with a global LMS market projected to be USD 15.72 billion in 2021 (Chaw & Tang, 2018). Moreover, 95% of UK higher education establishments have adopted LMSs not only as a platform for content but also as a medium for communication (McGill & Klobas, 2009).

2.2.3 Types of Learning Management Systems

There remain questions about the selection, implementation and deployment of LMS among academic institutions for the management of e-learning processes (Ülker & Yılmaz, 2016). Typically, educational institutions considered the return on investment a key point when investing on LMS (Ülker & Yılmaz, 2016). The solution plays a significant role in the transition from the conventional classroom setting into blended or online learning. LMSs can be divided into two different groups; proprietary are those associated with financial cost, and Open Source Software (OSS) are those which are free of charge (Pankaja & Raj, 2013; Ülker & Yılmaz, 2016). Proprietary LMSs require a purchased license fee per user, deployment cost, technical support, maintenance, integration and modification, and re-distribution is not permitted (Pankaja & Raj, 2013). However, proprietary software provides assistance and support to users when difficulties are encountered (Ülker & Yılmaz, 2016), which is seen as the greatest gain of a licensed LMS. OSS on the other hand, has its source code available and it is free to acquire, change and distribute the software for any purpose (Ülker & Yılmaz, 2016). Given this flexibility, the platform can be tailored to the preferences of universities or enterprises (Ülker & Yılmaz, 2016). OSS comes at low cost, and the service relies on an online community network to provide support. Given this, the support requires some technical knowledge and skill to customise and even to understand the given feedback (Ülker & Yılmaz, 2016).

Regarding LMS deployment, the LMS can be deployed locally as self-hosted (on-premise) or a cloud-based LMS (Chaw & Tang, 2018). An on-premises LMS requires infrastructure locally, so software buyers must install the system, provide training, and update the server regularly. This can be expensive in terms of time and effort, and may require technical personnel for continuous support and maintenance. The cloud based LMS is hosted in the cloud as Software as a Service (SaaS), and users can download the software from a vendor or access the service online. They are more flexible for learners, and scalability is an option because it is operated by vendors. Also it leverages the anytime- and anywhere-accessible characteristics of the Web (Walker et al., 2016).

2.2.4 Advantages of Learning Management Systems

An important advantage of LMS is the focus on the learners needs (Abaidoo & Arkorful, 2015). The followings are some advantages of the adoption of LMS in teaching and learning environment, as outlined by Abaidoo and Arkorful (2015) and Ellis (2010).

- Administration tools: LMSs support users registration and profiles, teachers assignment, content management and students assessment.
- Storage capacity: LMSs are valuable tools for storing, archiving, and retrieving materials.
- Ease of access: LMSs enable individuals to access a huge amount of information.
- Enhancing interaction: LMSs encourage collaborative interaction between students and between instructors and students though different communication channels. This will potentially eliminate any barriers that can hinder the students' participation, such as fear of speaking.
- LMSs are cost-effective, in the sense that educational resources are delivered to a large audience worldwide.

- LMSs help compensate for the shortage not only of academics but also of demonstrators, facilitators and lab technicians.
- Self-pacing: LMSs allow students to study at their own pace and speed, and this might increase student satisfaction.
- Flexibility: LMSs enable students to select the place and time of delivery.

2.2.5 Disadvantages of Learning Management Systems

LMSs, in spite of their advantages, can carry with them various well-known challenges, especially those encountered by its users. Learners may face technical issues with the system. Furthermore, limited customisation options for learners, lack of integration and lack of skilled personnel are posited as limitations of LMS implementation in education (Almarashdeh, 2016; Chaw & Tang, 2018). The lack of usability in LMS has been noted as a major hindrance to effective use of an LMS (Althobaiti & Mayhew, 2016; Roca et al., 2006; Ssekakubo et al., 2011). The consequences of this inadequacy may result in high cost, time and effort and an increase in learners' frustration (Minović et al., 2008; Ssekakubo et al., 2011). In the literature, the drawbacks listed in various studies include the following.

- The adoption of an LMS requires robust technical support at extra cost.
- The adoption of an LMS requires training programmes for users.
- Security issues: Security is a priority in LMS data management, concerning learners' information and proprietary content, module content and copyright materials.
- Lack of personal interaction and engagement: this might lessen personal relationships and reduce the participation in a human sense.
- Being remote: this requires learners to have strong motivation and time management to minimise the effects of being isolated.
- Impact on the quality of learning: even though there are many collaborative features embedded in the LMS, it might be less effective than the traditional

method of learning with respect to clarification, interpretation and explanation.

- Communication skills effects: students may excel academically, however they may not possess the required skills to disseminate knowledge to others.
- Not all modules can effectively use an LMS. Some disciplines (e.g., medicine and engineering) require hands-on practical experience so an LMS might be limited in delivery.

2.2.6 Blackboard LMS

Educational institutions implement LMSs such as Blackboard to administer their curricula with various types of functionalities, such as announcements, discussion boards, online assessment, and document sharing. These features have provided educators and learners with a variety of e-learning services that enrich pedagogical practices (Walker et al., 2016; Watson & Watson, 2007). The Blackboard system is the main system deployed as a learning management system at the majority of Saudi Universities (Aljuhney & Murray, 2015). Blackboard Learn™ (previously called Blackboard Learning Management System) is a comprehensive Web-based platform, consisting of various features and modules for teaching and learning purposes. It also assists in content administration and sharing and evaluating students' learning outcomes (Bradford et al., 2007). This complex system offers significant services that facilitate the pedagogical process such as assessment functionalities, support of mobile learning and implementation of plagiarism-detection tools, all in compliance with Web 2.0 standards, offering universities a wide range of options and features (Bradford et al., 2007). The system has a scalable design that offers integration with university information systems such as student enrolment and authentication services.

Most Saudi universities are equipped with a Blackboard system as the main application for learning and teaching. A more recent statistic indicated that Blackboard is by far the most prevalent LMS in Saudi higher education used by 90% of the Kingdom's public universities (Aldiab et al., 2019). In fact, the report showed that Moodle is implemented in a single Saudi university (University of Tabuk). Although the

Blackboard system is implemented largely in universities, there are cases where Blackboard has been introduced into K-12 public schools in Saudi Arabia (Alahmari & Kyei-blankson, 2016).

The system empowers tutors with the tools they need to administer and track the progress of students' performance throughout the entire educational cycle. It can also be used to set up modules, prepare assignments, report grades and give feedback. The system offers students a means whereby they can access different online materials, communicate with their module coordinator and individually study theoretical and practical modules online regardless of time and geographical constraints. Also, learners can employ the system to track their progress, submit assignments and check their grade and evaluation. The main aim of this software is to supplement face-to-face modules with online resources. The modules can be delivered either entirely online, or partially so, with few face-to-face interactions. Many studies have been conducted to evaluate the use of LMS, but few have been focused in the Saudi Arabian context and more specifically in the use of Blackboard system (Bouznif, 2018).

Based upon the previous discussion, it can be concluded that Blackboard Learn seems to be a more appropriate choice, especially in the Saudi Arabian context. The selection of the Blackboard system as the target system to be evaluated may be attributed to its overwhelming popularity in Saudi tertiary education. It is important to mention that Blackboard is no longer restricted to long distance learning only, as it is now incorporated as supplemental to the traditional face-to-face classroom interaction (Bouznif, 2018). It is also accessible and convenient to find in the state universities. The next section introduces technology acceptance theories to identify an appropriate theoretical framework for the research.

.

2.3 Technology Acceptance Theories

This section presents and discusses several competing models and theories that have been developed to be tested in various settings and contexts. These models and theories examine the individual and the choices that are made to accept or reject a particular system (Straub, 2009). They also indicate that there are various important factors that affect the individuals' acceptance and use of information technologies in diverse countries and cultures (Xu & Du, 2018). The technology adoption theories generally share three similar categories of characteristics: individual, technology and context (Straub, 2009). Individual differences such as personality traits, prior experience and state affect a person's use of technology. Technology features include ease of use, usefulness and visual design of the user interface (Agarwal & Prasa, 1998). Contextual characteristics are concerned with the environment in which the adoption process takes place such as organisational support (Straub, 2009). These classifications study how technology is perceived, accepted and used by individuals.

Not only this, but some researchers have assessed whether a particular system is integrated into the proper environment (Straub, 2009). There has been a continuous effort to test and validate the models in many contexts, so researchers adapt their models with further refinement and modification to fit the new environment. A sequential presentation of the most distinguished theories and their constructs will be given. Even though each of these streams has a specific focus and features different elements, they share similar properties and make significant contributions to understanding user acceptance and usage in different fields of studies.

2.3.1 Theory of Reasoned Action (TRA)

The first model is the Theory of Reasoned Action (TRA). Developed by Martin Fishbein and Icek Ajzen in 1967, TRA is a model designed to study conscious intentional behaviour from a social psychology perspective (Fishbein & Ajzen, 1975). TRA is one of the most fundamental theories of human behaviour (Venkatesh et al., 2003). The model aims to understand the relationship between intention as a mediator between attitudes and human behaviour. It takes a user's attitude towards target behaviour and a subjective norm about a particular behaviour as the main inputs to determine behavioural intention (refer to Figure 2.2). This leads to the prediction of a person's choices (Fishbein & Ajzen, 1975). The main determinants of intention are underpinned by a set of beliefs. The attitude construct is associated with behavioural belief: the perceived likelihood that performing the behaviour will lead to either favourable or unfavourable outcomes. Subjective norms, on the other hand, are linked with normative belief: perceived social pressure from certain referents and the individual's motivation to comply with these referents. The model has been successfully demonstrated to predict individuals' decisions to engage in a particular behaviour in many fields of study (Davis et al., 1989).

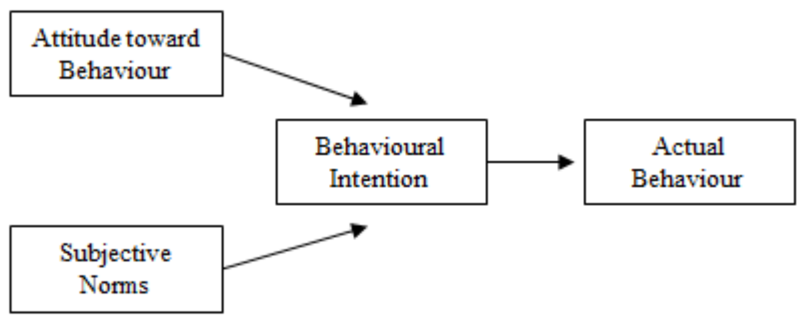

Figure 2.2 Theory of Reasoned Action
(Fishbein & Ajzen, 1975)

Nonetheless, and according to Davis (1989), the TRA theory appears to fail, especially in certain constraints, to predict individuals' behaviour, where target behaviour is completely under the individuals' volitional control (Sheppard et al., 1988). For instance, habitual actions and irrational decisions which are not consciously thought out cannot be explained by the TRA. So in order for the model to predict behaviour, the attitude and intention must agree on action, target, context, time and specificity (Sheppard et al., 1988). However, constraints such as limited ability, time and environmental factors could limit the freedom to perform the behaviour (Samaradiwakara & Gunawardena, 2014).

2.3.2 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour is based on the viewpoint of TRA, and expands the TRA with an additional construct of "perceived behaviour control" which connects beliefs and behaviour (Ajzen, 1991). Perceived behavioural control refers to the perceived ease or difficulty of performing a behaviour (Ajzen, 1991). The perceived behavioural control construct was proposed to compensate for the inadequacy of TRA that assumed that behaviour is under volitional control (Ajzen, 1991). The addition of the perceived behavioural control component, which considers the individuals with less control over behaviour, has also improved the predictive power of the model (Ajzen, 1991). More specifically, perceived behavioural control was placed among a general framework of belief, attitude, intention and behaviour. The attitudes toward behaviour, subjective norm and perceived behavioural control, were hypothesised as predictors of intention. This in turn predicts behaviour. The goal is to increase the chance of a person performing a specific action and actually doing it (Samaradiwakara & Gunawardena, 2014). Figure 2.3 depicts a the TPB. The model has also been successfully applied to examine goal-directed human behaviour (Taylor & Todd, 1995a).

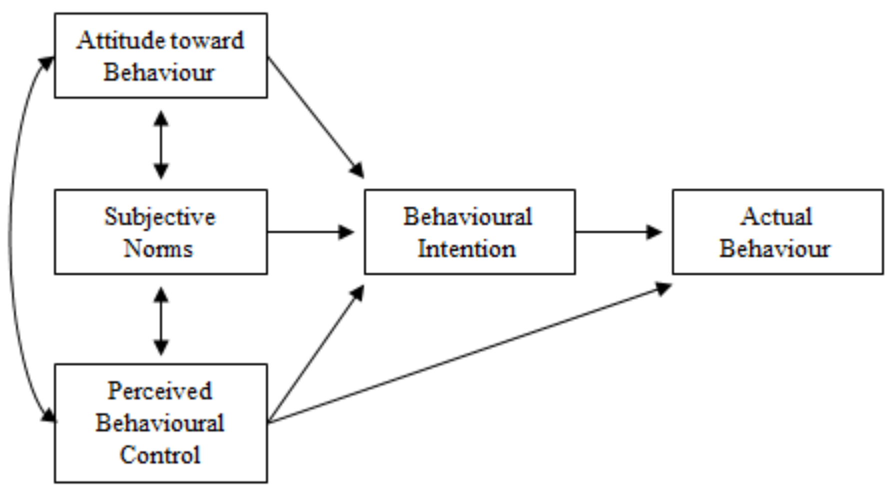

Figure 2.3 Theory of Planned Behaviour
(Ajzen, 1991)

Although the model has been used in measuring information technology acceptance, the issue of explanatory power of the model has been the subject of intense debate within the scientific community. Data from several studies showed that TPB explained only about 40% of the variance in individuals' behaviour. This view has been supported by Ajzen (1991), who argues that the model could be expanded with further determinants that can account for the variance in intention or usage behaviour.

Furthermore, the theory does not fully explain the utilisation of only one variable, perceived behavioural control, to present all non-controllable elements that influence individuals' behaviour (Taylor & Todd, 1995a). Beliefs behind perceived behavioural control are aggregated here to create a measure of it, so there are no specific variables which might predict behaviour. This, in turn, may produce biased results (Taylor & Todd, 1995a).

2.3.3 Technology Acceptance Model (TAM)

Based on the TRA proposition, the technology acceptance model was developed to predict technology acceptance and the intensity of system usage. The model utilises perceived usefulness and perceived ease of use to determine attitudes for the adoption of a new technology (Davis, 1989). The two key constructs are used extensively to determine users' intentions and use of a system. Based on many studies in different contexts with different technologies, it is considered one of the most influential theories in the information systems field and has been extensively applied to various systems and users to predict the adoption and update of a technology (Davis et al., 1989; Sánchez & Hueros, 2010; Venkatesh & Davis, 2000). TAM has been seen as the first research to examine how an individual's perceptions of a technology influences the eventual use of that technology (Straub, 2009).

The TAM theory suggests that beliefs about perceived usefulness and perceived ease of use are the key determinants of technology acceptance and adoption in an enterprise (Davis, 1989). While perceived usefulness is "the degree to which a person believes that using a particular system would enhance his or her job performance," perceived ease of use is "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989). The two beliefs influence in a significant way the attitude of an individual using the e-learning system. The model places specific emphasis on the prediction of adoption and its core parameters have been reviewed for over three decades. The theory links an individual's cognitive, affective and behavioural responses towards an information technology. In comparison with the Theory of Planned Behaviour (TPB), TAM emphasises that an individual's cognitive beliefs (perceived usefulness and perceived ease of use) have an influence on attitudes toward behaviour (affective response), which predicts the forming of a behavioural intention (behavioural response) to use, and this in turn leads to an actual behaviour or act (Taylor & Todd, 1995a). TAM adopts a well-established causal chain of belief-attitude-intention-behaviour from the theory of reasoned action and planned behaviour (Ajzen, 1991; Fishbein & Ajzen, 1975). This relationship is used to investigate how people accept or reject an information system (Davis, 1989). Figure 2.4 illustrates the primary elements of the original TAM.

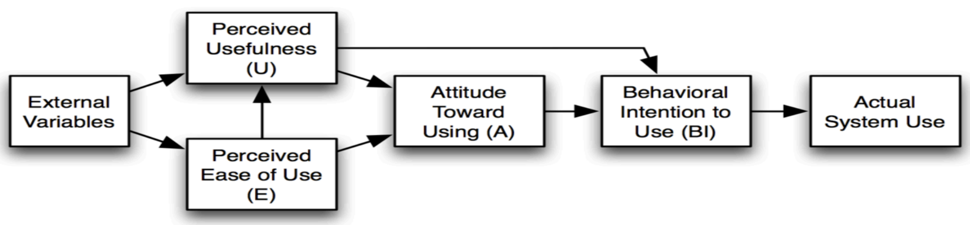

Figure 2.4 Technology Acceptance Model
(Davis, 1989)

This model has been critical in technology acceptance as it has initiated a conversation about the importance of an individual's perceptions of a technology. Nonetheless, these claims have been strongly contested in recent years by a number of writers. Although the original TAM model is claimed to be the most influential and frequently cited theory in the literature, Bagozzi (2007) warns that as TAM's parsimony makes the model far more prevalent, parsimony in itself could be considered a limitation and a liability as the model's simplicity cannot fully explain the behavioural and attitudinal decisions of individuals across different contexts and with varied technologies. The model might behave differently in a population as different groups within a population may also differ in their beliefs about perceived usefulness and perceived ease of use. The concept of parsimony has also been criticised by Taylor & Todd (1995b) as the balance between parsimony, and the understanding of model constructs and their contribution should be well-thought-out in evaluating the theory. Hence, the predication of individuals' behaviour based on perceived ease of use and usefulness is seen as inadequate, undermining the theoretical accuracy of the model (Benbasat & Barki, 2007; Chuttur, 2009; Straub, 2009). This limitation might be attributed to the absence of other organizational and technological factors that are recognized in later models (Straub, 2009). Furthermore, TAM is believed to predict technology acceptance success in between 30% and 40% of the cases, which indicates a limited explanatory power and a lack of usefulness in research on acceptance of technology (Bagozzi, 2007; Benbasat & Barki, 2007; Chuttur, 2009; Legris et al., 2003; Sun & Zhang, 2006; Teo, 2011; Venkatesh & Davis, 2000). In another significant study of students' acceptance of web-based learning technology, TAM was found to explain only 15% of student actual use, placing another constraint on the model validity and reliability (Martins & Kellermanns, 2004). This demonstrated inconsistencies in the findings of different studies regarding TAM's prediction of individual acceptance (Al-Aulamie, 2013; Sun & Zhang, 2006).

There appear to be a flaw in the idea that perceived ease of use is mapped directly to self-efficacy (Straub, 2009). Perceived ease of use corresponds with qualities of technology while the self-efficacy variable is related to the capability of individuals. In this regard, a significant study indicated that the two variables are conceptually different (Venkatesh & Davis, 2000). Another criticism of much of the literature on TAM is its lack of appreciation of individual differences (Agarwal & Prasad, 1999). The model did not acknowledge the importance of the moderators such as gender, age and prior experience that might influence the users' adoption (Straub, 2009). Agarwal and Prasad (1998) also explicitly criticized the absence of moderating influences in TAM, and called for more research to examine the moderating effect on the use and perception of an IS. For instance, when including gender as a moderating variable, the explanatory power of TAM increases to 52% compared to approximately 35% without moderators (Sun & Zhang, 2006). From an educational perspective, TAM has a limited capacity to understand individuals' predispositions to adoption. For instance, social influence is not included in TAM because the model was based on the technology used on individual level such as word processing (Davis, 1989). However, since LMS is far from an individual application, the social component is deemed to be a fundamental principle that explains individuals' acceptance of e-learning technology (Chu & Chen, 2016; Park, 2009; Šumak et al., 2010; Weng et al., 2015; Williams et al., 2015). Generally, students are inclined to be influenced by their teachers, friends, relatives and colleagues' emotions, opinions and behaviour that eventually affect their decision to adopt technology. Moreover, TAM does not recognize the intricacies and relevancy of an educational environment. For instance, TAM appears to lack recognition of the informative facilitating conditions which prove to be essential elements of technology acceptance (Buchanan et al., 2013; Venkatesh et al., 2003). The characteristics of the e-learning environment are a crucial element that determines the student's decision to adopt an innovation such as an LMS. Based on the analysis of TAM empirical research, Legris, Ingham, and Collerette (2003) concluded that "TAM is a useful model, but has to be integrated into a broader one which would include variables related to both human and social change processes".

Although the model has been one of the most widely accepted behavioural model in the field of information systems, the theory underwent various changes and evolutions since it was developed. For instance, Venkatesh and Davis (2000) developed the Technology Acceptance Model 2 (TAM2) which sought to remedy some of the shortcomings of TAM. TAM2 extended the original model by adding social influence processing factors (subjective norm, voluntariness, experience, and image), and cognitive instrumental processing factors (job relevance, output quality and results demonstrability) in the literature, the better to explain the usage behaviour of an information system. Figure 2.5 depicts TAM2. Based on the Venkatesh and Davis (2000) longitudinal study of 156 employees, the results confirmed the success of the model. Perceived usefulness accounted for 40-60% of the variance and behavioural intention attributed to 34-52% of the overall variance in the model. Furthermore, the influence of subjective norms on perceived usefulness and behavioural intention tends to decrease when experience is increased. The inclusion of experience is considered significant in the development of TAM2. Venkatesh and Davis (2000) postulated that in mandatory system usage, the subjective norm will directly affect behavioural intention in the early stages of implementation and the influence will decrease over time.

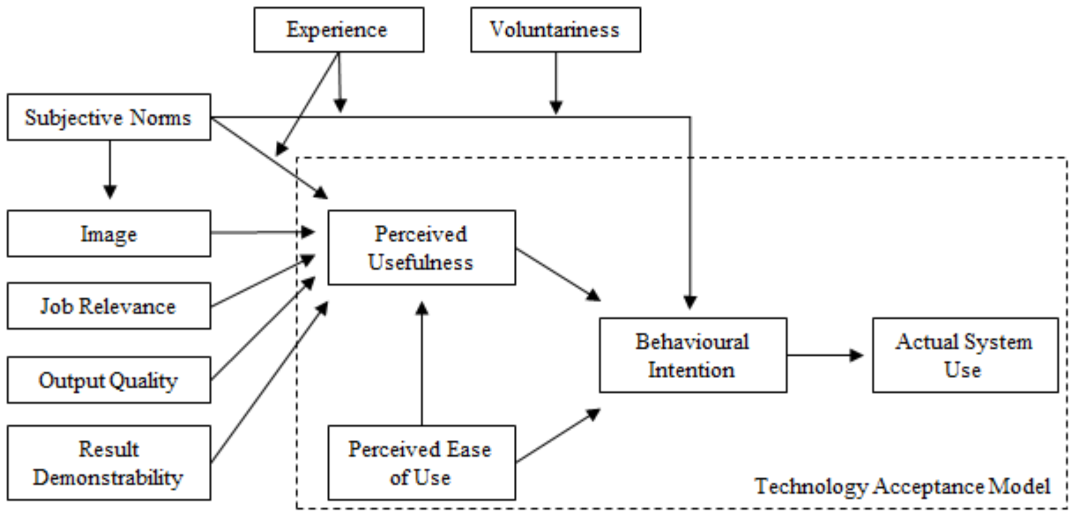

Figure 2.5 Technology Acceptance Model 2
(Venkatesh & Davis, 2000)

The most recent version of TAM is the Technology Acceptance Model 3 (TAM3). This was developed to include external variables that enhance employees' adoption and use of IT in an ecommerce context (Venkatesh & Bala, 2008). The key contribution of the TAM3 is in addressing the determinants of perceived ease of use and perceived usefulness (Venkatesh & Bala, 2008). The authors further expanded TAM2 to include anchors (computer self-efficacy, perceptions of external factors, computer anxiety and computer playfulness) and adjustments (perceived enjoyment and objective usability) (Venkatesh & Bala, 2008). These parameters were hypothesised to influence perceived ease of use (Venkatesh & Bala, 2008). It has been postulated that the influence of the adjustments, perceived enjoyment, and objective usability on perceived ease of use will be salient with increased experience (see Figure 2.6).

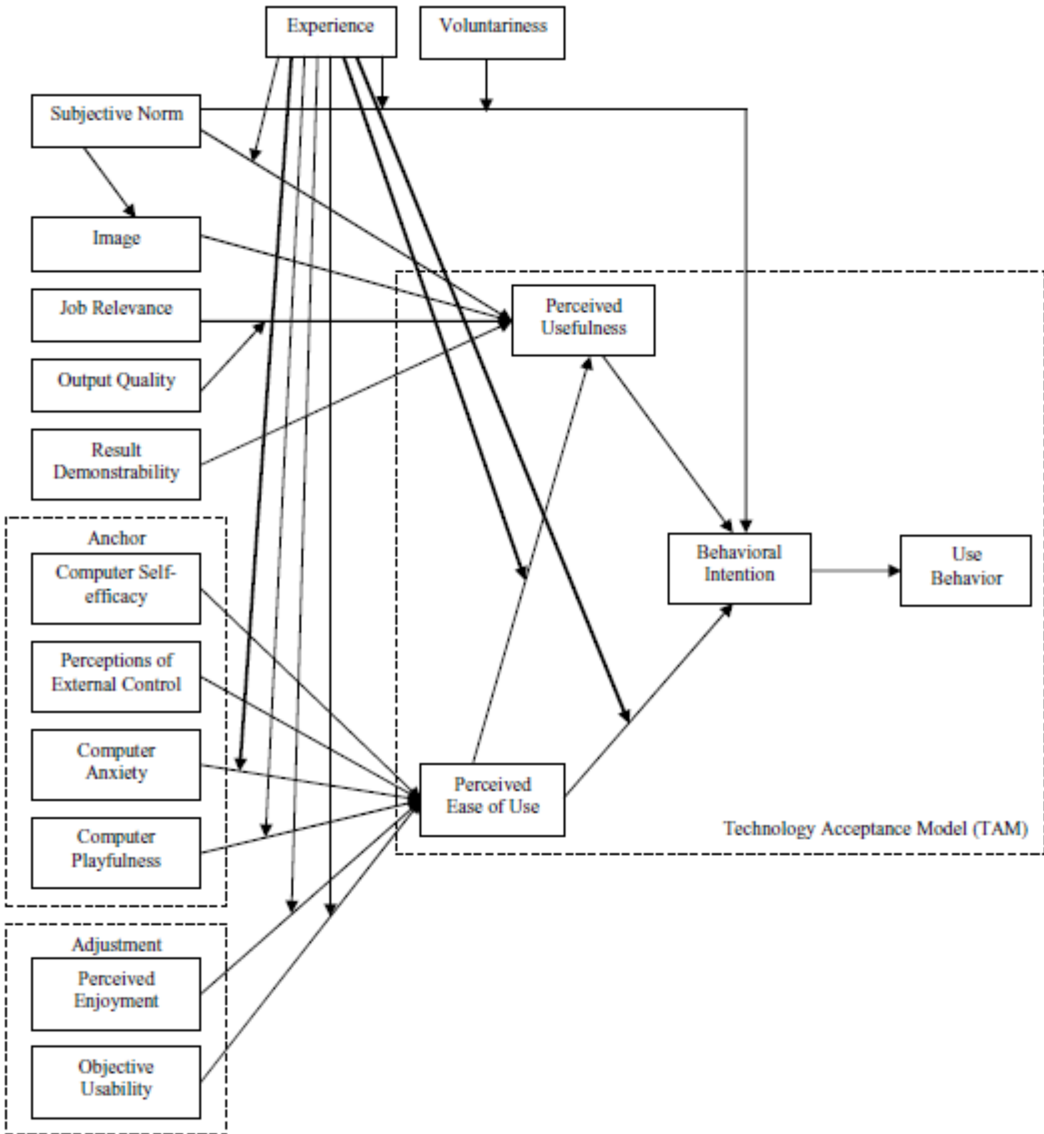

Figure 2.6 Technology Acceptance Model 3
(Venkatesh & Bala, 2008)

Extensions to TAM have been evolving over time. To further build upon the progress made with previous studies on TAM, Venkatesh et al. (2003) developed UTAUT, which addresses the criticisms of TAM evolutions to devise an extended model that compensates for the aforementioned inadequacies.

2.3.4 UTAUT Model Formulation

In an attempt to improve the explanatory power of TAM, information system practitioners have been searching for a better model that can make better predictions and be applied to diverse environments. In fact, scholars have stressed the need for further augmentation of TAM into broader models that have various constructs (Straub, 2009). It can be observed that previous models have been criticised as being fragmented and lacking a cohesive model that accounts for the various elements that affect the use of a technology (Venkatesh et al., 2003). As a result of previous technology acceptance research, Venkatesh and colleagues (2003) developed a UTAUT model based on a comprehensive review of diverse theories for predicting computer use. The model unifies the theoretical models in information system studies and integrates human and social constructs to form a unique extensive model (Venkatesh et al., 2003). The model is primarily quantitative and is employed to inform organisations how individuals adopt a technology.

In Venkatesh et al.'s (2003) project to develop a synthesis view of user technology acceptance, a model was generated based on the eight dominant models in technology adoption behaviour. Despite the maturity of the prior models, Venkatesh et al. (2003) have reviewed and compared these models and identified and addressed five limitations in their work. These include the following.

- The technology studied in previous models was simple and individual-oriented rather than more complex and sophisticated organizational technology.
- Most of participants in the earlier tested models were students except some in non-academic settings.
- The timing of measurement generally was after acceptance or rejection of the usage decision, rather than during the introduction of the technology.
- The nature of measurement in most of the prior studies was cross-sectional.
- Most of the tests were conducted in voluntary settings, leading to difficulties when generalizing results to a mandatory context.

The measurement was carried out at three different points in time – post training, one month after implementation, and three months after implementation – while actual usage behaviour was measured over a six-month post-training period. The data were divided into two samples for the eight models, according to the mandatory and voluntary settings. The authors also studied the effect of some moderating variables that have been reported in previous research to affect the usage decision. These were experience, voluntariness, age, and gender. Results showed that, with the exception of Motivational Model (MM), and Social Cognitive Theory (SCT), the predictive validity of the models increased after including the moderators. Figure 2.7 illustrates the UTAUT model.

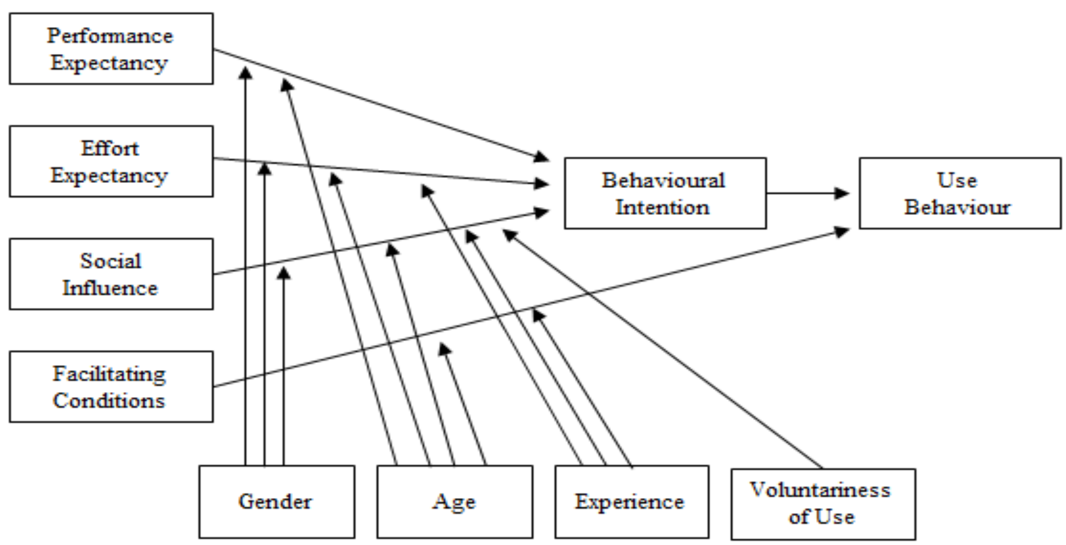

Figure 2.7 General UTAUT Model
(Venkatesh et al., 2003)

The UTAUT model is believed to address the other theories' limitations. The model integrates salient components across eight prominent user acceptance models and empirically compares them with four different organisations in longitudinal field studies (Venkatesh et al., 2003). Venkatesh et al. (2003) examined the commonalities between the eight models, and revealed that seven constructs emerged to be significant determinants of intention and usage behaviour. The model established a unique measure with four essential constructs of user behavioural intention and usage, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence

(SI) and necessary Facilitating Condition (FC). These predictors are defined as follows (Venkatesh et al., 2003).

1. Performance Expectancy (PE) is the degree to which an individual expects that his or her performance will be enhanced when performing a certain behaviour.
2. Effort Expectancy (EE) is the degree of ease associated with the use of the system.
3. Social Influence (SI) is the degree to which an individual believes that people think he or she should perform a certain behaviour.
4. Facilitating Condition (FC) is the degree to which an individual believes that organisational and technical infrastructure are available to support use of the system.

All these elements are direct determinants of user intention and behaviour. Results of prior studies and comparing the model with others showed that the three other constructs of attitude, computer self-efficacy, and anxiety were hypothesized to have an indirect effect on behavioural intention.

Demographic characteristics such as age, experience, gender and voluntariness of use are posited to moderate the influence of the four key constructs on behavioural intentions (refer to Figure 2.7). The results of the Venkatesh et al. (2003) analysis showed that gender and age moderate the influence of performance expectancy on behavioural intention so it is more salient for male and younger workers. Similarly, the influence of effort expectancy on intention is moderated by gender, age and experience so the effect is more important for female, senior and less experienced users. The UTAUT model suggests that all gender, age, experience and voluntariness of use interact with social influence, so women, older, mandatory users and those with less computer experience were found to be salient in the model. Age and experience moderate the effect of facilitating conditions on usage behaviour, and social influence is more salient for older and experienced users. Unlike TAM, the amalgamation of the core constructs and the moderating inputs has improved the predictive efficiency to

70% of the variance in behavioural intention to use technology (Venkatesh et al., 2003).

The UTAUT inclusion of important parameters such as required resources, available infrastructure and social components, that could potentially impact an individual's decision to adopt or reject a technology, has made the model more robust in terms of its explanatory power over the other developed theories (Khechine et al., 2016). Indeed, Venkatesh et al. (2003) examined the eight developed models across four organisations with three points of measurement and the explanatory power was found to be between 17% and 53% of the variance in the users intention to use an information system. Furthermore, the presence of demographics moderators in the UTAUT framework has added another significant value to the model. Some of these inputs had been overlooked in the previous technology acceptance literature. Moreover, the predictive validity of the examined models increased after including the moderators. The theory has been said to offer the highest predictive power with the fewest constructs available (Bagozzi, 2007). The integration was grounded on the argument that many of the parameters of IS acceptance models are similar in nature, so it was rational to map existing frameworks to generate an integrated theoretical model (Venkatesh et al., 2003). Furthermore, the model excels in that it is readily applicable to different contexts, including diverse educational systems (Straub, 2009). Thus, UTAUT is seen as the most appropriate model in scholarly published studies about IS adoption. This enables technology acceptance to be better predicted (Jong & Wang, 2009).

Nevertheless, UTAUT theory has not escaped criticism from professionals and academics. Firstly, the model is somehow new, so further validation and replication of the UTAUT model is required (Marchewka et al., 2007; Straub, 2009). The model also theorizes that the constructs of self-efficacy, anxiety and attitude toward using technology have an indirect influence on intention to use. Further analysis suggests that these factors are captured by different constructs in UTAUT, essentially the effort expectancy and performance expectancy constructs. The attitude factor has been dropped in most refinements of TAM as it is limited in adding to explanatory ability (Venkatesh et al., 2003). Furthermore, previous research findings into attitudes toward technology have been inconsistent and contradictory, especially in explaining the usage of utilitarian systems such as an LMS (Hornbæk & Hertzum, 2017). Closer scrutiny of UTAUT self-efficacy shows that the measure does not evaluate overall self-efficacy, but rather, the specific self-efficacy of a particular system. Thus, there is a call for research communities to review self-efficacy, especially outside corporate institutions (Straub, 2009; Venkatesh et al., 2003). Venkatesh et al. (2003) acknowledged the importance of further validation of the model with an emphasis on content validity. They suggested the development and validation of appropriate scales for each of the UTAUT constructs and the revalidation and extension of the model with new measures in other contexts. To add to this, many researchers acknowledge that the UTAUT model does not include some of the system characteristics such as usability parameters which might influence users' acceptance of a technology (Holden & Rada, 2011). Importantly, there is still another significant limitation pertaining to the context of the study and the sample population size, particularly in higher education. Overall, the UTAUT model validation has not been tested with the system characteristics variables in the Saudi context. The model needs to be tested meticulously in higher education, capturing the specific requirements of usability metrics pertaining to an e-learning environment (Marchewka et al., 2007).

2.3.5 Extended Unified Theory of Acceptance and Use of Technology

The issue of acceptance has grown in importance in the light of recent innovation sophistications. Even though UTAUT provides a robust and detailed model for acceptance and use of technology, Venkatesh et al. (2012) extended and adapted the UTAUT to examine the technology acceptance in the consumer behaviour context. The recent model, referred to as UTAUT2, incorporates three constructs into UTAUT including hedonic motivation, price value, and habit. The moderators of age, gender and experience are posited to influence the effect of these constructs on consumer intention and usage behaviour, with voluntariness being dropped from the previous

UTAUT (Venkatesh et al., 2012). The model also adds a direct link between facilitating conditions and behavioural intention and habit is theorised to directly influence consumer intention and use behaviour. Figure 2.8 shows a graphical representation of UTAUT.

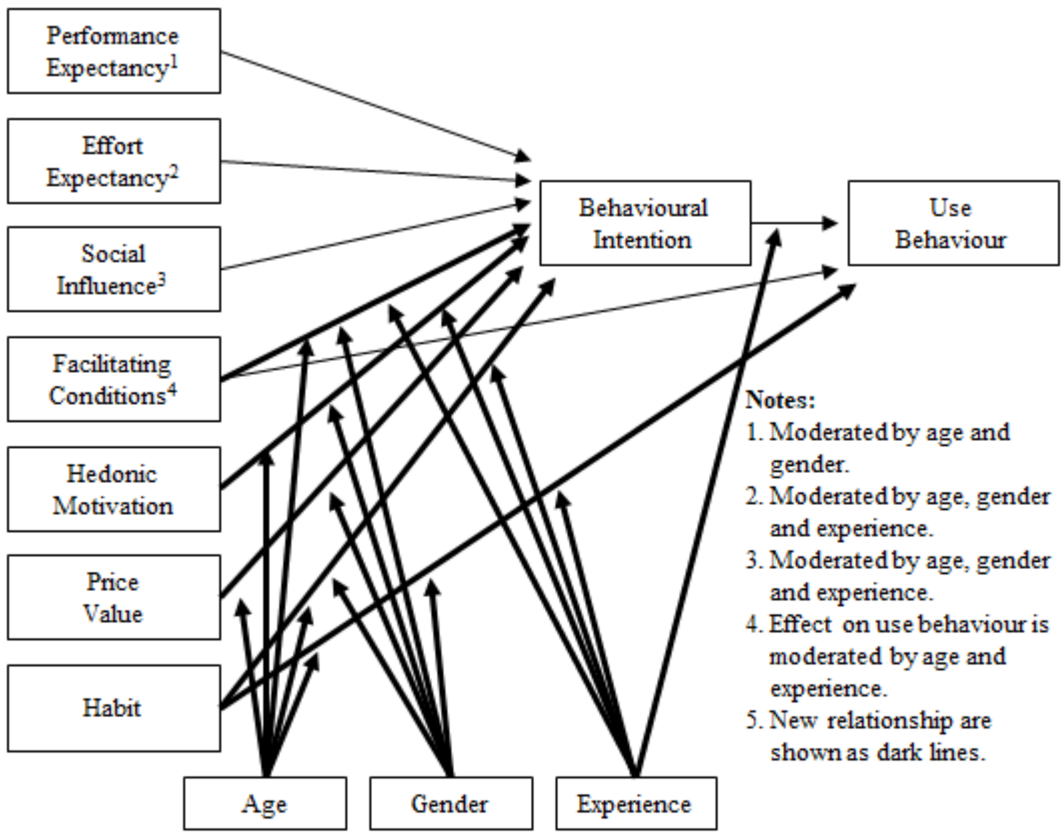

Figure 2.8 Unified Theory of Acceptance and Use of Technology 2
(Venkatesh et al., 2012)

The empirical validation of UTAUT2 with 1512 users has revealed the success of the model in voluntary settings. Compared to UTAUT, the model's explanatory power has improved to reach 74% in the variance of behavioural intention and 52% in use behaviour (Venkatesh et al., 2012). Nevertheless, the model has proved to be deficient in fully explaining behaviour in a specific task environment, accentuated by the necessity to eliminate or augment the model with additional variables (e.g. the price value is less relevant in educational environment) (Raman & Don, 2013). Moreover, the model has produced biased results across cultures, undermining the model's accuracy across regions (El-Masri & Tarhini, 2017).

2.3.6 Diffusion of Innovation Theory (DOI)

Grounded on sociology, diffusion of innovation theory seeks to describe how innovations diffuse through societies and how individuals accept new innovations. The theory provides a foundational understanding of adoption theories which has been used since 1960s to study the adoption of a variety of tools (Rogers, 1962; Venkatesh et al., 2003). Rogers distinguished between the diffusion and adoption process where the former is related to society and the latter corresponds to an individual. These factors have been used in information systems research to evaluate the communication of innovations that are developed gradually by users over time (Rogers, 1995). The DOI theory contains innovation-decision process, innovation characteristics, adopter characteristics and opinion leadership. Figure 2.9 illustrates the different stages involved in adopting or rejecting an innovation. The first stage is knowledge, which occurs when a person or other decision-making unit observes the presence of innovation. Under the persuasion phase, the perceived characteristics of the innovation give rise to a favourable or unfavourable attitude that form on the part of the adopter. These characteristics are relative advantage, compatibility, complexity, trialability and observability (Rogers, 1995). In the decision phase, the person (or a unit) engages with the activities that lead to the choice of adoption or rejection of the innovation. In the implementation stage, actual use behaviour is formed. The individual, in the confirmation phase, forms a decision to adopt or reject an innovation. The decision might change with experience (e.g., problems with innovation).

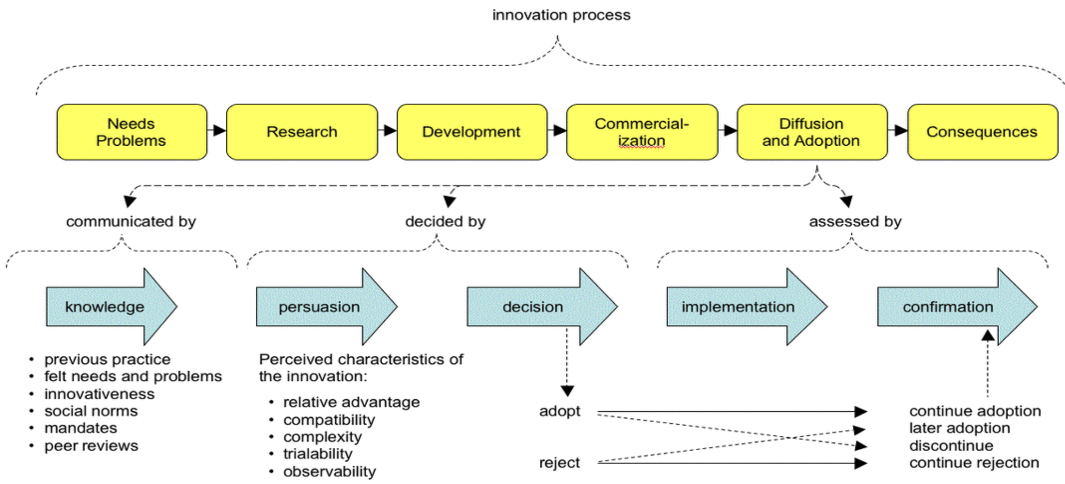

Figure 2.9 Innovation-decision Process
(Rogers, 1995)

Although this theory is critical in predicting change, it is not easily applied to understanding adoption (Straub, 2009). For instance, there is some doubt about the extent to which DOI can be applied to different cultures (Clarke, 1999). Many of its elements may be specific to the culture in which it was derived (e.g., North America in the late 60s), and hence less relevant in, for example, East Asian and African countries (Clarke, 1999). Furthermore, Clarke (1999, p. 17) stated that the classical DOI theory is "at its best as a descriptive tool, less strong in its explanatory power, and less useful still in predicting outcomes, and providing guidance as to how to accelerate the rate of adoption". However, the model is particularly important as it has influenced many other models in the acceptance and adoption literature e.g. UTAUT (Venkatesh et al., 2003). Within an information system, Moore and Benbasat (1991) adopted Roger's model and proposed a set of constructs to study individual technology acceptance. These attributes are the relative advantage, complexity, compatibility, image, result demonstrability, visibility and trialability (Moore & Benbasat, 1991). Following a rigorous analysis, the authors developed and validated an instrument to measure the model variables. There are various pieces of research which have used the scale to investigate technology adoption (Agarwal & Prasa, 1998).

2.3.7 Social Cognitive Theory (SCT)

The Social Cognitive framework deals with cognitive, emotional and behavioural factors for understanding and predicting the barriers and enablers of technology acceptance (Bandura, 1986). It is claimed to be one of the most useful theories of human behaviour as it measures the relationship between personal, behavioural and environmental factors (Venkatesh et al., 2003). A great number of publications have applied SCT to explain the determinants of computer performance and usage (Compeau & Higgins, 1991; Compeau & Higgins, 1995).

2.3.8 Information System Success Model (IS Success Model)

Based on a comprehensive review of 180 research articles, DeLone and McLean (1992) proposed a model for evaluating the information system success. The initial development of the theory comprises six variables: system quality, information quality, use, user satisfaction, individual impact, and organizational impact, that were posited to affect the success, usage and satisfaction of an information system (Figure 2.10). These dimensions are interrelated rather than independent.

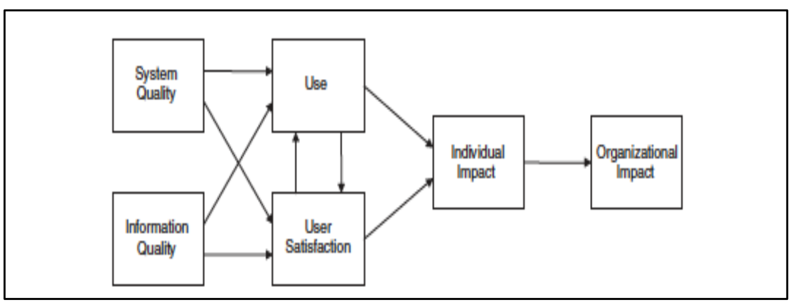

Figure 2.10 Original IS success model
(DeLone & McLean, 1992)

A decade later, DeLone and McLean (2003) further refined the model to compensate for a rapid change in IS over time. The updated model asserted that system quality, information quality, service quality, intention to use, user satisfaction and net system benefits, are the main determinants of the IS success model (see Figure 2.11). Although the revised model is among the most influential theories in understanding and measuring the dimensions of IS success (Halawi & McCarthy, 2008; Mohammadi, 2015), the model is regarded as focusing on the IS characteristics, a partial view of the entire system (Azeemi et al., 2013). The model is appropriate when applied in a static context, but the dynamic nature of other contexts (e.g., educational context) requires a holistic approach (i.e., with additional constructs) to measure success (Azeemi et al., 2013). There are still many unanswered questions about the applicability of the IS success model for hedonic IS (Petter et al., 2008). Some of the model variables may no longer be relevant for gaming or social networking, so other metrics can be utilised to predict the system's success (Petter et al., 2008).

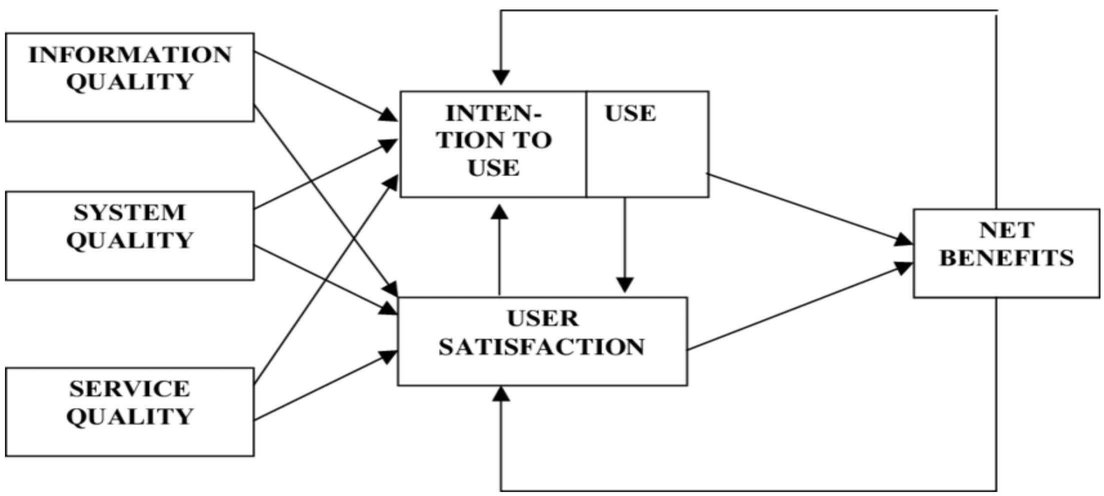

Figure 2.11 Updated IS success Model
(DeLone & McLean, 2003)

2.4 Literature review of studies which use UTAUT

There are many studies that focus on measuring users' acceptance and adoption (Al-Gahtani et al., 2007; Almaiah & Alyoussef, 2019; Bellaaj et al., 2015; Khechine et al., 2014; Marchewka et al., 2007; Salloum & Shaalan, 2019; Šumak et al., 2010, 2011). For the purposes of this study, prior research of user acceptance and adoption of technology were reviewed to recognise the significant variables that might influence e-learning uptake, especially in higher education. Over the last decade, the evaluation of e-learning innovations using the UTAUT model has increased substantially, especially in developed countries. It was reported that the challenges of implementing e-learning in a new context can be addressed through use of the UTAUT model (Salloum & Shaalan, 2019). Hence, it is important to evaluate the e-learners' experiences of using an LMS, their behavioural intention to use and their actual use behaviour (Pynoo et al., 2012; Salloum & Shaalan, 2019; Selim, 2007; Sun et al., 2008; Venkatesh & Davis, 2000). In this section, some of the most relevant studies are highlighted, capturing major themes and explaining the rationale behind this research.

Marchewka et al. (2007) investigated the students' perceptions of the Blackboard system in higher education using UTAUT. The results of the correlational analysis revealed that the association between performance expectancy and behavioural intention was not supported. While effort expectancy and social influence appeared to influence the students' behavioural intention to use Blackboard, the age and gender moderation influence in Blackboard use was not found. The authors were sceptical regarding the applicability of the UTAUT scale in an e-learning environment as mixed results were observed. They suggested a direction to improve the model in educational settings. This case study confirms the importance of further revision of the UTAUT model, and an extension of the model to include more usability concerns is needed.

In the same vein, Efiloğlu Kurt and Tingöy (2017) conducted a comparative study by applying the UTAUT model to two different countries, Turkey and the United Kingdom, to evaluate the acceptance and use of LMS in higher education. From a total of 1032 students from the two samples, the findings indicated that performance expectancy had a greater effect on behavioural intention in the UK sample than in Turkey, whereas the effort expectancy variable had a more prominent effect on the sample in Turkey. In Turkey, the social influence construct had the most significant effect on the intention to use an LMS. The facilitating conditions variable was significant in both countries. Surprisingly, the influence of behavioural intention on use behaviour revealed a significant effect for the sample in the UK and an insignificant effect for the sample of Turkey. The results showed some variances between the two countries, indicating that the UTAUT behaviour might differ in a dissimilar country such as Saudi Arabia.

In the same way, Šumak et al. (2010) measured all components of the UTAUT framework to analyse factors that affect both students' attitude towards using and their intention to use Moodle , an open source web-based LMS. The UTAUT moderators were not included in the model. The results showed that performance expectancy and social influence were found to have a significant, direct influence on students' attitudes, where performance expectancy had a superior effect on the attitude towards using Moodle . However, performance expectancy, effort expectancy and attitudes toward using technology were statistically insignificant in determining the students' behavioural intention towards Moodle , though social influence had a strong effect on students' behavioural intention. In contrast to earlier findings, however, there was no evidence of influence of Moodle's ease of use on students' intention and on their attitude towards using the LMS. Nonetheless, the results of the study demonstrated that the UTAUT model is applicable in measuring a student's acceptance behaviour towards an LMS.

UTAUT provides a useful account of how individuals accept web-based learning technology. Khechine et al. (2014) conducted a UTAUT study of the effects of moderators, gender and age, on the acceptance of a Webinar system in a blended learning module. They found that age had a salient moderating influence on intention, while gender did not. Performance expectancy was the strongest motivator for younger students, as they are better equipped technologically while the more senior students were concerned with facilitating conditions. In tandem with the previous result, the effort expectancy construct failed to predict students' intention to use the system. However, all other three independent associations were supported, and this was explained by 51% of the variance in intention to use. While this study provided a practical and theoretical discussion especially regarding moderating inputs, an LMS is more comprehensive than a Web conferencing tool. Hence, this limitation could be avoided in future research. A consideration of students' needs and preferences is thus crucial in LMS lesson preparation. In online learning and teaching, tutors should keep in mind the different technological skills of students in relation to their age and gender.

In the same vein, Raman, Don, Khalid and Rizuan (2014) investigated the differential impact of UTAUT variables on postgraduate students using an LMS (Moodle). The main purpose was to examine the students' behavioural intention to use Moodle, disregarding the use behaviour factor. The most notable finding of this study was that effort expectancy did not affect behavioural intention. Further statistical tests revealed that gender, as a moderator, did not have a significant positive influence on performance expectancy, effort expectancy or social influence towards behavioural intention. The overall response to the survey was positive. Moodle was proven to be an effective tool for the learning and teaching process. However, further validation and elaboration of the model was recommended.

Thongsri, Shen and Bao (2019) combined UTAUT with an IS success model to investigate students' acceptance of an e-learning system. Based on 307 completed questionnaires, Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyse the data. The empirical findings demonstrated that system quality, information quality, performance expectancy and social influence had a significant effect on students' behavioural intention to use the system. These attributes accounted for 58.1% (R^2 = 58.1) of variance in the behavioural intention. However, service quality and effort expectancy were insignificant determinants for the intention. The research highlighted the importance of the system's quality attributes and how they impacted the student's intention to use the system. Therefore, successful assessment of student intention to use e-learning should take into account the usability factors.

In the Arab world, Ameen et al. (2019) conducted a similar study to analyse the factors that influence the students' behavioural intention and use of an e-learning system. A selection of factors from three models, UTAUT, TAM and the IS Success model, were performed to address the dearth of studies in this area. Partial least squares structural equation modelling (PLS-SEM) was used to analyse the data received. The findings suggest that perceived usefulness (PU), perceived ease of use (PEOU), subjective norms (SNs), information quality (IQ), system quality (SQ), technical support (TS) and self-efficacy (SE) had significant effects on behavioural intention (BI), while BI and TS had significant direct effects on the actual use (AU) of the e-learning system. The research also reported that the moderating factors of age, gender and experience did not significantly moderate most of the relationships in the model. The only exception was age, which moderated the relationship between TS and IQ. The authors stressed the need to deliver e-learning training to students directly by expert and provide the appropriate technical support team that assist students with system difficulties.

Salloum and Shaalan (2019) employed the UTAUT model to investigate the students' behavioural intention and use of an e-learning system in two United Arab Emirates universities using PLS-SEM techniques. After surveying 280 students, the findings revealed that all factors influenced the students' behavioural intention to use the e-learning system. However, effort expectancy was not found to have a significant impact on student intention towards the system. While the study provided insights into the factors that affected the use of an LMS in the UAE, more exogenous parameters could be incorporated into the UTAUT model to enhance its predicative capability in the Gulf region.

In a like manner, Al-Gahtani et al. (2007) adopted the UTAUT model to examine computer software acceptance in a Saudi Arabian context. They addressed the effects of culture on the UTAUT attributes on the basis of Hofstede's cultural dimensions (Hofstede, 1997). In corporate settings, a total of 1190 responses, both mandatory and voluntary, were analysed. In line with Venkatesh et al. (2003), performance expectancy positively influenced individual intention. However, the relationships were not moderated by the inputs of gender or age. In terms of effort expectancy, the association with intention was not supported but with sustained experience, the ease of use became less important in Saudi culture. Social influence had a significant positive influence on employees' intention to use the technology. However, age and experience revealed a negative interaction in this connection. This result may be explained by the fact that Saudi Arabia is characterized by low individualism and high power-distance culture, signifying that peoples' behaviour tends to show an inclination towards deference to authority and conformance to the expectation of others. The relationship between facilitating condition and intention to use was not supported. It may be the case therefore that these variations would suggest more validation for the UTAUT model in Saudi Arabia, especially in the educational context.

In the same vein, Bellaaj et al. (2015) carried out a study based on UTAUT that investigates the students' continued use of a web-based learning platform in a Saudi university. The focus of the study was on the effects of moderating inputs (age, gender and the Internet experience) on the students' continued use of an LMS. This experiment adopted the three main constructs of UTAUT (performance expectancy, effort expectancy and social influence). The facilitating conditions factor was not included in this study, as only the intention of e-learning use was considered rather than actual use. The results of this study showed that performance expectancy and effort expectancy have remarkably positive impacts on the continued use intention of LMS, whereas social influence is proved to have no statistical significance on the continued use of the e-learning system. However, with increasing Internet experience, the effects of effort expectancy decreased compared to the increased influence of performance expectancy. Surprisingly, there was a strong weight of social influence on continued use by female students. The findings also showed that students' age and gender did not show any significant influence on performance expectancy and effort expectancy. The gender moderated the effect of social influence on intention only. The study concluded with the suggestion that the usability of the e-learning platform should be enhanced and improved.

In the same context, Bouznif (2018) utilised UTAUT to investigate students' willingness to use the Blackboard system, with particular emphasis on the Business School at King Saud University (KSU) in Saudi Arabia. SEM was used to test the overall efficacy of the UTAUT model and the mediating relationship among variables, focusing on the major determinants of students' satisfaction and its effect on the usage behaviour of Blackboard system. Facilitating conditions and usage behaviour constructs were overlooked in the proposed model and instead, the role of satisfaction was added as an outcome variable. There were minor adjustment to the social influence factor to focus only on the students' perceptions toward their lecturers. The author excluded fresh students due to their insufficient experience and the graduates for their lack of intention to continue use of the LMS. Unexpectedly, the results of this study indicated that there is no direct statistical relationship between performance expectancy, effort expectancy, superior influence and the student's behavioural intention to use Blackboard. Nonetheless, the relationship was demonstrated through the mediating variable of satisfaction. The study also proved the statistically significant influence between satisfaction and the students' continued usage intention of the system. Although the study provides a significant contribution through the incorporation of the satisfaction construct into the model, the study lacks generalization to other colleges or academic institutions, due to the sample being restricted to the business students. Some limitations which might undermine this study were the exclusion of the facilitating conditions and the modifications to the measurement of social influence which might exhibit an impact the function of the overall UTAUT model.

2.5 Usability

Usability is grounded in the Human Computer Interaction discipline, in which the usability evaluation of a user interface is a core concept in the HCI field (Gray & Salzman, 1998). System usability has been researched for more than 50 years (Zaharias, 2009). Usability is a quality attribute of users' experiences when interacting with interactive technologies that assess the ease of use of the user interface (Preece et al., 2015). It has a focus on the quality of the different system components, primarily optimizing peoples' interaction with the user interface (UI) (David, 2014). The usability assessment task is concerned with the identification of system usability problems with the purpose of interface improvement and enhancements for its potential users (Ssemugabi & De Villiers, 2007). Learners regarded the interface of the e-learning system as being the most significant attribute for utilization where high level interactions occur (Shee & Wang, 2008). In an educational context, usability is considered to be one of the most important quality factors for evaluating the quality of an LMS user interface (Dix et al., 2004). In the next section, the usability definition is presented. This is followed by describing the term "perceived usability", discussing the different usability evaluation methods and ends with a section on the importance of usability assessment in an e-learning environment.

2.5.1 Usability Definition

The definition of usability varies among usability professional and practitioners and is commonly discussed in HCI literature (Jimenez et al., 2016; Teo et al., 2003). The term usability refers to the methods that are used for system ease-of-use improvement during the design phase (Nielsen, 1993). The term usability is more than a single attribute (Althobaiti & Mayhew, 2016) and cannot be perceived as only ease of use (Shackel, 2009). Usability is a non-functional requirement that cannot be measured directly. It has to be broken down into measurable attributes and qualities that generate results in quantitative or/and qualitative outputs (Hornbæk, 2006). According to Nielsen (1996), it is the measure of system acceptability and functionality in which the combination of five elements such as software learnability, efficiency, memorability, general accuracy, and the overall satisfaction of system users, are examined. Nielsen (2012) further defined the five quality measures for the assessment of general user interface as follows.

1. Learnability: How easy is it for users to accomplish basic tasks the first time they encounter the design?
2. Efficiency: Once users have learned the design, how quickly can they perform tasks?
3. Memorability: When users return to the design after a period of not using it, how easily can they re-establish proficiency?
4. Errors: How many errors do users make, how severe are these errors and how easily can they recover from errors?

5. Satisfaction: How pleasant is it to use the design?

Shackel (2009) defined usability as “the capability to be used by humans easily and effectively” where easily means the specified level of the users’ subjective assessment and effectively refers to the specified level of the users’ performance. He then produced more operational criteria for usability assessment, namely effectiveness, learnability, flexibility and attitude. Flexibility is defined as the extent to which the system can accommodate changes desired by the user beyond those first specified whereas learnability is the time and effort required to reach a specified level of use performance with the system (Petrie & Bevan, 2009; Shackel, 2009). Shackel (2009) also in his usability proposition considered the cost and training required for supporting users.

Koohang and Du Plessis (2004, p. 38) stated that “usability in an e-learning context refers to diverse things such as the platform specifications; screen layout; the navigational system and structure; the aesthetic qualities of a product or platform; and all the traits that promote user-friendliness. All these aspects then support instruction, and consequently instructional design for e-learning.” Thus, usability is the influential dynamic of the platform’s capacity to fulfil the users’ interactive needs and expectations. The term centred on making the product or the system easy to use and learn, as well as satisfactory for a target audience.

ISO standard 9241 (ISO 9241-210, 2010), pertaining to user centred design and the specification of usability, has provided a more formal and widely accepted definition of usability as “the effectiveness, efficiency and satisfaction with which specified users achieve specified goals in particular environments”. The definition contains three classifications of usability components to evaluate a product namely effectiveness, efficiency and satisfaction. The definition overlaps with the definitions of Nielsen (1993) and Shackel (2009). Effectiveness is the accuracy and completeness with which specified users can achieve specified goals. It is defined as the user’s successful completion of goals and the accuracy of procedures. Efficiency refers to the total resources expended on the task so once students have learnt the design, how fast they can complete the tasks. Satisfaction is related to the subjective enjoyment with the system use. The term also highlights that usability is determined by the context of use and that encompasses users and their activities, hardware and software components and the physical and social settings in which the product is implemented and used. In this definition, usability also implies the users' interaction with the system and can be viewed as an application's capability to satisfy the target audience's expectations. While the ISO definition can be applied in the context of enterprise and work-related applications, the definition is limited to describe human interaction in an educational environment that needs certain usability goals (Green & Pearson, 2011).

Shneiderman (2017) proposed five measurable guidelines central to usability evaluation comprising the speed of task performance, time to learn, the rate of errors by users, retention over time and the subjective satisfaction. Bevan (2008) extended the definition of usability to include learnability, accessibility and safety, which contribute to the overall user experience. Accessibility refers to the available access to the system for accomplishing specific tasks (Rubin & Chisnell, 2008). It is usually concerned with usable and accessible system design for people with disabilities or with special needs. Bevan (2008) further added user satisfaction metrics for measuring user experience, including hedonic parameters such as likeability, pleasure, comfort and trust.

Many others classify a User Experience (UX) term as covering more aspects beyond the traditional task-related usability paradigm, to include the experiential and emotional aspects of using technology such as beauty, hedonic and affective qualities of persons' experience (Hassenzahl & Tractinsky, 2006). UX is seen as a holistic layer, covering an individual's internal state, qualities of a designed technology and the environment for which the technology was implemented, and the interaction that occurred (Hassenzahl & Tractinsky, 2006). Bevan (2008) presented UX as an umbrella term that includes all user's emotions and behaviour, implying that usability is subsumed into user experience.

It is clear from the previous discussion that there is a lack of consensus about the definition and parameters of usability (Agarwal & Venkatesh, 2002; Gray & Salzman, 1998). Gray and Salzman (1998) acknowledged the challenge that is facing researchers and practitioners regarding the definition of usability. The term has no absolute definition as it depends on different system users, goals, and the context of use that are specific to each particular environment (Pearson et al., 2007).

Hence, transferring the above attributes to an e-learning setting would be considered far too broad to yield significant information about learners' experiences with learning materials. Hornbæk (2006) argued that e-learning technology requires new usability measures to adequately capture specific characteristics in the educational context. This view is shared by Zaharias (2009) in which the heuristics employed by Nielsen (1993) and Shneiderman (2017) are generic usability attributes, and the need for more customised criteria for e-learning systems is evident. Thus, evaluation of e-learning systems requires an additional set of qualities which are more specific to an online learning and teaching environment.

2.5.2 Perceived Usability

Perceived usability is concerned with the users' subjective experience with the system resulting from their interaction (Hertzum, 2010). Although other scholars define perceived usability as synonymous with perceived ease of use (Flavián et al., 2006) and as covering the three system attributes of usefulness, information quality and interface quality in the post-study system usability questionnaire (Lewis, 1995), agreement has not yet been reached regarding the perceived usability definition. However, the users' subjective assessment goes beyond their personal perceptions of usability, as it influences their performance, interaction, outcomes and usage behaviour (Venkatesh et al., 2003). In research on technology acceptance, a fair amount of variance can be explained by the perceived usability variables of usefulness and ease of use, signifying their importance in technology adoption and usage behaviour (Davis, 1989; Hertzum, 2010). Perceived usability is related to the students' belief about the LMS performance characteristics (Bhuasiri et al., 2012). Davis (1989) stated that system characteristics directly influenced users' beliefs and use. The study of perceived usability can be obtained using user-based inquiry methods such as a questionnaire, typically expressed in a rating scale (Hertzum, 2010).

Feldstein (2002) highlighted the importance of eliciting students' perceptions about usability characteristics in the assessment of an e-learning system. Importantly, if the e-learning system is easy to use but perceived otherwise, this might impede the learners' adoption of the system (Cho et al., 2009). There is a debate about whether perceived usability is adequate in explaining the overall usability of a system across entire system functions and tasks. Nevertheless, the measurement of perceived usability in e-learning is centred around the learners and is considered vital in the system preferences, adoption, usage, satisfaction and like/dislike (Cho et al., 2009; Hertzum, 2010; Hornbæk & Hertzum, 2017; Jimenez et al., 2016).

2.5.3 Usability Evaluation Method (UEM)

The increasing demand for successful products and services has led to the proliferation of research regarding the construction of different usability evaluation methods. There are different methodologies for assessing human interactions with user interfaces. The aim is not only to detect usability problems, but also to promote improvement and enhancement in the user interface design (Gray & Salzman, 1998; Jimenez et al., 2016). Prior studies have proposed a wide number of well-established usability methods to adopt for the evaluation of digital systems. Regarding the type of evaluation performed by the UEMs, a wide range of usability evaluation techniques have been examined with different systems and products. However, there are three main categories of usability evaluation method, based on the usability issues that have been identified (Hasan, 2014).

- User-based methods (user-testing methods): These are grounded on the involvement of actual users in the process of identifying usability problems. They are conducted using different inquiry methods such as observation, questionnaires and interviews to measure users' performance as well as preferences and thoughts about the user interface.

- Evaluator based methods: These are based on techniques that directly involve the usability evaluators or experts for usability violations detection. Heuristics evaluation is an example of this category where there is a number of web domain specialists that are selected to assess the user interface and judge the user interface compliance with a set of criteria (heuristics, parameters or attributes).
- Tool-based methods: In these methods, usability problems in the UI are automatically identified using software tools. Most of these technologies assess the quality of the HTML code of a website against predefined usability guidelines (e.g., log analyser, user simulators, HTML checker).

According to Gray and Salzman (1998) there are two basic approaches that are currently being adopted in research into usability. One is the analytic approach, and the other consists of empirical techniques (Gray & Salzman, 1998). Analytic methods encompass experts' evaluations such as cognitive walkthrough and heuristic evaluation, while empirical techniques involve user based assessment such as user testing and think aloud protocols (Gray & Salzman, 1998). Ivory and Hearst (2001) proposed a taxonomy of usability evaluation methods in which they were categorised into five classes: testing, inspection, inquiry, analytical modelling and simulation evaluation techniques. The usability testing approach involves evaluators' observations of representative users who interact with the system to perform typical tasks with the purpose of identifying usability issues (i.e., unsuccessful task completion). Different techniques have been used in user testing to detect usability problems (e.g., think-aloud protocols, remote testing, log file analysis) (Barnum, 2001).

Inspection entails usability experts examining the user interface and judging its compliance with a set of design principles (heuristics), for the purposes of identifying potential usability issues (using e.g. heuristic evaluation, guideline reviews, or cognitive walkthroughs) (Nielsen & Mack, 1994). The most popular type of expert evaluation is heuristic evaluation (Nielsen & Mack, 1994). Heuristic evaluation was developed to determine whether a tested system conformed to a set of guidelines. In the inquiry-based approach, usability evaluators collect subjective information about the users' perceptions, needs and preferences, typically through inquiry methods such as questionnaires, interviews and focus groups (Nielsen, 1993). It also can identify the issues in relation to navigation, design and accessibility.

The analytical modelling method presents an engineering approach to predict usability problems, whereby an evaluator employs interface models that cover many aspects of user interface attributes, and then conducts a task analysis procedure (e.g. GOMS analysis, Cognitive Task Analysis) (Diaper & Stanton, 2003). Simulation is a usability method in which a program that mimics a user interaction with the interface is developed. The software automatically captures quantitative measures such as input events that potential users might perform (mouse clicks and errors made) and reports the outcomes of interaction (e.g., Petri net models, information scent). Another alternative would be to use eye tracking techniques, though this has certain prerequisites such as special equipment and technical expertise (Blecken et al., 2010).

The choice of which technique to employ is subject to time and cost constraints, the stage of software development life cycle, the availability of skills and required expertise of the assessment and the goals of evaluation as well as the extent of need for an objective, subjective or systematic evaluation (Bak et al., 2008). It is also possible to conduct usability evaluation using different methods such as user-based evaluation and expert evaluation.

Much of the current literature on e-learning evaluation pays particular attention to Nielsen's heuristics or slight variations thereof, without considering the e-learning characteristics (Albion, 1999). In the context of e-learning environments, the non-specific nature of Nielson heuristics might not articulate the particular attributes of an e-learning system. The need for a more specific quality of education and pedagogy is apparent (Zaharias & Koutsabasis, 2011). However, it is sensible to mention the list of Nielsen and Mack (1994) heuristics as general guidelines. The guidelines come from the usability evaluation of 11 applications with 250 usability issues. The following are Nielsen's ten usability heuristics, with explanation. The description of each criterion was adapted from the relevant literature (Albion, 1999; J Nielsen & Mack, 1994; Squires & Preece, 1999; Samuel Ssemugabi & de Villiers, 2007).

1- Visibility of System Status: It is crucial to constantly keep informing users about system status, giving clear feedback regarding the users' interaction with the system within a reasonable time.

2- Match Between System and the Real World: The e-system should speak the users' language, with words, phrases and concepts familiar to the user, and follow real-world conventions. All terminologies should be recognizable for all users.

3- User Control and Freedom: Users need to recover from input errors once they have occurred. An emergency system reversion sign should be visible. Users may leave the unwanted state without having to go through an extended dialogue. The system should support undo and redo.

4- Consistency and Standards: Users should not have to wonder whether different words, situations, or actions mean the same thing. The user interface should be consistent and has to follow standard design conventions.

5- Error Prevention: The system should be carefully designed to prevent common problems from occurring in the first place. The program should also eliminate error-prone conditions and provide a confirmation option when an unexpected error occurs.

6- Recognition Rather than Recall: The objects, actions, and options should all be visible. Users do not have to remember information from one part of the program to another. Instructions for use of the system should be visible or easily retrievable so users do not have to memorize the icons or any elements in the user interface.

7- Flexibility and Efficiency of Use: The system is designed to speed up interactions for expert users, but also to cater to the needs of the less experienced ones.

8- Aesthetic and Minimalist Design: The user interface should not contain information that is irrelevant. The screens should also not be loaded with too many items.

9- Help Users Recognize, Diagnose, and Recover from Errors: The system should articulate the error messages in plain language that does not include programmer code but indicates the problem, and should constructively suggest a solution.

10- Help and Documentation: The system should provide help and documentation. Information should be easy to search, focused on the user's task, list concrete steps to be carried out, and not be too large.

The above parameters have been well-documented in the prior studies and employed in an extensive research as a protocol for usability assessment. It is worth mentioning however, these usability heuristics are often incorporated with tailored metrics that fit various web site designs (Jimenez et al., 2016; Oztekin et al., 2010; Reeves et al., 2002; Zaharias & Poylymenakou, 2009). For instance, in the e-learning context, Reeves et al. (2002) developed an elaborated checklist that integrated Nielsen and Mack (1994) usability heuristics with the instructional design heuristics that are specific to e-learning systems. They expanded the Nielsen and Mack (1994) original 10 heuristics to 15 heuristics that focused closely on online learning. Interactivity, message design, learning design, instructional assessment and media integration were further added for the assessment of e-learning solutions, given that content design and interaction are vital aspects of students' and lecturers' experiences. This supports the view that e-learning systems should include specific heuristics that are aligned with instructional design. The main contribution of this study was the inclusion of an e-learning heuristic evaluation protocol. Several researchers employed Reeves et al. (2002) heuristics in e-learning contexts (Dringus & Cohen, 2005; Oztekin et al., 2010; Zaharias, 2009). In an empirical measurement, the heuristic sets exhibited a high coverage of usability problems at 95 percent of the identified usability issues (Zaharias & Koutsabasis, 2011). Although the authors asserted that the developed heuristics are considered all-inclusive, evaluators may modify, add or delete some of guidelines based on the nature of the assessment as well as the specific e-learning system in question. Yet the need for further empirical validity and reliability in the Zaharias and Koutsabasis's model (2011) is still evident.

Many standardised questionnaires have sought to evaluate the usability of the system as a whole (such as System Usability Scale SUS). In an inquiry-based method, several standardized questionnaires have been developed for usability evaluation. For instance, "Software usability measurement inventory" (SUMI), "Questionnaire for user interface satisfaction" (QUIS), and System Usability Scale (SUS), Website Analysis and Measurement Inventory (WAMMI), Computer System Usability Questionnaire (CSUQ), and Usefulness, Satisfaction and Ease of Use (USE) are the most common criteria in the literature. While this method offers valuable holistic usability results, some researchers argue that it is more effective to assess usability components in isolation and examine the impact of users' experiences on their use of specific technology (Hornbæk & Hertzum, 2017). These questionnaires were specifically developed to evaluate aspects of system usability for which validity and reliability have been established. However, these standardised generic instruments are considered to be broad, and do not reflect the context of use under consideration and in some cases, limit the scope of usability evaluation (Hornbæk, 2006). For instance, SUS is composed of ten general statements about system usability in which no attempt is made to rate different usability variables such as learnability and consistency in a more detailed manner. Although the scale includes a fixed number of factors, it remains insensitive to other usability factors that are important to users or to the context and system under investigation (Hertzum, 2010). Furthermore, David (2014) showed that the level of abstraction on some designs principles are rather inconsistent and confusing. The usability can be composed into different qualities and attributes subject to the type of system under investigation. Therefore, some usability measurements can be viewed as too broad to adapt in a specific context such as the LMS context. Thus, based on the study's objectives, specific e-learning attributes will be selected to assess student's reactions to these elements

2.5.4 The Importance of Usability in E-learning Context

It is important to emphasize that usability is distinct from instruction. Instruction can be viewed as the teaching and learning (the message) while usability can be understood as a way to facilitate and optimise the instruction (the wrapping of the message) (Koohang & Du Plessis, 2004). The authors emphasised that usability is a critical aspect of an e-learning system for effective learning outcomes. In fact, there has been a connection between the utilization of the most LMS features and the students' better academic performance (Jo et al., 2014). Students who frequently logged into an LMS and accessed and used most of the e-learning system functionalities during the module lifecycle, attained greater academic performance compared to others (Jo et al., 2014). However, more usage does not necessarily mean more benefits (DeLone & McLean, 2003). The quality and effective use of an LMS is also critical in students' outcomes (DeLone & McLean, 2003). Hence, usability assessment has become important for the effective use of LMS.

However, the increased use of e-learning systems in education has posed many challenges to both students and lecturers. The ease or difficulty that learners experience with these complex systems determines their success or failure. Users might encounter significant challenges with an e-learning system interface – navigational issues, the lack of visibility and consistency and the lack of access functionality – yet these users still interact with the system interface without realizing how these problems affect their learning and interaction experience (Dringus & Cohen, 2005). It has previously been observed that the frustrating experiences that users have confronted in using software was due to absent, hard to find and unusable features of the system (Lazar et al., 2006). For instance, inconsistency, unnecessary complexities and lack of functionalities are obstacles that lead to poor user performance

(Shneiderman et al., 2017). It has been reported in many studies that deficient usability of e-learning applications may lead to several nuisances such as lack of control, navigational disorientation, poor instructional assessment, and poor interactivity and feedback problems (Zaharias, 2009). In fact, some educational institutions seem to fail to accomplish their strategic goals and objectives due to the absence of usability.

The usability issues of e-learning systems should be addressed in order to create an effective learning environment (Althobaiti & Mayhew, 2016). In particular, the quality and effectiveness of e-learning systems is an important factor to explore for usability assessment (Inversini et al., 2006). Liaw (2008) in his notable study of e-learning effectiveness, found that e-learning system quality and interactivity significantly contributed to LMS effectiveness. He also found that some learners were dissatisfied with the Blackboard system and drew the conclusion that understanding learners' perceptions of the usability qualities of the system is crucial for effective system usage (Liaw, 2008). Also, a strong correlation was observed between students' behavioural intention and Blackboard system effectiveness (Liaw, 2008). Several lines of evidence reported that identifying learners' attitudes towards an LMS is considered significant for e-learning success (Selim, 2007). So students would prefer to use the e-learning system if it facilitates their learning process and helps them achieve their goals. Therefore, research concludes that in order to assess the effectiveness of an e-learning system, it is necessary to understand the target group's perceptions towards the system (Liaw et al., 2007; Selim, 2007). Hence, it has become evident that students' needs, preferences and expectations should be assessed in order to have successful and effective learning. The investigation of learner attitudes is underpinned by some usability criteria such as ease of navigation, learnability, visual design, consistency, content and communication tools' capability (Zaharias, 2009). Similarly, Asarbakhsh and Sandars (2013) emphasised that it is essential to consider technological design aspects such as navigation, learnability, visual design and consistency in the evaluation of e-learning systems.

An empirical study by Roca, Chiu and Martínez (2006) found that system usefulness along with the systems' information and service quality are important factors influencing e-learning system success. They affirmed that usability attributes such as ease of use and usefulness are important elements in e-learning system acceptance. An e-learning system that is easy to use, consistent and user-friendly will motivate users to use it (Roca et al., 2006). In a similar study, system quality of a virtual learning environment was found to have considerable impact on students' behavioural intention to use the system (Poelmans et al., 2008). Therefore, system quality is considered as an important indicator of the effective implementation of an e-learning system. It encompasses many features such as usability, security responsiveness and personalization (Shee & Wang, 2008).

In a Saudi educational context, a mixed method approach was employed to investigate the critical success factors for e-learning implementation (Noorulhasan et al., 2017). The results found that the system and technological dimensions were the most critical to the success of e-learning implementation. Factors such as ease of access, ease of use, technical support, e-learning infrastructure and appropriate feedback significantly influence the usages of e-learning systems in Saudi universities (Noorulhasan et al., 2017).

In a similar study, Alhabeeb and Rowley (2018) have examined and prioritised the critical success factors for e-learning systems in Saudi Arabian higher education. Students have regarded technology infrastructure, students' characteristics, e-learning system resources and support and training as being the most important factors for their academic success. In particular, ease of browsing, ease of access and communication tools are of prime importance. They also consider instructors' characteristics, including instructors' enthusiasms, competency and motivation for using an e-learning system, as critical factors to student's success. Alotaibi (2017) demonstrated that a proprietary LMS seems to be implemented without proper focus on usability criteria, so there is a plenty of scope for conducting a usability evaluation, emphasising the usability issues in relation to the use of an LMS. Yet there is a need for a framework to evaluate the usability of an LMS (Alotaibi, 2017). Understanding the system characteristics and their impact on student behavioural intention and use of e-learning contribute to the current and future technology design and implementation process (Holden & Rada, 2011).

Therefore, in order to implement a successful LMS, usability principles, tailored to the system, should be considered. Table 2.1 presents some usability studies in the e-learning context. The evaluation of e-learning tools should take into consideration several design principles pertaining to e-learning (Granić, 2008). This leads to an improvement in the system ease of use, reducing the time spent in learning and accomplishing tasks, boosting productivity and greater user satisfaction. As the proliferation of e-learning technologies for module delivery is accelerating rapidly, practitioner and developers need to examine the effectiveness of these applications regarding usability principles (Scott & Vanoirbeek, 2007). There is a consensus among educationalists that usability attributes should be carefully measured in order to evaluate the effectiveness of an LMS (Alotaibi, 2017; Althobaiti & Mayhew, 2016; Kim & Lee, 2008; Liaw et al., 2007; Mtebe, 2015; Roca et al., 2006; Sun et al., 2008).

Table 2.1 Domain-Specific Usability Evaluation Studies

Study	Context	Methodology	Attributes	Validation
Koohang and Paliszkiewicz (2016)	e-Learning system	Literature review	Developed a theoretical model of four interrelated components: Fundamental (simplicity, comfort, user friendly, control, navigability and load time) Appearance (recognition, visual appearance, consistency, and well-organized) Information presentation (understandability, relevancy, adequacy, and right to the point) Communication (technical communication, direction/instruction, feedback, visual models of all content, provision	A Likert-scale instrument was tested using a variance-based Structural Equation Modeling (SEM) package that uses Partial Least Square (PLS) in USA

Study	Context	Methodology	Attributes	Validation
			of basic information via Q&A, and search/inquiry)	
Orfanou, Tselios, and Katsanos (2015)	e-Learning system	Literature review	System Usability Scale (SUS)	Inquiry-based method They conducted eleven studies with 769 students.
Mtebe & Kissaka (2015)	LMS	Existing heuristics and studies	10 Nielsen's heuristics Instructional materials Collaborative learning Learner control Feedback and assessment Accessibility Motivation to learn	Heuristics evaluation with five experts in Africa
Granić and Ćukušić (2011)	e-Learning system	End users assessment and expert inspection (quantitative and qualitative analysis)	Memorability: Memory test for System functions Attitude questionnaire: SUS scale Interview Usability criteria: accuracy of task completion, task completion time and satisfaction	Students, teachers and experts of several European countries
Davids et al. (2013)	e-Learning	Heuristics evaluation and user testing	10 Nielsen's heuristics Intuitive visual layout	Six inspectors to identify usability problems and assign severity scores to each problem end users are directly observed while using the application
Oztekin, Kong, and Uysa (2010)	e-Learning system	Existing heuristics in usability and quality-related checklist	Error prevention Visibility Flexibility Course management Interactivity, feedback and help Accessibility Consistency Assessment Memorability Completeness Aesthetics Reduce redundancy	Learner-based questionnaires , factor analysis and Structural Equational Modelling in USA
Alsumait and Al-Osaimi (2009)	Child e-learning application	Guidelines and existing heuristics	10 Nielsen's heuristics Multimedia representations Attractive screen layout	Using four experts and user testing in Kuwait

Study	Context	Methodology	Attributes	Validation
			Appropriate hardware Challenge the child Evoke child mental imagery Support Child Curiosity Learning content design Assessment Motivation to learn Interactivity Accessible	
Zaharias (2009)	e-Learning application	Literature review	Learnability Accessibility Consistency Navigation Visual design Interactivity Content and resources Instructional feedback Instructional assessment Media use Learner guidance and support Learning strategies design	None
Zaharias and Poylymenakou (2009)	e-Learning application	Literature review	Content Learning support Visual design Navigation Accessibility Interactivity Self-assessment and learnability Motivation to learn	Two empiricalstudies of learner-based questionnaires and factor analysis in corporate settings
Ssemugabi and De Villiers (2007)	Web-based e-Learning application	Existing heuristics, model and learning theories	10 Nielsen's heuristics Navigation Relevance of content Clarity of objectives Collaborative learning Learner control Support significant approaches to learning Cognitive error recognition, diagnosis and recovery Feedback Context meaningful to domain and learner Motivation	Student-based questionnaires and focus groups in South Africa
Dringus and Cohen (2005)	e-Learning system	Expanded existing heuristics	Visibility Functionality Aesthetics Feedback and help	Faculty and students testing of online modules to produce an

Study	Context	Methodology	Attributes	Validation
			Error prevention Memorability Course management Interactivity Flexibility Consistency Efficiency Reducing redundancy Accessibility	adaptable usability checklist
Reeves et al. (2002)	e-Learning application in USA	Existing heuristics	Visibility and System Status Match between system and weal world Error recovery and exiting Consistency and standards Error prevention. Navigation support Aesthetics Help and documentation Interactivity Message design Learning design Media integration Instructional assessment Resources Feedback	Using experts in the USA

2.6 Summary

This chapter has presented and discussed three themes – e-learning, technology acceptance theories and usability – which are significant for this research. The first theme provided an overview of e-learning, its definitions, characteristics, types, advantages and disadvantages. It then defined learning management systems and the system under investigation (i.e., Blackboard). The next section reviewed the existing literature in relation to technology acceptance models. In particular, this literature review presented and discussed the theoretical background of the UTAUT framework and the published works for a better understanding of students' behavioural intention to use and adopt an LMS in Saudi higher education and internationally. The studies reviewed varied significantly in terms of research aim and objectives, research approaches (e.g., quantitative vs. qualitative), research data (e.g., students, instructors), and context of study (e.g., country, location, culture). The last theme dealt with usability. It began by defining usability, and then presented an overview of perceived usability. Then the most common usability evaluation methods were presented. The section also emphasised the importance of usability in an e-learning context. The next chapter will outline the theoretical framework used for this study. It is the foundation of the current research that encompasses the UTAUT variables, usability attributes and moderators.

CHAPTER 3: CONCEPTUAL FRAMEWORK

3.1 Introduction

In formulating a theoretical perspective for studying the behavioural intention and use of LMSs in Saudi higher education, UTAUT provides a useful prototype. The conceptual framework is a set of structural relationships, that is, connections between the conceptual variables that formalize a theory. The constructs that constitute the theory represent broad thoughts about abstract ideas, and typically, researchers establish indicators (questions) to measure (Sarstedt et al., 2016). The conceptual framework in this study will be developed based on UTAUT discussed in the literature review. UTAUT will be extended with the identified usability attributes to measure students' behavioural intentions and their actual use of an LMS in Saudi higher education. This unified conception indicates that a set of attributes were posited to influence the use of the LMS in Saudi tertiary education. The proposed model will frame the empirical inquiry, the data collection and the analysis of this research. The objective is to enhance the model with usability metrics that might influence the students use of the e-learning system and empirically validate the model in a non-western context.

This chapter presents a justification for, and explanation of, the conceptual framework that is central to this research. To begin with, the justification of UTAUT selection is presented. Since the perceived usability is incorporated into technology acceptance theory (UTAUT), the prior literature that linked the two concepts is discussed subsequently. The discussion further justifies the proposition of the selected usability parameters. The last element of this chapter is a detailed description of the UTAUT variables, usability attributes and the moderators as well as the proposed hypotheses. This form the fundamental phenomena under investigation.

3.2 Justification of the Utilization of the UTAUT Model

The investigation of the acceptance of e-learning technologies and their adoption has been based on the prior literature of information systems acceptance. Many models have been applied in previous studies of technology acceptance, each of which attempts to explain the determinants of user behaviour and how users come to accept and use an information system. To begin with, the foundation of UTAUT is grounded in eight original models and theories of an individual's acceptance and motivations. These robust theories were developed over a long time from diverse research areas such as information systems, behavioural psychology and innovation. Unlike other models which deal with a specific type of adoption environment, UTAUT is particularly designed for the adoption of computer-based information technologies. The model has been adopted in measuring individual's acceptance and the adoption of a technology (Venkatesh et al., 2003). Despite the claim that UTAUT is a relatively new model, several published studies have extensively extended and tested UTAUT validity, applicability and reliability in many organisational environments, including online banking (Al-Qeisi et al., 2015) e-government (AlAwadhi & Morris, 2008), and commercial enterprises (Algharibi & Arvanitis, 2011). It is a well-recognised model in understanding the acceptance and use of a technology (Venkatesh et al., 2003).

The inclusion in the UTAUT of important moderators such as age, gender and experience has made the model more robust than other developed theories (Venkatesh et al., 2003). Moderators assist in explaining the role of different personal characteristics on user acceptance (Sun & Zhang, 2006). However, much prior research has overlooked the effect of moderating variables which might be distorting the actual performance of the theory (Dwivedi et al., 2011). To overcome this inadequacy, this study is enriched by studying four personal moderators in a non-Western context such as Saudi Arabia, which made the UTAUT model a useful prototype.

Furthermore, in the light of the extensive literature review of various technology acceptance theories, the selection of UTAUT was also due to its comprehensiveness and powerful explanatory power in the students' willingness to use the e-learning system (Khechine et al., 2016). The integrated UTAUT model shows a powerful predictive explanation, amounting to 70% of the variance in behavioural intention to use technology (Venkatesh et al., 2003). It is now well established from a variety of studies, that the UTAUT model is robust in the IS acceptance research (Khechine et al., 2016).

From a cultural perspective, there are still contexts in which UTAUT needs to be applied and explored. LMSs at educational institutions in Saudi Arabia to facilitate the learning process is a case in point. A meta-analysis of UTAUT examinations shows that the model has already been validated and used in developed countries but highlights that UTAUT models have been insufficiently validated in culturally dissimilar environments (Straub, 2009; Venkatesh et al., 2003). UTAUT needs to be meticulously assessed to validate its relevance in developing countries (Schaik, 2011; Straub, 2009), such as the Saudi Arabian educational setting. The motivation for further investigation of UTAUT within the Saudi environment was derived from the need for LMS acceptance to be measured nationally in a context where gender education is segregated. It has been shown that the attitudes of individuals towards a web-based application are different across cultures (Li & Kirkup, 2007). Similarly, there is a number of large cross-sectional studies which suggest that standard learning management tools have been shown to have cultural differences (Al-Gahtani et al., 2007; Algharibi & Arvanitis, 2011; Im et al., 2011; Li & Kirkup, 2007; Oshlyansky, 2007; Venkatesh & Zhang, 2010).

In the literature on technology acceptance, the relative importance of UTAUT validation in dissimilar cultures has been subject to considerable discussion. In an attempt to validate UTAUT, Oshlyansky (2007) carried out a study that examined the model against nine countries, including Saudi Arabia. The data were collected from both postgraduate and undergraduate students. The study confirmed that only native responses were used for the analysis to ensure the homogeneity of representatives among the study sample. The UTAUT instrument worked as intended for each sample and the translation did not affect the performance of UTAUT. The statistical procedure of Principle Component Analysis (PCA) was used to analyse the collected data. Even though all factors were loaded together in the sample, some appeared to have a varying amount of influence. In particular, social construct emerged significantly in Saudi Arabian participants, signifying that the social influence variable had greater weight on website acceptance in the Saudi context than other nations. The UTAUT model seems to be robust across cultures, withstanding translation into dissimilar languages. Although the model is valuable in explaining behavioural intention and use of technology in cross-cultural environments, there has been limited utilization of studies of UTAUT theory in Saudi higher education (Alshehri et al., 2019a). Furthermore, in other studies, the relationship between constructs in the UTAUT model tends to be affected by cultures (Im et al., 2011; Taiwo & Downe, 2013), which is another motivation to adapt the UTAUT theory.

Drawing on the arguments discussed in the previous sections and the critically reviewed literature presented in section 2.4, the UTAUT seems to be the most appropriate model to adopt in this research. It has become important to apply the model to different non-western contexts such as Saudi Arabia. The employment of the model in the Saudi educational environment could add to existing literature with regard to the validity and reliability of the model. The model's comprehensiveness, reliability and validity act as powerful stimuli to adapt and validate in a different context such as Saudi Arabia. It will thus be used to identify the factors that influence the students' acceptance and adoption of an LMS in Saudi higher education.

Although the UTAUT model is deemed robust in measuring the behavioural intention of individuals, the theory was not designed to be validated in an educational environment without any modifications or extensions. The educational environment is not comparable with that in a firm, where the UTAUT have been tested, hence the special characteristics of learning and teaching should be reflected. The data reported here appear to support the assumption that UTAUT fails to include significant usability principles such as learnability, navigation, visual design, information quality, instructional assessment, and interactivity. Therefore, usability attributes are to be incorporated with the UTAUT model variables in which e-learning adoption could be better explained by such amalgamation.

3.3 Technology Acceptance and Usability

Despite the growing interest in system usability, little is understood about the relationship between the usability factors and the users' attitudes and intention behaviour. Usability parameters exhibited positive correlations with the learners' intention to use an LMS (Liaw et al., 2007). However, a review of prior studies and the attempts made to link usability parameters with technology acceptance can provide useful insights, key resources to understand the phenomena (Maxwell, 2012).

Several lines of evidence have detailed how design choices influence perceived usefulness and overall learning (Asarbakhsh & Sandars, 2013; Chaw & Tang, 2018; Oztekin et al., 2010; Van Nuland et al., 2017; Zaharias & Poylymenakou, 2009). Chaw and Tang (2018) examined the LMS system and service quality influence with LMS use, and found that those factors had a statistically significant relationship with LMS system use, as well as on the overall learning effectiveness. For instance, if a gradebook button is hidden or not located in the visible area of a webpage, students will spend time to find it, select it and check their grades. This adversely affects the usability of the system, which in turn reduces the e-learning system efficiency. Thus, the changes in usability variables will affect the students' perceived usefulness and perceived ease of use, influencing their behaviour and use of the system.

Pituch and Lee (2006) explored the effects of system characteristics as external variables on the students' intention to use the e-learning system in two modalities, supplemental and distance learning. The authors examined the influence of e-learning system functionality, interactivity and the response time on the use of the system, using a structural equation modelling technique with LISREL. For those three endogenous variables, the effects were found to be significant on both the users' beliefs and the e-learning use outcomes. The study accentuated that specific e-learning system factors can promote or inhibit the use of the e-learning system.

Theng and Sin (2012) explored the influence of four usability attributes including interaction, navigation, user interface and personalisation, on the TAM's perceived ease of use and usefulness. It was revealed that interaction had a significant influence on perceived usefulness, whereas perceived ease of use was affected by navigation and user interface qualities. However, the effect of personalization on perceived usefulness and ease of use was not found. The study further stressed the importance of including usability measures for improving the use of the LMS.

Alrawashdeh et al. (2012) structured the UTAUT model to include some critical usability attributes, such as system flexibility, system enjoyment and system interactivity that may be relevant in shaping users' intentions to use a web-based training system. The use of moderators was excluded. The findings showed that all UTAUT independent variables, including system flexibility, system enjoyment and system interactivity characteristics, significantly influence behavioural intention. The results also indicated that the three new success attributes of usability affected performance expectancy and effort expectancy. From this study, it can be seen that the new usability attributes have a significant influence on individuals' behaviour.

Similarly, Holden and Rada (2011) extended the TAM model to include usability measures for evaluating the influence of usability on the usage behaviour of educational technology. He included six usability measurements to the students' perceived ease of use element including productivity, effectiveness, learnability, functionality, navigation and memorability to understand their impact on the e-learning system use. The study implemented a questionnaire to garner the subjective perceptions of individuals regarding the proposed usability metrics. Utilizing various statistical techniques and procedures for analysis, the combined elements of perceived ease of use and perceived usefulness explained 63% in the variance, whereas the perceived ease of use with usability parameters explained 77% of the variance in the outcome variables. The findings validated that the incorporation of perceived usability variables into the TAM model was more influential in individual behaviour than TAM factors, as it has explained more variances. The authors emphasized the need to evaluate usability when examining users' acceptance and adoption of the e-learning system.

In Saudi tertiary education, Almaiah and Alyoussef (2019) extended the UTAUT model to explore the role of module design, module content support, module assessment and instructor characteristics on the use and acceptance of LMS among students. The results revealed that module design, module content support, module assessment and instructor characteristics have a positive significant effect on the behavioural intention as well as performance expectancy. So usability variable such as LMS visual design and content and assessment are expected to play an important role in students use of LMS in Saudi universities.

It is now well established from a variety of studies that the TAM model and its successors have been limited in informing design for consumer products (Hornbæk & Hertzum, 2017). TAM was developed mainly to predict the use of an information system in an enterprise. Usability research, on the other hand, put a great emphasis on the experience and the consequences of using interactive systems. The experience refers to the users' perceptions about the system whereas, the consequences of experience is typically understood as the summary evaluation such as the overall judgment of satisfaction afterwards use. The interface quality aspects are central to systems usability, making it broader than technology acceptance in terms of informing design characteristics and their impact on consumer products. Still, the overlap between technology acceptance research and usability studies is lacking and a combination of the two strands of research is needed to enrich the body of knowledge of user adoption. This view is supported by Holden and Rada (2011) who suggested extending the technology acceptance model with usability variables to form a unified framework for the better assessment of the usage behaviour of a given system. The two directions can be converged on that, prediction informs the design, and the usability factors solidifies prediction in technology acceptance (Hornbæk & Hertzum, 2017). Thus, the proposed model will be extended to incorporate the perceived usability attributes of an educational system. This allows examination of the users' views on different usability components and attempting to progress the research forward in this area. The ultimate aim of this endeavour is to examine the perceptions of students using an LMS and the influence of perceived usability factors on technology acceptance and use.

Drawn from the previous literature, one can observe the importance of incorporating perceived usability into the technology acceptance models. As noted, generally, there is a dearth of research of the influence of usability metrics on technology acceptance and use. To be specific, such expositions are even more scarce when it comes to e-learning context in a developing country such as Saudi Arabia. The generalisability of these results is subject to certain limitations. For instance, some of these studies target an institution or organisation, so researchers are cautious about drawing any conclusions based on a single study. In addition, most of the previous research adapted general usability attributes and these might not sufficiently reflect the specificity of LMS environment, such as the LMS information quality. It is logical to conclude with a conceptual framework that integrates relevant usability attributes with UTAUT theory to investigate the factors and potential constructs that affect students' perceptions of LMS use in Saudi tertiary education. This area of research has received little attention with respect to learning management systems in developing countries such as Saudi Arabia. Therefore, the goal of this endeavour is to understand the influence of usability, social and organisational factors on a student's decision to use, or not to use, an LMS.

3.4 Justification for the Selected Usability Attributes

It is essential to identify the usability variables desired for a learning management system in the educational environment in Saudi higher education. It is often believed that choosing usability measures is difficult, especially with the different variety of factors available (Hornbæk, 2006). The usability cannot be directly measured, it has to be broken down into small components (e.g., navigation and interactivity), and these components differ depending on system and context (Hornbæk, 2006). Hence, the question of which measures of usability to select is therefore central in many approaches to the design and development of user interface (Hornbæk, 2006). The goal is to identify the usability metrics that have the most influence on the students' learning process in an educational context. It has thus been suggested to explore the current studies and check for measures that are relevant in an e-learning context (Hornbæk, 2006). The usability of an LMS goes beyond module management to the technological attributes that are necessary to facilitate the assimilation of students into the online learning community, where students can interact, exchange knowledge and collaborate to enhance the learning process (Medina-Flores & Morales-Gamboa, 2015).

A seminal study in this area is the work of Zaharias and Poylymenakou (2009) which described the questionnaire-based usability evaluation method that extends the current research practice, to include affective considerations that might affect e-learning usability. Eight usability attributes were identified: content quality, learning support, visual design, navigation, interactivity, accessibility, instructional assessment, and learnability. The proposed framework also combines Web and instructional design attributes with affective learning indicators such as intrinsic motivation to learn. The new usability measurement was tested in two extensive empirical studies in corporate settings with the primary focus on reliability and validity of the method. The results presented valuable evidence as to the reliability and validity of the method, verifying that the technique could be employed with confidence in e-learning usability evaluation. A further surprising finding was the high correlation between the e-learning usability and motivation to learn. The findings also allowed more reliable versions of the questionnaire to be used in further experiments. However, researchers stressed the need for further validation, especially in a different e-learning context. They also suggested a further elaboration of the checklists to measure learners' perceptions of e-learning usability.

Similarly, Dringus and Cohen (2005) developed an adaptable usability checklist for e-learning system usability evaluation. The heuristics comprise visibility, functionality, aesthetics, feedback and help, error prevention, memorability, module management, interactivity, flexibility, consistency, efficiency, reducing redundancy and accessibility. The list is comprehensive and contains concise items that can be employed easily in a learning management system evaluation. Although the checklists unveiled many usability issues and inconsistencies in the e-learning system, the need for reliability and validity analysis of the heuristics was evident.

Oztekin, Kong and Uysa (2010) drew on a Dringus and Cohen (2005) idea to produce a novel usability model (UseLearn) for e-learning systems. The study provided a categorisation of items that were found to be important and to yield the most critical and problematic usability issues in e-learning evaluation, so a usability analyst could start dealing with the classification based on their order of importance. Error prevention items stood out as being the most critical items, whereas consistency and functionality were regarded as the least important questions. Overall, the checklists not only picked up significant usability problems in the e-learning system, but provided a priority ranking of them based on their importance.

Surveys such as that conducted by Althobaiti and Mayhew (2016) assessed the usability of the Jusur system, an LMS developed and operated by the National Center for E-learning and Distance Learning (NCeDL) in some of the Saudi Arabian Universities. They used a questionnaire-based method, incorporating Zaharias and Poylymenakou (2009) usability principles into a survey including content, learning and support, visual design, navigation, accessibility, interactivity, self-assessment, learnability, and motivation. The overall response to the survey was positive. Most students appeared to agree with positive statements regarding usability attributes, signifying that the Jusur e-learning system is usable and desirable from the students' perspective.

In a study which set out to determine the students' major usability concerns regarding their learning management system (Sakai), Boateng (2017) discovered the need to improve usability, especially regarding navigation, learnability, visual design, consistency and design simplicity. The study confirmed, in the design and evaluation of the e-learning system, that the usability elements should be considered, to enable learners to successfully engage in an online environment.

Drawing on the previous relevant literature, one can observe that the usability factors -pertaining to e-learning-system evaluation have been diverse, and there is no consensus between scholars and experts about the dimensions and factors that should be utilised in the educational environments. This claim is supported by Orehovački, Granić and Kermek (2013), who claim that there is no agreement about the quality standards that reflect the e-learning system. Hence, there is abundant room for further progress in determining the significant and relevant usability factors in the e-learning system usability assessment. Furthermore, most of the reviewed studies reported several problems with perceived usability in e-learning systems, either organisational, technical or functional issues, from different stakeholders. To this end, this research will attempt to identify the important usability parameters in the use of LMS in a Saudi context, and then evaluate their influence in the students' behavioural intention and use of the system.

In this research, the UTAUT theory was extended with six usability dimensions: System Navigation (SN), Visual Design (VD), System Learnability (SL), Information Quality (IQ), Instructional Assessment (IA) and the E-learning System Interactivity (ESI). There are many variables collected in prior studies. However, due to the overlapping features, the identified metrics were classified, and similar ones were grouped together to form the main criteria. It is claimed that most usability studies contain many overlapping items so methods and checklists could be merged to generate a customised method in the specific e-learning context (Oztekin et al., 2010). In fact, it is difficult to employ the entire dimensions with all sub-item questions for the e-learning system usability evaluation. Thus, an attempt was made to decrease the number of dimensions to select variables that measure similar concepts. This is why usability specialists prefer to specify the most important usability features in a given context in order to improve the overall usability (Oztekin et al., 2010). This is also in line with Zaharias and Koutsabasis's (2011) conclusion, which states that the current research of some models in usability heuristics of e-learning systems is in the initial stage and requires further elaboration and testing.

There are four reasons why these six attributes have been specifically employed in the research's theoretical framework. To begin with, the variables have been validated extensively in prior studies of e-learning system evaluation (Alshehri et al., 2019b; Althobaiti & Mayhew, 2016; Binyamin et al., 2019a; Reeves et al., 2002; Zaharias & Koutsabasis, 2011; Zaharias & Poylymenakou, 2009). The heuristics have been employed specifically in the design and evaluation of e-learning systems and were found to identify common areas of usability problems across web-based learning applications. The indicators have been well-established in, and performed well in terms of validity and reliability, in prior quantitative research on e-learning systems. It has been shown that system characteristics is a major area of interest within the field of e-learning system which seems to be important *a priori* (Hornbæk & Hertzum, 2017). Secondly, a study was carried out to identify the most important usability metrics in e-learning system evaluation from Saudi students' point of views (Alshehri et al., 2019b). A quantitative approach was adopted to classify usability variables based on student's preferences and perceptions in Saudi higher education. These parameters have been collected from the usability measures that were examined in the educational context. Based on 181 students' perceptions, the six usability criteria were found to be important in the use of the e-learning system in Saudi higher education (Alshehri et al., 2019b). Thirdly, the selected usability principles were tested in Saudi tertiary education, adding to the validity and reliability of the variables in a new context. As outlined previously by many experts (Althobaiti & Mayhew, 2016; Oztekin et al., 2010; Zaharias & Poylymenakou, 2009), considerably more work will need to be done to validate the usability attributes in diverse contexts, with different systems and users; hence this was another motivation to apply the variables in the Saudi Arabian educational context. Finally, the proposed model has been tested using PLS-SEM, a sophisticated multivariate analysis. This not only enhances the validity of the variables in Saudi Arabia using PLS-SEM but also adds to the novelty and originality to the current study.

3.5 The Research Conceptual Model

The conceptual framework is a visual representation of the variables and the presumed relationships among them (Maxwell, 2012). It is a theory or a model to be examined, that is not fully understood (Maxwell, 2012). It has been advised that the most productive conceptual frameworks are often those that connect ideas of different approaches or theories that no one has previously investigated (Maxwell, 2012). In this study, the UTAUT is conceptualised as a knowledge base and the model is further extended with usability principles. The UTAUT predictors and usability attributes will form the independent variables, and the study will measure the influence of the independent variables on the students' intentions and use of an LMS, considering the posited moderating effects of gender, age, experience and training on the model's key determinants. The study's conceptual model is depicted in Figure 3.12. In total, the theoretical model postulates ten factors that are hypothesized to influence behavioural intention to use the LMS in the Saudi context. The determinants are those who (probably) cause or influence outcomes. They are also called independent predictors and antecedent attributes (Creswell & Creswell, 2018).

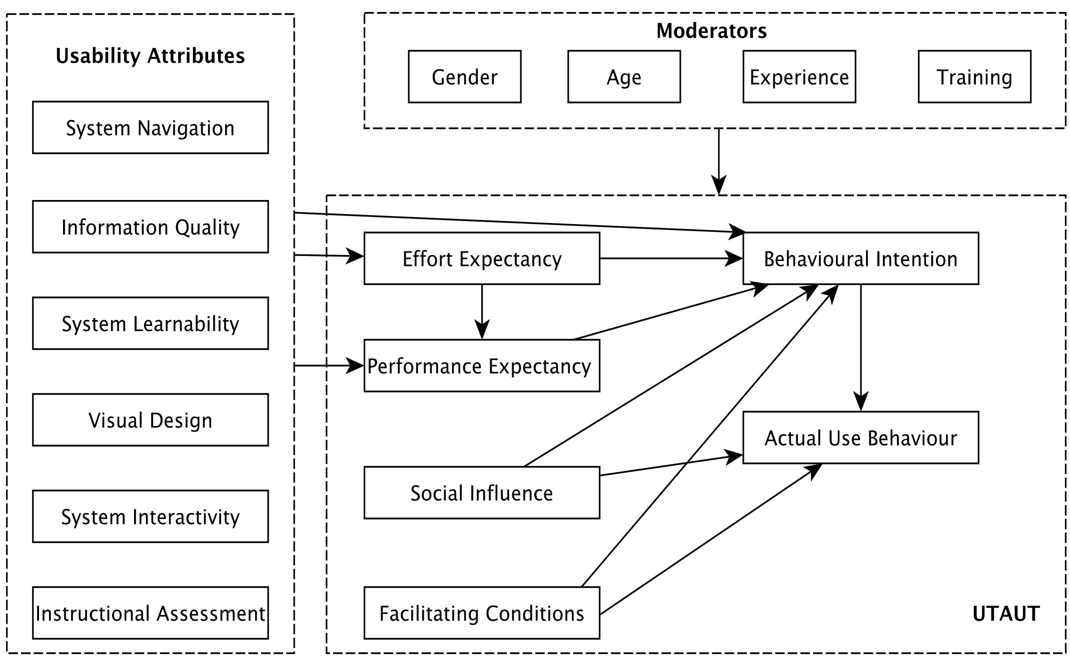

Figure 3.12 The Proposed Conceptual Model

This chapter lays out the theoretical dimensions of the research and looks at the UTAUT variables and the usability attributes with the hypotheses. The first category to be discussed comprises the UTAUT predictors, which include Performance

Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). It also comprises the dependent variables, namely Behavioural Intention (BI) and Actual Use (AU). The second category consists of the identified usability variables: System Navigation (SN), Visual Design (VD), System Learnability (SL), Information Quality (IQ), Instructional Assessment (IA) and E-learning System Interactivity (ESI). The third category is a group of moderators – gender, age, experience and training – that might influence the relationship between the variables (refer to Figure 3.12). The study will evaluate the effects of usability variables with UTAUT factors on student intention and use of an e-learning system. Throughout the rest of this chapter, a discussion of the model constructs will be presented. In particular, the direct relationships between the proposed model's variables are hypothesised and justified by reviewing previous studies that proposed similar hypotheses in the domain of acceptance and use of e-learning systems.

3.6 UTAUT Variables:

The theoretical framework begins by discussing the base model (UTAUT) variables as follows.

3.6.1 Performance Expectancy (PE):

Performance expectancy is concerned with individuals' beliefs that a system use will enhance their job performance to perform various tasks (Venkatesh et al., 2003). In this study, it is the extent to which students believe that using an e-learning system will enhance the learning outcomes by accomplishing the learning activities. This particular learning uplifts the students' educational performance and skills by achieving excellent grades in their coursework (Salloum & Shaalan, 2019). This scale represents a similar function to perceived usefulness in TAM and relative advantage in IDT. In fact, PE was derived from a combination of five similar constructs found in the previous models, including perceived usefulness, relative advantage, outcome expectation, job-fit and extrinsic motivation (Venkatesh et al., 2003). Users tend to use the system if they believe that the system helps them perform their job better

(Davis, 1989; Lin, 2013). The more presumptions that learners form about the promising usefulness of an e-learning system, the more chance there is that they will use or continue to use the system in the future (Halawi & McCarthy, 2008). The e-learning system enables students to access various resources regardless of time and geographical boundaries, add more flexibility and control over their work and ultimately enhances their productivity (Ameen et al., 2019). In the absence of this PE, the system will not be utilised even if it easy to use, easy to learn, and satisfying to use. The driver for using stems from the fact that the system supports users in achieving their specific goals.

Many studies have shown that PE is a significant determinant of BI to use e-learning system (Alrawashdeh et al., 2012; Bellaaj et al., 2015; El-Masri & Tarhini, 2017; Salloum & Shaalan, 2019; Šumak et al., 2010; Usoro et al., 2013). It was noted by Venkatesh et al. (2003) in his original development of the UTAUT model, that this factor is the greatest predictor of the user's behavioural intention in all points of voluntary and mandatory settings. Similarly, Chiu and Wang (2008) found that PE had a direct influence on the BI to use a Moodle system. In prior studies, the PE construct exhibited the maximum weight on the students' intention to use the system (Chiu & Wang, 2008; Decman, 2015; Raman et al., 2014; Thongsri et al., 2019). A large and growing body of literature has revealed that the PE->BI relationship has been significant in most analysed cases of UTAUT research (Dwivedi et al., 2011; Khechine et al., 2016; Taiwo & Downe, 2013). In Saudi higher education, Ahmed et al. (2019a) and Bellaaj et al. (2015) found that PE has remarkably positive impacts on the students' intention to use an LMS. Thus, these findings suggest that the students are driven to accept the e-learning system primarily on the basis of its usefulness. In contrast, the influence of PE on students behavioural intention was statistically insignificant, and this contradicts the postulations of the original authors (Attuquayefio et al., 2014). However, in this research, it is believed that students will exhibit a willingness to use an LMS if they perceive that the system is useful in performing their academic activities. Based on the above discussion, it is hypothesised:

***H1**: Performance expectancy has a direct positive influence on students' behaviour to use an LMS.*

3.6.2 Effort Expectancy (EE)

Effort expectancy (EE) is defined as the degree of ease associated with the use of the system (Venkatesh et al., 2003). In this context, it is the students' perception of the system of either ease or difficulty associated with LMS usage. It is comparable with the TAM perceived ease of use and the complexity construct of IDT (Kijsanayotin et al., 2009). Venkatesh et al. (2003) claim that the users' acceptance of an application is determined by users' perceived ease of use. This is in line with the seminal study of TAM (Davis, 1989).

Meta-analysis such as that conducted by Khechine et al. (2016) has shown that EE is a significant determinant of BI to use an LMS. Although data from several sources have identified a significant association between EE and BI to use learning technologies (Alenezi et al., 2011; Alrawashdeh et al., 2012; Bellaaj et al., 2015; Usoro et al., 2013), this claim was not the case in other studies (Alshehri et al., 2019a; Attuquayefio et al., 2014; Jong & Wang, 2009; Park, 2009; Salloum & Shaalan, 2019; Šumak et al., 2010). El-Masri and Tarhini (2017) in their comparative analysis of 833 students between two universities in Qatar and in the USA, found the EE->BI was statistically significant in the Qatari sample, but not in the American sample. Similarly, in the studies of e-learning system acceptance of four public universities in Iran, the relationship between the system's ease of use and intention was insignificant, whereas the association between ease of use and usefulness was demonstrated to be significant (Mohammadi, 2015). Despite this discrepancy, however, this link is found to be significant in both voluntary and mandatory settings particularly at early stages of experience (Venkatesh et al., 2003). Davis (1989) validated in his classical TAM model that ease of use has a significant influence on behavioural intention as well as users' perceptions of usefulness. In fact, in prior technology acceptance research, perceived ease of use was postulated to be antecedent to perceived usefulness and BI such as those of TAM (Davis, 1989), TAM2 (Venkatesh & Davis, 2000) and TAM3

(Venkatesh & Bala, 2008). To the extent that effort expectancy leads to improved performance, the current research hypothesises is that effort expectancy has a positive effect on performance expectancy as demonstrated by several empirical investigations e.g. Ameen et al. (2019) and Moreno et al. (2017). In a Saudi university, Al-Gahtani (2016) asserted a positive relationship between the students' perception of ease of use and their perception of usefulness, as well as their behavioural intention. This is in Tandem with similar studies conducted in Saudi Arabia (Alenezi et al., 2011; Alenezi, 2012a; Binyamin et al., 2019a). Thus, when students see that an e-learning platform is easy to use, this will lead them to perceive it to be useful, which further encourages them to use it. Since the LMS is in its early stages in Saudi higher education, EE is believed to be a major quality for student's BI to use the system, as well as for the students' perception of PE. Thus, in order to further assess the relationship and confirm whether it is valid in the e-learning system with the Saudi students, it is hypothesized that:

***H2**: Effort expectancy has a direct positive influence on students' behavioural intention to use an LMS;*
***H3**: Effort expectancy has a direct positive influence on performance expectancy.*

3.6.3 Social Influence (SI)

This construct relates to individuals' perception of whether important people (friends, colleagues and family members) believe that they should use the system (Venkatesh et al., 2003). It takes into account the person's perception of other people's opinions in using technology. SI was not considered in the original TAM model, but it is similar to the subjective norm of TRA and social factors in MPCU, and image in IDT (Eckhardt et al., 2009; Venkatesh et al., 2003). In this study, it is the students' perceptions of the influence of university officials, lecturers and peers on motivating students to use an e-learning system. Thus, when students in the educational environment think they should adopt the system, they tend to conform to the opinions of others (e.g., university officials, lecturers and peers) and adopt the system (specific behaviour) (Eckhardt et al., 2009). The construct has been recognised as fundamental to technology adoption as the influence of peers, change agents, organizational pressure, and societal norms are inevitable (Rogers, 1995).

UTAUT recognizes the importance of incorporating a social component into the model such as friends' and relatives' opinions of the actual users. So individuals would become sensitive to other opinions and this influences the decisions of acceptance consistent with a set of social norms and practices. The SI construct is more relevant in e-learning since students interact with lecturers and peers when they use technology (Chu & Chen, 2016). It is expected that the relationship will be stronger in the early stages of experience in using the system. This is because the influence is stronger when individuals are more sensitive to the opinion of others (Venkatesh et al., 2003). The theory suggests that SI becomes insignificant in voluntary settings; however, the effect is stronger when the use of technology is mandated (Venkatesh et al., 2003; Venkatesh & Davis, 2000).

Previous studies have established the relationships between SI and BI in educational environments (Alrawashdeh et al., 2012; Chu & Chen, 2016; Khechine et al., 2014; North-Samardzic & Jiang, 2015; Raman et al., 2014; Salloum & Shaalan, 2019; Šumak et al., 2010; Thongsri et al., 2019; Williams et al., 2015). The direct effect of SI on BI is justified by the fact that people may be influenced by the opinions of others such as peer pressure, and thus involved in certain behaviour even if they do not want to, so the members tend to act in a way that conforms to a specific person or group (Chu & Chen, 2016). Research further suggests that the effect might be more pronounced in developing countries. El-Masri and Tarhini's (2017) study demonstrated the significant association between SI and BI in the Qatari sample but failed to prove that with the American students. Likewise, Efiloğlu Kurt and Tingöy (2017) found that the SI variable had the strongest effect on BI among the Turkish sample of students rather than the UK subpopulation. The SI, such as peer and faculty pressure, was important in students' acceptance of the e-learning system in South African context (Olasina, 2019). A similar finding was obtained in the Indonesian context, such as that of Mahande and Malago (2019) and in the Tanzanian context, such as that of Lwoga and

Komba (2015). In a Saudi context, SI was found to be an important factor for the individuals' intended behaviour towards the usage of LMS in the Saudi universities (Alshehri et al., 2019a; Soomro, 2018). In Alshehri et al.'s (2019a) study, the examination of the strength of the association between SI and BI appeared to be the strongest among all associations. Indeed, the relationship appeared to explain a third of the variance in the SI to use an LMS in the Saudi context. Park (2009) found the SI construct to be the second most important construct in influencing students BI to use an e-learning system in South Korea. Taken together, these results suggest that there is a significant association between SI and BI to perform a focal behaviour with LMS.

In addition to BI, SI can predict the students' system usage behaviour. The significant effect of SI on student's actual use behaviour was demonstrated in Jong and Wang's (2009) research. In contrast, Lwoga and Komba (2015) were unable to find a significant effect of SI on student e-learning system usage behaviour with the Tanzanian web-based LMS. Yet most studies in the field of technology acceptance have overlooked the association between SI and usage behaviour (Eckhardt et al., 2009; Weng et al., 2015). Given the uniqueness of Saudi social characteristics along with conflicting findings of previous literature, the social influence relationship with actual use will be scrutinised. Hence, the research proposes that the significant effect of SI on AU can be explained within Saudi Arabia's cultural context. In this research, the SI of instructors, students and university management will be considered as stimuli that motivate students to use LMS, thereby promoting its acceptance (Martins & Kellermanns, 2004). Following the guidelines of UTAUT, this research will study the direct effect of SI on BI as well as on the system usage behaviour. Therefore, we hypothesize that:

***H4**: Social influence has a direct positive influence on students' behavioural intention to use an LMS;*

***H5**: Social influence has a direct positive influence on students' actual usage behaviour.*

3.6.4 Facilitating Conditions (FC)

Facilitating conditions (FC) are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system (Venkatesh et al., 2003). It captures concepts derived from three previous models' constructs, including perceived behavioural control (TPB/DTPB, C-TAM-TPB), facilitating conditions (MPCU), and compatibility (IDT). In the e-learning context, FC measures whether individuals have the personal knowledge and the institutional resources available to use the system. In other words, it is the individuals' perception of how well the university provides support to overcome the challenges in using the e-learning system. It is believed that high-performance outcomes from both students and educators result from the university's support for technology. Thus, ensuring technological infrastructure is rich, reliable and capable of providing the needed support for stakeholders is a critical element for e-learning success (Selim, 2007). It is also believed that the availability of environmental resources, organisational and technical infrastructures would help the students to employ in their learning activities, thereby promoting their use of e-learning system.

This factor is believed to be significant in a voluntary and mandatory context in the initial usage experience; however, its influence decreases as the usage advances. Furthermore, Venkatesh et al. (2003) demonstrated that when both PE and EE constructs are present, FC becomes insignificant in predicting intention. However, some theoretical foundations acknowledge the effect of facilitating conditions on BI (Ajzen, 1991; Taylor & Todd, 1995a), and this was supported by the empirical findings of Eckhardt et al. (2009), Foon and Fah (2011) and Dwivedi et al. (2017). These lines of evidence reinforce the association between FC and BI even in the presence of PE and EE, in contrast to the original model (Dwivedi et al., 2017).

Even though the original UTAUT shows the effect of FC on actual usage only, we also postulate the influence on BI. Many prior studies have demonstrated a significant positive influence between FC and BI (Ain et al., 2015; Dwivedi et al., 2017; Lewis et al., 2013; Venkatesh et al., 2012), and between FC and actual use of the e-learning system (Buchanan et al., 2013; Efiloğlu Kurt & Tingöy, 2017; Khechine et al., 2014; Salloum & Shaalan, 2019). In Saudi tertiary education, the FC construct was excluded from the UTAUT model in Bellaaj (2015) and Bouznif's (2018) studies. Nonetheless, Alshehri et al.'s (2019a) study revealed that FC was the strongest predictor of LMS use in a Saudi university. Considering all of this evidence, it seems that FC will exhibit and influence students' intention to use, and usage behaviour. Thus, the following hypotheses are proposed:

H6*: Facilitating condition has a direct positive influence on students' behavioural intention to use an LMS;*
H7*: Facilitating condition has a direct positive influence on students' actual use of an LMS.*

3.6.5 Behavioural Intention (BI)

BI is defined as the probability that individuals will perform the behaviour in question (Venkatesh et al., 2003). The term BI also involves the assessment of the users' willingness to use the system (Rubin & Chisnell, 2008). In many seminal studies, the BI has been proposed to be a direct antecedent of the actual behaviour (Ajzen, 1991; Davis, 1989; Fishbein & Ajzen, 1975; Taylor & Todd, 1995a; Venkatesh et al., 2003, 2012; Venkatesh & Davis, 2000). Based on a survey of more than 400 college students using e-learning, there was a significant positive relationship between intention and behaviour (Liaw, 2008). Thus, the greater the intention that an individual forms about a certain behaviour, the more likely that performance is to occur. Taylor and Todd (1995a) found that the association between BI and actual usage behaviour was strengthened when individuals had prior experience of the technology.

In the e-learning field of study, the majority of studies revealed that the students' actual use of LMS is positively influenced by BI (Al-Gahtani et al., 2007; Alshehri et al., 2019a; Ameen et al., 2019; Mohammadi, 2015; Šumak et al., 2010). Dwivedi et al. (2011) in their meta-analysis showed that BI influence on AU is strongly correlated compared with other relationships in the UTAUT model. However, this was not the case in Attuquayefio et al.'s (2014) study, which found an insignificant effect of BI on students' usage behaviour. Nonetheless, the majority of the studies reviewed here support the hypothesis that BI influences behaviour. So the intent of the learners in employing e-learning systems plays a central role in predicting their actual use. Thus, the following hypothesis is proposed:

***H8**: Behavioural intention to use LMS has a direct positive influence on the actual usage behaviour.*

3.6.6 Actual Use (AU)

This is the actual use behaviour and adoption of a technology. It is the dependent variable in UTAUT and many previous technology acceptance theories (e.g., TRA and TPB) (Ajzen, 1991; Fishbein & Ajzen, 1975; Venkatesh et al., 2003). Usage behaviour is one of the success measures in the literature. The construct has been found to be significantly correlated with behavioural intention determinant (Davis, 1989; Fishbein & Ajzen, 1975; Taylor & Todd, 1995a; Venkatesh et al., 2003). The relationship has also been tested and validated in the development of the UTAUT model (Venkatesh et al., 2003). In this context, LMS usage is often operationalized using self-reported measures of the actual use of the system. In this endeavour, the influence triggered by the predictors on this actual use will be investigated.

3.7 Usability Variable

The following describes the usability parameters of the framework.

3.7.1 System Navigation (SN)

The quality of the system interface plays an indispensable role in the success of any technology or innovation. Website navigation has been verified to be one of the most important design characteristics across various domains, such as finance, e-commerce, entertainment, education, government as well as health and medical websites (Gilani et al., 2016; Zhang et al., 2001). As the name suggests, navigation quality concerns the visible navigational structure such as menus, links and tabs that grant individuals many options over the system elements (Gilani et al., 2016). There is a direct link between ease of navigation and the success of the use of any website (Fang & Holsapple, 2007; Gilani et al., 2016; Oztekin et al., 2009). Effectively navigating the architecture of an e-learning system is viewed as a vital condition that the students encounter when they set out to accomplish learning tasks (Koohang & Du Plessis, 2004; Triacca et al., 2004; Van Nuland et al., 2017).

In an e-learning context, and based on 8425 students, Naveh, Tubin, and Pliskin (2012) found that ease of navigation was among the success factors in using the LMS. Navigational tools enable students to locate specific content items and instructional elements, as well as to identify their position in the sequence of commands to enhance the amount of learner control. The system interface features should be well-organised and the navigation structure should be simple and intuitive, so that students can quickly and easily access all interface functionalities and navigate through the logical flow of information (Orehovački et al., 2013). Furthermore, students' perceptions of usability formed the central focus of a study by Selim (2007) in which the author found that navigation in an e-learning system impacted the decision to adopt and use the e-learning system. Students can navigate the system characteristics and functionalities (e.g., access module components) in which navigation buttons, menu, site map, movement buttons (forward, backward, and exit) and link simplicity are significant elements for the students' effective use of e-learning (Clark & Mayer, 2016).

Asarbakhsh and Sandars (2013) highlighted that navigation should be one of the primary factors to be included in the usability evaluation of the e-learning system. In a dual study that evaluated LMS usability, this attribute was found to the major obstacle that distracts students from achieving their goals (Guo et al., 2009; Tee et al., 2013). Similarly, in a Saudi university, learners encountered difficulties navigating through the e-learning system content and other features in the menu (Alturki et al., 2016). Besides, Alelaiwi and Hossain (2015) found that the majority of Saudi university students reported inconsistency in the e-learning navigation format and even that the results of clicking links might be confusing. Ahmed et al. (2019) demonstrated that system navigation emerged as the students' second most important category in the evaluation of an LMS. If the navigation structure is complicated and contains broken links, users might become disorientated when navigating and experience a heavy cognitive load when moving around the site (Tsai et al., 2017).

In a study which set out to determine the effects of usability attributes on the website acceptability in an e-commerce context, Wu et al. (2009) reported that navigation is a key indicator that promotes the BI to use. Likewise, Green and Pearson (2011) confirmed the effect of navigation on consumers' perception of ease of use. This view is also supported by Scholtz et al. (2016) in which the significant influence of navigation was demonstrated on users' perceptions of ease of use and usefulness of ERP settings. Jeong (2011) found that the navigational structure significantly correlated with the perceived ease of use and indirectly with perceived usefulness and BI to use the e-library system. In the Khan and Qutab (2016) conclusion, navigation had a higher influence on ease of use than on the usefulness of the higher education digital library in Pakistan.

In educational settings, Theng and Sin (2012) found that the navigation of LMS has a positive influence on students' perceived ease of use. This also corroborates with Tsai et al.'s (2017) research. As for antecedents to the learners' belief of ease of use and usefulness, Cheng's (2015) study revealed that e-learning system navigation has the greatest total impact. In Saudi universities, Binyamin et al. (2019a) demonstrated the significant effect of LMS navigation on students' perceptions of ease of use, yet, the effect of navigation on the students' perception of the system usefulness was not confirmed. This combination of findings provides some support for the premise that a relationship of e-learning navigation is evident. Hence, we hypothesise that:

H9: *System Navigation has a direct positive influence on performance expectancy;*
H10: *System Navigation has a direct positive influence on effort expectancy;*
H11: *System Navigation has a direct positive influence on students' behavioural intention to use an LMS.*

3.7.2 Visual Design (VD)

This attribute focuses on the aesthetic aspects of the system by considering the effects of images, colours, fonts and general layouts (Usability.gov, 2013). An effective visual structure and design ensures that the content remains central to the system. The structural design of the interface offers features and support whereby users can interact with the system components. The choice of colour in the e-learning system not only catches learners’ attention, but also improves learnability and ease of use (Zaharias, 2009). In an e-learning context, it is crucial for learners to find and understand the content of the e-learning modules easily and effectively, so the appropriate use of graphics and colour should facilitate this process. Similarly, the design of the e-learning system should be attractive and consistent throughout the system. It is argued that more simple and flexible the system user interface is, the less effort the students need to use the system. Overall, aesthetic appeal is essential for students’ engagement, ease and motivation with the technology, and the application interface should draw e-learners’ attention and improve the learnability and ease of use.

In an empirical finding, the overall perception of visual interface design was determined to be a critical factor in the students' acceptance and use of the e-learning system (Cho et al., 2009). Shee and Wang (2008) demonstrated that a well-designed and user-friendly user interface for an e-learning system is the most significant driver for students’ utilization of that system. Simple and flexible interface design with control toolbars and menus will promote accessibility and add further enhancement to the e-learning system’s usefulness (Cho et al., 2009). This lessens the student’s effort to access the functions and will help them to find information with ease and speed, and ultimately learn with an effective manner (Cho et al., 2009). Lanzilotti et al. (2006) proposed that the right combination of text and graphic features inspires students to stay longer in the e-learning module and explore it further. Following a series of measurements in two extensive empirical studies, Zaharias and Poylymenakou (2009) found that the usability VD indicator exhibited a high score in the e-learning system usability evaluation. Yet, the VD of an e-learning system is often overlooked and in many cases, treated as a minor cosmetic detail (Horton, 2011). In fact, the -learning system VD was confirmed to have an impact on students’ learning outcomes (Kirsh, 2014). The success of an e-learning system depends largely on the visual presentation of the tools, content and support (Kirsh, 2014). Thuseethan et al.’s (2014) study revealed that visual inconsistencies in e-learning system design resulted in chaos and lack of interaction from the students' perspective. In Saudi higher education, a recent study confirmed the importance of LMS aesthetic design on the utilization of LMSs at universities (Almaiah & Al Mulhem, 2018; Noorulhasan et al., 2017).

Previously published studies on the effect of VD on technology acceptance seem to be limited (Binyamin et al., 2019a), and in many cases, tend to be indeterminate. It has been demonstrated that visual cues play a key role in the consumers' intention in an e-commerce context (Shaouf et al., 2016). This corresponds with the study conducted by Jeong (2011) who found statistical evidence as to the link between screen design and the usefulness of e-library systems. Cho et al. (2009) have found that perceived user-interface design of an e-learning system indirectly influences continued usage intention through perceived usefulness and perceived ease of use. It was also found that the LMS interface design affected considerably the usefulness of the system (Cho et al., 2009; Khedr et al., 2011; Mouakket & Bettayeb, 2015). However, Binyamin et al. (2019a) were unable to demonstrate the effect of visual interface design on the students' perception of the LMS ease of use and usefulness in the Saudi context while Al-Aulamie (2013) has proved the effect to be on the LMS ease of use but not usefulness. Using UTAUT, Almaiah and Alyoussef (2019) found that VD has a significant effect on performance expectancy and usage behaviour of LMS in a Saudi university where the latter has the highest effect. This finding would encourage the students to use the system and thus enhance e-learning system acceptance. However, in other contexts, Theng and Sin (2012), Khedr et al. (2011), Cheng (2012) and Liu et al. (2010) have demonstrated the influence of interface design on the perceived ease of use. In this communication, students' responses and behaviour regarding the LMS VD were elicited. It is assumed that LMS user interface design will enable students to accomplish their goals, affect the easiness of the system and subsequently influence their intention and use of the system. Hence, the following hypotheses are proposed:

H12: *Visual design has a direct positive influence on performance expectancy;*
H13: *Visual design has a direct positive influence on effort expectancy;*

H14: *Visual design has a direct positive influence on students' behavioural intention to use an LMS.*

3.7.3 System Learnability (SL)

The learnability dimension is related to the ease of learning – the degree to which students can learn how to use the LMS without difficulty (Holden & Rada, 2011; J. Nielsen, 1993; Orehovački et al., 2013). The term is also concerned with the capability (ease and speed) of the e-learning system that enables students to become more familiar with the application without referring to software manuals (Lastrucci et al., 2009). There is a consensus among researchers that learnability is an essential component of usability (Dix et al., 2004; Nielsen, 1993; Shackel, 2009; Shneiderman et al., 2017). Some argue that it is considered a subcategory and the most significant quality of usability (Nielsen, 1993).

Most researchers acknowledge that learnability is particularly important in e-learning systems due to system complexity, intricate pedagogy and the diversity of users (Junus et al., 2015). E-learning systems with high learnability enable learners to start using the system with a minimum of training, help and orientation (Marzanah et al., 2013). Learnability problems result in additional training modules, personnel, support and maintenance costs (Lindgaard, 1994). Kiget et al. (2014) found a positive significant relationship between learnability and usability, signifying that learnability is an important indicator for students' adoption of e-learning system. Besides, the value of learnability parameter was shown to exhibit the highest score in the students' assessment of e-learning system (Thowfeek & Salam, 2014). Thus, it is crucial to consider learnability for the e-learning system assessment.

Few lines of research have investigated the impact of learnability on students' ease of use and usefulness. Using the Structural Equation Modelling technique, Scholtz et al. (2016) verified that learnability significantly influenced TAM perceived usefulness and perceived ease of use which in turn increased the usage of the ERP system. Likewise, Aziz and Kamaludin (2014) revealed that the learnability of a Malaysian university website positively influenced students' perception of the system's ease of use and usefulness. Yet, in Lin's (2013) study, the correlation between learnability and perceived ease of use was not evident. In Saudi higher education, the effect of LMS learnability was demonstrated with the system ease of use but not for usefulness (Binyamin et al., 2019a). Up to now, far too little attention has been paid to the influence of the learnability variable on the students' intention and use of an e-learning system in the Saudi Arabian context. In this research, the concern is whether the learnability variable influences students' performance expectancy and effort expectancy as well as their intention to use the system. Thus, the following hypotheses are proposed:

H15: *System Learnability has a direct positive influence on performance expectancy;*
H16: *System Learnability has a direct positive influence on effort expectancy;*
H17: *System Learnability has a direct positive influence on students' behavioural intention to use an LMS.*

3.7.4 Information Quality (IQ)

Information quality refers to the information and content that is provided by the e-learning system (Ameen et al., 2019; Aparicio et al., 2017). IQ is considered an important factor for measuring the effectiveness of an e-learning system because the students' items for learning are contained in the system (Alsabawy et al., 2016; Aparicio et al., 2017). DeLone and McLean (2003), in their information systems' success model, asserted that IQ is a crucial variable that influences user satisfaction and intention. It is also an important measure for a system's success (Freeze et al., 2010; Petter et al., 2008), and among the most important qualities component in the evaluation of the e-learning system (Mustafa & Faryadi, 2013). Learners place a great value on the e-learning system content (Shee & Wang, 2008). A well-organised effectively presented and useful e-learning system content enables learners to have a higher retention and satisfaction rate (Shee & Wang, 2008).

It was also shown that e-learning system information content significantly affects website usability (Bringula & Basa, 2011). Furthermore, Zaharias and Poylymenakou's (2009) analysis found that the content factor explained 36% of the variance. Ahmed et al. (2019b) in his usability principles prioritisation study found that IQ was the most important variable that influenced the students' use of the e-learning system across all attribute categories, signifying its importance in the assessment of e-learning acceptance and use. Besides, qualitative research conducted in Saudi higher education showed that e-learning system content quality was regarded as a critical success factor for effective e-learning system acceptance and use (Alhabeeb & Rowley, 2017).

Empirical evidence has shown that IQ influences the effectiveness of computer-mediated learning (Ameen et al., 2019; Aparicio et al., 2017; Binyamin et al., 2019a). Recently, researchers have shown that IQ has a significant effect on the intention to use an LMS in the Thai context (Thongsri et al., 2019). Similarly, Wu et al. (2009) revealed that the e-learning system content quality promotes user's BI to use the system. It was verified that students' high perceptions of the system information quality will lead to a higher level of usefulness (Al-Fraihat et al., 2019; Alsabawy et al., 2016; Ameen et al., 2019; Aparicio et al., 2017; Lee et al., 2014; Wu et al., 2010), and is positively correlated with learners' satisfaction (Al-Fraihat et al., 2019; Chiu et al., 2007; Mohammadi, 2015). Among the factors influencing the students' intention to use of e-learning system, the IQ factor had a remarkable positive effect in an Iranian context (Mohammadi, 2015). In an Arab context, meanwhile, it was confirmed that there is a positive relationship between IQ and the continued intention to use an e-learning system (Almahamid & Rub, 2011), and on students' perceived ease of use and on perceived usefulness (Alkandari, 2015; Salloum, 2018). More specifically, in Saudi higher education, it was empirically found that the IQ of an LMS is a determinant of students' perceived ease of use and usefulness (Binyamin et al., 2019a). However, other researchers found different results. For instance, Al-Aulamie (2013) and Ameen et al. (2019) demonstrated the insignificance of the association between IQ and BI. Nonetheless, few studies have examined the relationship between IQ and the willingness to use the system (Petter et al., 2008). Based on the previous discussion, the researcher considers that IQ will have an influence on the students' PE, EE and their BI to use LMS. Therefore, the following hypotheses are proposed:

H18: *Information quality has a direct positive influence on performance expectancy.*
H19: *Information quality has a direct positive influence on effort expectancy.*
H20: *Information quality has a direct positive influence on students' behavioural intention to use an LMS.*

3.7.5 Instructional Assessment (IA)

Instructional assessment is concerned with e-learning system instructional assessment that facilitates students' learning activities through the use of various useful tools, including tests, quizzes, surveys, electronic submission of assignments and the grade book (Zaharias & Poylymenakou, 2009). The construct also includes an evaluation of the effectiveness of the e-learning system feedback facility for online assessment. The e-learning assessment tool is an indispensable element in the students' learning processes. In addition, the self-assessment tool can help students to understand the educational module materials (Kayler & Weller, 2007). This enables students to identify areas of difficulty and become more engaged with the module materials (Kayler & Weller, 2007). In a survey that evaluated the usefulness of LMS features, students rated the assignments' function as the most important, followed by the gradebook function (Martin, 2013). The diversified evaluation methods within the e-learning systems stimulate students to interact with the assessment tools, and this might lead to better academic performance (Sun et al., 2008). The interaction between lecturers and students through the feedback received enhances the communication between the two groups (Sun et al., 2008). This also encourages participation in online discussion (Kayler & Weller, 2007). The perceived interaction through the use of Blackboard assessment tools had a significant influence on students' satisfaction (Sun et al., 2008).

In a usability study of the Moodle platform, teachers valued the grading mechanism as it is a more cost-effective compared to the paper test format and they were more satisfied with Moodle assignment quality (Ivanović et al., 2013). However, the assessment tools of Moodle received several negative remarks especially regarding the tools' utilization and value from students' point of view. Likewise, Storey et al. (2002) evaluated Blackboard assessment features using a questionnaire-based method.

Blackboard online quizzes and assignment submission facilities were easy to use and effective from the students' perspective. However, there were some remarks about the need for improvement, especially in the system feedback (Storey et al., 2002).

Regarding the influence of IA on e-learning acceptance, one study conducted by Binyamin et al. (2019a) examined the relationships of LMS instructional assessment on students' perception of LMS ease of use and usefulness. They found that both links were supported in Saudi higher education. Similarly, another recent research has revealed that module assessment has a significant positive effect on performance expectancy and the actual use of e-learning systems in a Saudi university (Almaiah & Alyoussef, 2019). To date, LMS system characteristics such as instructional assessment influence on the students acceptance of the system are far from conclusive, so the current research explored the role of assessment in students' intention as well as on PE and EE. Thus, we hypothesize the following:

H21: *Instructional assessment has a direct positive influence on performance expectancy;*
H22: *Instructional assessment has a direct positive influence on effort expectancy;*
H23: *Instructional assessment has a direct positive influence on students' behavioural intention to use an LMS.*

3.7.6 E-learning System Interactivity (ESI)

Interactivity concerns the e-learning system's collaborative tools that facilitate the interaction among students and between students and instructors. This is evident in the LMS in which many collaborative functionalities such announcements, mail, chat and discussion are used, not only for student-student, student-instructor interaction but also as a convenience to communicate module matters and support instructional tasks (Junus et al., 2015). These functions enable learners and teachers to communicate offline through email or online through real-time chat. In an online module, students' learning performances tend to be higher than face-to-face counterparts, especially for those who appear to participate closely in the online discussion forum (Kramarski & Mizrachi, 2006). LMS communication tools are fundamental, and foster constructive and meaningful interaction among students and teachers (Rubin et al., 2010).

The previous literature indicated that interactivity has positively influenced students' learning perceptions and outcomes (Sun & Hsu, 2013). Meiselwitz and Sadera, (2008) reported that the e-learning system communication tool plays a significant role in students higher learning outcomes. In the Moodle system, the system communication capabilities were underused (Ivanović et al., 2013). These differences can be explained in part by the lack of students' perceptions about the e-learning system communication tool and their effects on the utilization of the e-learning system.

Several studies have demonstrated a direct relationship between system interactivity and perceived usefulness (Alkandari, 2015; Alrawashdeh et al., 2012; Baleghi-Zadeh et al., 2017; Binyamin et al., 2019a; Cheng, 2012; Moreno et al., 2017; Pituch & Lee, 2006) and perceived ease of use Binyamin et al. (2019a) and Cheng (2012) as well as the behavioural intention to use an e-learning system (Agudo-Peregrina et al., 2014; Uğur & Turan, 2018; Wrycza & Kuciapski, 2018). For instance, Pituch and Lee (2006) found that system interactivity had the greatest direct and total effect on perceived usefulness and e-learning system usage behaviour. A recent study in Iraq indicated that interactivity has a significant positive influence on students' perceived usefulness of an e-learning system (Moreno et al., 2017). Nonetheless, Abbad, Morris, and de Nahlik (2009) analysis did not substantiate the effect of ESI on student's perception of usefulness and ease of use in a Jordanian university. In Saudi higher education, Alenezi (2012b) indicated that the interactivity construct has a positive relationship with perceived usefulness and perceived ease of use, as well as the students' behavioural intention to use an e-learning system. Binyamin et al. (2019a) performed a similar series of experiments, and concluded that interactivity influenced the perceived usefulness and perceived ease of use of e-learning system in Saudi tertiary eduction. In tandem with this, Al-Harbi (2011b) found that perceived interactivity was a determinant for e-learning system usefulness in the Saudi higher education.

Nonetheless, more information on the influence of interactivity on the acceptance and use of LMS would help us to establish a greater degree of accuracy on this matter in Saudi higher education. Therefore, it is assumed that the higher the interactivity of the system, the stronger the students' beliefs about its usefulness and ease of use and accordingly, the more willingness to use the system. Thus, we hypothesize the following:

H24: *ESI has a direct positive influence on performance expectancy;*
H25: *ESI has a direct positive influence on effort expectancy;*
H26: *ESI has a direct positive influence on students' behavioural intention to use an LMS.*

3.8 Moderating Variables

These independent factors stand between the predictors and the dependent variables. They enhance or reduce the strength of the relationship between the predictors and the dependent variables (Creswell & Creswell, 2018). In the literature, it is evident that the majority of structural equation models have not examined the moderating effects (Henseler & Fassott, 2010). However, moderating variables are considered important, as specific variables are often expected to influence the relationships of between the predictors and the outcomes (Hair et al., 2018; Henseler & Fassott, 2010; Sarstedt et al., 2017). Venkatesh et al. (2003; 2012) demonstrated the moderating variables: gender, age, and experience to have important effects on the individual use of technology. Sun and Zhang (2006) stressed the importance of examining the moderating effects on user technology acceptance. Not only does this contribute to the potential increase in models' explanatory power, but also leads to a better understanding of the dynamics of the user technology acceptance phenomenon (Sun & Zhang, 2006). The proposed model considered the moderators of gender, age, experience, and training that could influence the direct determinants.

3.8.1 Gender

The first moderating variable is gender. Many researchers have acknowledged the role of gender in predicting the individual usage behaviour of technology (Tarhini et al., 2014a; Venkatesh et al., 2003; Venkatesh & Morris, 2000; Wang et al., 2009). Prior research has demonstrated that males and females are different in their decision-making processes, so the differences in perceptions of system usefulness and ease of use are evident in technology acceptance (Arenas-Gaitán et al., 2010; Venkatesh & Morris, 2000). For instance, it was found that men seem to utilize computers more than women (Venkatesh & Davis, 2000). A key study comparing male and female students' perceptions of information technology is that of He and Freeman (2010), in which they found that females feel less confident with computers because they have learned less and practised less, and feel more anxious about using computers when compared with male counterparts. In the UTAUT model, gender significantly moderates the influence of the UTAUT independent variables on the BI to use technology (Venkatesh et al., 2003). The prior research on gender has shown that males tend to be more task-oriented than females (Venkatesh et al., 2003). Men tend to place more emphasis on work, accomplishment and eminence whereas women seem to be placing more importance on the subjective norm, being more expressive, more aware of others' feelings, and more compliant compared with men (Venkatesh & Morris, 2000). Furthermore, PE is found to be significant on males as they are motivated by achievement needs whereas females are more concerned with EE aspects in technology adoption and use (Venkatesh et al., 2003). Concerning social influence, females tend to be more sensitive to others' opinions so peer influence and affiliation tends to be more salient to women in the study of technology adoption and use (Venkatesh et al., 2003). Indeed, the explanatory power of the TAM model has increased considerably at 52% when gender is included as a moderator (Sun & Zhang, 2006). In relation to e-learning system visual design, the results of Shaouf et al.'s (2016) study were found different across genders, such that system images, shapes and animations are more influential on males' responses than on females.

Gender differences also occur across cultures (Gefen & Straub, 1997; Sun & Zhang, 2006). This is evident in the Arab culture, as it has been shown that women tend to be less powerful and less independent than men (Kelly & Breslin, 2010), and they are more reserved (Ameen, 2017). Women have fewer chances to obtain a job, are (more) compliant and participate less in the labour force, so gender divide is expected to act as a moderator in the Arab world (Ameen, 2017). There are also variations between males and females in the use of technology. In an investigation into technology usage among Saudi Arabian undergraduate students, Alothman et al. (2017) found that location and gender influence the duration of the use of technology: students in small towns spend less time on technology compared with their counterparts in the capital city. The study also revealed that some female colleges forbid their students to bring and use laptops and smartphones (Alothman et al., 2017). Similarly, Al-Harbi (2011b) concluded that Saudi male students showed more positive attitudes to use e-learning system than female students.

Conversely, studies (Ameen et al., 2019; Arenas-Gaitán et al., 2010; Decman, 2015; Khechine et al., 2014; Marchewka et al., 2007; Raman et al., 2014; Ramírez-Correa et al., 2015) have failed to prove the effect of gender on the use of e-learning system. In the Saudi educational context, it was revealed that most relationships in the model did not differ between male and female students (Binyamin et al., 2019a). Bellaaj et al.'s (2015) research, too, demonstrated a single relationship that was moderated by gender. Still, the influence of gender role in technology acceptance is far from conclusive (He & Freeman, 2010; Ong & Lai, 2006), and even less in relation to e-learning systems (Arenas-Gaitán et al., 2010; Tarhini et al., 2014a), so this study postulates that:

H27: *Gender moderates all relationships in the proposed model.*

3.8.2 Age

Literature has shown that age is an important factor in technology and acceptance research (Chung et al., 2010; Sun & Zhang, 2006; Tarhini et al., 2014a; Venkatesh et al., 2003). While age has exhibited a moderating effect on behavioural intention and use of technology in different seminal studies (Venkatesh et al., 2003, 2012; Venkatesh & Davis, 2000), in general, the effect of age has not been treated in much detail (Chung et al., 2010; Sun & Zhang, 2006). In the UTAUT model, Venkatesh et al. (2003) reported that age showed a substantial moderation in the relationship between PE, FC and BI. As an illustration, younger age groups appear to be more willing to adopt and use the system than older groups. In contrast, increased age was associated with difficulties in processing complex tasks and allocating attention to content (Venkatesh et al., 2003). Also, the relationship between EE, SI and BI was stronger for older employees in technology acceptance and use (Venkatesh et al., 2003). Culturally, Venkatesh and Zhang (2010) revealed that the effect of gender and age was different between Chinese and American contexts. For instance, for the effect of social influence on behavioural intention, the moderating role of gender and age were not significant in China compared with the significant effect in the US sample. The authors argued that the effect of social influence in China is different from what is observed in the US, indicating that culture is an important factor in the study of technology adoption (Venkatesh & Zhang, 2010).

In the educational context, age was found to moderate the relationship between perceived ease of use, perceived usefulness, self-efficacy and BI; however, no differences were detected in terms of the social norm influence on BI to use an LMS in England (Tarhini et al., 2014a). Khechine et al. (2014) conducted a UTAUT study of the effects of moderators, gender and age, on the acceptance of a Webinar system in a blended learning module. They found that age had a salient moderating influence between performance expectancy and facilitating conditions on intention, while gender did not. Furthermore, Altawallbeh et al. (2015) demonstrated that age moderated the attitude, subjective norm and perceived behavioural control on students' acceptance and use in Jordanian universities. In a similar line of investigation, Chawla & Joshi (2012) discovered that students aged 25 and under have a more favourable perception of e-learning systems than those over 25. However, the study of Julie, Becker, & Newton (2017) has been unable to demonstrate the effect of age on users intention and satisfaction with e-learning system in an Australian context. The age variable was demonstrated to influence the utilization of the Jusur LMS in Saudi higher education (Asiri et al., 2012). Considering the dissimilar conclusions, overall, there remain questions as to whether the age variable has an influence in the students use of LMS in Saudi higher education. Thus, the following hypothesis is proposed:

H28: *Age moderates all relationships in the proposed model.*

3.8.3 Experience

Experience refers to the individuals' involvement with the system over a period of time (Venkatesh et al., 2003). In this research, the experience indicates the number of years that students have of using the system, as suggested by Venkatesh and Morris (2000). It is an important moderating variable in IT adoption contexts as individuals' reactions toward an IT may change over time (Taylor & Todd, 1995b; Venkatesh et al., 2003, 2012; Venkatesh & Bala, 2008). In one study that set out to compare the determinants of IT usage for experienced and inexperienced users, it was shown that there are some significant differences in the effect of the predictors on the usage behaviour depending on experience (Taylor & Todd, 1995b). For instance, the perceived usefulness was the strongest predictor of intention for the inexperienced group compared with the construct of perceived behavioural control in the experienced group (Taylor & Todd, 1995b). Venkatesh et al. (2012) postulated that experience will moderate the effect between behavioural intention and actual use behaviour, and that it will be stronger for less experienced users.

Extensive research has shown that the student experience in the use of an LMS can change the intention and usage behaviour (Liao & Lu, 2008). Perceptions of intention differed significantly between students with and without prior experience (Liao & Lu, 2008). Zhang et al.'s (2017) findings demonstrated the significant difference of the effect of usage experience, as a moderator, in the students' attitude and intention to use LMS. The intention in low experienced users was influenced by information quality and perceived usefulness while for high experienced users, the intention was influenced positively by information satisfaction, interaction satisfaction and perceived usefulness (Zhang et al., 2017). Consequently, this stimulus would affect students' intention and actual use of the targeted system. The previous student experience came as the most critical factor in the e-learning success model with a validity coefficient of 0.89 (Selim, 2007). The experience was found to moderate the association between the students' perceptions of usefulness and ease of use and the targets determinant of TAM3 in Saudi higher education (Al-Gahtani, 2016). Nonetheless, Ameen (2019) reported that experience did not significantly play a role in the students' intention to use an e-learning system in the Iraqi context.

Drawn up for the previous discussion, it is assumed that different factors within the model may have different influences on students' perceptions of performance expectancy and effort expectancy as well as on intention to use, depending on the students' experiences with the LMS. Since the experience variable has the potential to modify the model relationships, this study will postulate that the student experience of LMS moderates the interaction of the model variables:

H29: *Experience moderates all relationships in the proposed model.*

3.8.4 Training

The success of the e-learning system implementation depends primarily on training and professional development (Al-Alwani, 2010; Asiri et al., 2012; Mulhim, 2014). Individuals can benefit for many forms of training such as workshops, online tutorials, and seminars (Al-Busaidi & Al-Shihi, 2012). Training programmes affect significantly the individuals' computer self-efficacy (Higgins & Compeau, 1995) and the perceived usefulness (Igbaria et al., 1997). The study emphasised that training promotes greater understanding, favourable attitudes, more frequent use, and more diverse use of applications (Igbaria et al., 1997). Problems of using technology are likely to arise if users are not provided with adequate training (Higgins & Compeau, 1995).

In a study set out to determine the effect of demographic characteristics on the acceptance and use of technology, the training determinant was found to be the most important driver of user perception of technological innovation (Quazi & Talukder, 2011). The training can also boost the user's confidence with regard to the capability to learn and the use of technology (Quazi & Talukder, 2011). The effect of training moderation is lacking in the IS/IT acceptance research, especially in the Arab context (Rouibah et al., 2009). The availability of training has a direct effect on individuals' beliefs of perceived usefulness and perceived ease of use, where the latter is affected the most by the training variable (Rouibah et al., 2009).

External variables such as system training can affect the user beliefs in using the system (Burton-Jones & Hubona, 2006; Davis, 1989). The training has been also reported to affect the instructors' satisfaction with an LMS (Al-Busaidi & Al-Shihi, 2012). Hu, Clark, and Ma (2003) compared the moderating effect of teachers' training on the TAM model relationships. The model was longitudinal, tested with and without training over the course of an intensive four-week training program. They found changes in the teachers' influence over time. Several noticeable changes in TAM key acceptance drivers and their influence patterns or magnitudes were observed over the course of the training (Hu et al., 2003).

Data from several sources have concluded that the scarcity of training has been considered among the most significant barriers in the use of e-learning system services in Saudi higher education (Asiri et al., 2012; Mulhim, 2014). In the study conducted by Asiri et al, (2012), the individuals' characteristics of training were reported to be a critical factor that influenced the utilization of LMSs in Saudi Arabia. Similarly, and based on a survey of 408 students in five Saudi universities, Alenezi et al. (2011) demonstrated that training has significantly contributed to the students' acceptance of e-learning system. Furthermore, in an investigation into LMS acceptance in Saudi tertiary education, Alshehri et al. (2019a) found that the majority of students had no previous training in the use of an LMS (64.3%) while a minority (32.2%) reported some training (1-5 hours). Driven by the lack of LMS training in Saudi educational institutions and the significant effect of training on students use, the following hypothesis was proposed:

***H30**: Training moderates all relationships in the proposed model.*

3.9 Summary

The aim of this chapter is to explain and discuss the development of the proposed conceptual model in e-learning settings. It has further provided a justification for the use of the UTAUT model, along with usability factors as key determinants in the current research. The proposed framework has been built on existing research knowledge in order to investigate the e-learning system acceptance and use. The model has integrated the usability parameters with the UTAUT model in Saudi higher education, a non-western context. The generic web usability factors have been augmented with parameters stemming from instructional design to be applied in Saudi Arabian settings. It is, nonetheless, a primary formulation of different indicators which can be treated as a starting point for generating guidelines for e-learning systems acceptance and use.

In essence, the theoretical model has three main components: UTAUT, usability and moderating variables. Firstly, the UTAUT predictors are PE, EE, SI, FC (independent variables) and the target constructs of BI and AU (dependent variables). The usability dimensions include SN, VD, SL, IQ, IS and ESI, which represent key determinants of the target constructs. The moderating variables consist of gender, age, experience and training. The discussion and operational definition of each variable were presented. A total of thirty hypotheses with justifications were formulated. The following chapter will explain the research methodology used to answer research questions and empirically validate the conceptual framework.

CHAPTER 4: RESEARCH DESIGN AND METHODOLOGY

4.1 Introduction:

The research methodology explains a set of processes used for data collection and analysis (Bryman & Bell, 2015). Primarily, this research was set out to develop a theory and hypotheses, and to design a strategy to test the hypotheses Thus, the literature review is placed at the beginning to deductively introduce the technology acceptance theories with usability attributes. The goal is to test the developed conceptual model in a developing country: Saudi Arabia.

This chapter describes the research philosophy and methods adopted to answer the research questions and test their hypotheses. The chapter begins by discussing the research paradigm and design – the nature of research that guides the investigation. It also discusses and justifies the sampling technique, sample size and the study's instrument (development, content, and psychometric properties). This is followed by the justification of the selection of the most suitable methodological procedures for the study. The chapter ends with introducing PLS-SEM, the statistical approach used for data analysis.

4.2 Research Paradigm

A paradigm, also called worldview, is a general philosophical orientation which refers to a set of beliefs and feelings about the world and how it should be understood and studied (Creswell & Creswell, 2018). To this end, a brief description of the research worldview assumptions, design and methods are presented.

Positivism in research relies on measurable proof that is independent of the observer (researcher) (Bryman & Bell, 2015). The positivist approach is in line with developing numeric measures, based on instruments, to study the behaviour of an individual (Creswell & Creswell, 2018). Contrary to the interpretivism perspective, positivist studies usually adopt deductive reasoning, the aim of which is to develop hypotheses based on existing theory and verifies them through statistical analysis techniques

(Orlikowski & Baroudi, 1991; Saunders et al., 2012); testing theory and increasing the predictive understanding of the phenomena (Orlikowski & Baroudi, 1991).

4.2.1 Justification of Using A Positivist Paradigm

The selection of a philosophical position and method is grounded on the nature of research, the research problem and questions that are under investigation (Saunders et al., 2012). Thus, the aim of this research is to develop and test a theoretical framework based on the UTAUT model. The model was extended to include usability variables that affect students' use of the e-learning system. Positivism focuses on testing hypotheses through quantifiable measures of variables to explain individual behaviour (Neuman, 2013). The goal is to validate the proposed model and test the hypotheses through the examination of quantifiable measures of variables to gain insight into and understanding of the topic in question from students in Saudi universities. According to Orlikowski and Baroudi (1991) the criteria for selecting a positivist paradigm are underpinned by hypotheses testing, quantifiable measures of variables, evidence of formal propositions as well as the drawing of inferences about a phenomenon from the sample to a stated population. Table 4.2 presents the rationale behind the selection of the positivist paradigm in the research

Table 4.2 Criteria and Rationale for the Positivist Paradigm Choice

Positivist Criteria	Research Rationale
Formal Propositions	Literature review maintained defined propositions of the relationships between the constructs in the proposed model (Orlikowski & Baroudi, 1991).
Quantifiable Measures of Variables	Independent Variables (UTAUT and Usability Variables and Outcome Variables (behavioural intention and actual Use)(Creswell & Creswell, 2018; Myers, 2019).
Hypothesis Testing (deductive reasoning)	Developed to test the relationship between the independent and the dependent constructs (Bryman & Bell, 2015; Creswell & Creswell, 2018; Myers, 2019).

Generalization	Probability sample randomly selected (using clustering) from Universities in Saudi Arabia (Orlikowski & Baroudi, 1991; Saunders et al., 2012).

The results also allow one to understand the usability, social and organisational factors that affect the use of e-learning in Saudi higher education, so we can infer knowledge about the real world. The research is concerned with social subjects where students' perceptions and behaviour are evaluated and where the researcher is independent of the study and there are no provisions for human interests. Therefore, this is another driver for the choice of a positivist world view.

Furthermore, as evidenced by a systematic study, publications that concentrate on information technology acceptance have a main theoretical drive to adopt a positivistic orientation (Orlikowski & Baroudi, 1991). The positivist paradigm is the dominant approach in recent trends in adoption and diffusion studies, with more than 75% of research having employed this school of thought; the interpretive paradigm accounts for 14% of the studies and the remaining papers were unclear (Williams et al., 2009). From a statistical position, research that applies structural equation modelling (SEM) usually follows a positivist epistemological belief (Urbach & Ahlemann, 2010).

Following these justifications for adopting a positivist research paradigm, the next section elucidates the research design used in this study.

4.3 Research Design

The research design is described as being a blueprint for conducting the study and answering the research questions (Sekaran & Bougie, 2016). As the current research reflects positivist philosophical assumptions, as discussed in subsection 4.2.1, a quantitative method was selected for this study. The examination of the proposed model relationships, using a survey design, is central to answer the research questions and hypotheses. The following subsections shed light on the selected research design and justify its selection.

4.3.1 Quantitative Approach

Quantitative research employs deductive reasoning, whereby a theory is developed about a certain phenomenon with a number of hypotheses and questions to be verified in a given environment (Saunders et al., 2012). This approach emphasises quantification in the collection and analysis of data (Bryman & Bell, 2015), such as correlational design, where the investigator uses statistics to measure the degree of significance of the relationships between variables (e.g., using the structural equation modelling technique).

The main justifications for selecting the quantitative strategy in this study are as follows.

- *Positivist orientation:* Positivism focuses on testing hypotheses through quantifiable measures of variables to explain individual behaviour (Neuman, 2013). Since this research utilises quantifiable measures of UTAUT and usability variables to explain students' acceptance of an LMS, a quantitative design was chosen to accomplish the research aims (Bryman & Bell, 2015; Creswell & Creswell, 2018).
- *Literature analysis:* It has been demonstrated that 91% of a large number of prior studies in technology acceptance have been empirical (Williams et al., 2009). Thus, the prevalence of quantitative approaches within the IT/IS field is evident.
- *Deductive approach:* This research is concerned with developing and testing the hypotheses with observations, based on an extended version of the UTAUT theory.
- *Generalisability:* The study employed a multi-stage clustering technique to collect data from five regions of Saudi Arabia with 605 participants. The quantitative strategy provides a foundation for producing broad generalizability of the findings to Saudi higher education, as suggested by Saunders et al. (2012).

4.3.2 Survey Research Method

A survey provides a numerical description of trends, attitude or perceptions of a population based on studying a sample of that population (Creswell & Creswell, 2018). The choice of data collection methods relies on many factors such as nature of the study, targeted population, available resources, facility, location, associated cost, time-span and the degree of accuracy (Sekaran & Bougie, 2016). However, the typical form of a cross-sectional study in quantitative data design is that of survey research or structured observation on a sample at a single point in time (Bryman & Bell, 2015). Drawn from the above discussion and considering the study nature and the PLS-SEM statistical technique, a cross-sectional design was chosen.

Within the survey research approach, data are usually collected through several methods such as telephone, the Internet, mail, email, personal interviews and group administration, as well as self-administrated questionnaires (Fowler, 2014). To reach a large audience (Fowler, 2014), this research employed the self-administrated questionnaire as a data collection method. In a self-administrated questionnaire (also called self-completion questionnaire), the respondents answer the questions themselves without the influence or involvement of the researcher.

There are several rationales behind the choice of a survey method to collect data. To begin with, the majority of publications that concentrate on users' perceptions more frequently adopt subjective measures using surveys (also called self-reported data) (Hornbæk, 2006; Williams et al., 2015). More specifically, in technology acceptance research, survey instruments have been the most predominant methodological approach used in different forms such as questionnaire survey, telephone survey, and web-based survey (Williams et al., 2015). In the current research, the purpose is to investigate the usability, social and organisational attributes that affect the students' intention and use behaviour of the e-learning system. There are a number of large cross-sectional studies which suggest using inquiry methods such as surveys to examine users' attitudes and perceptions towards the system interface or other phenomena such as the website content and the outcome of interaction (Bryman &

Bell, 2015; Choudrie & Dwivedi, 2005; Creswell & Creswell, 2018; Myers, 2019; Orlikowski & Baroudi, 1991; Williams et al., 2009).

The survey is predominantly used to collect extensive data regarding feedback and views from the users' perspective (Choudrie & Dwivedi, 2005; Orlikowski & Baroudi, 1991; Williams et al., 2009). Hock, Omar, and Mahmud (2015) reviewed the literature from 2004 to 2015 and found substantial evidence for the survey-based method prevalence in LMS usability and acceptance research. In the context of this study, the survey was developed to elicit students' views about e-learning system usability and acceptance in Saudi universities. Since this research was based on the cluster random sampling of five regions of Saudi Arabia, inferences could then be made about some characteristics, attitudes, or behaviours to all students in Saudi public universities, as suggested by Creswell and Creswell (2018).

As Saudi universities are dispersed around a large geographical area, an online survey provides a useful tool to collect the data from different regions, reducing geographical dependence. The survey can be administered remotely (via online) and is capable of collecting responses from a large number of respondents who would be difficult, if not impossible, to reach using other channels (Sekaran & Bougie, 2016). In particular, the online survey was employed to reach a wider population from female colleges, as female students study on gender-segregated campuses

The Internet-based survey approach has a number of attractive features: economy in design and distribution, rapid turnaround, more accessibility and minimising missing data issues (Creswell & Creswell, 2018; Hair et al., 2017). This method is also cost-effective and inexpensive to administer, as opposed to other methods such as interviews (Bryman & Bell, 2015; Fowler, 2014; Sekaran & Bougie, 2016). Using an online questionnaire enables researchers to reach groups and individuals who would be difficult to access through other channels (Wright, 2006). An online questionnaire is considered more convenient for the respondents, as it allows them to have time to read and understand the concepts of items which minimize the occurrence of outliers in the research (Aaker et al., 2012; Saunders et al., 2012; Sekaran & Bougie, 2016).

This can be seen as a downside whereby the researcher is not present to ensure the questions are clear and ambiguous (Sekaran & Bougie, 2016), moreover drawbacks include Internet connection unavailability, high non-response rate, survey fraud and the presence of patterned answers. Taking into consideration the large higher education student population in Saudi and also the structural equation modelling technique for analysis, the survey is the most suitable approach and it is very expensive and time-consuming to use another form of research method (Hair et al., 2014).

What follows is an account of the population and sampling and the justification for the selection of the sampling technique.

4.4 Population and Sampling

In survey research, it has been recognised that the sampling technique is a critical phase for the research in order for a sample to represent the entire population and to eliminate the basis for potential errors in generalizing the findings (Bryman & Bell, 2015). Therefore, the following will present and discuss the population, the sampling techniques and the major distinction between probability and non-probability sampling and their categories, the sample frame and the representative sample size

4.4.1 Population

The population refers to the set of units or groups for which the sample is selected (Bryman & Bell, 2015). The term population has a broader meaning than the total number of people in a nation, as it can mean other entities such as cities, regions and firms. The sampling frame is the set of target population members from which the sample will be collected (Fowler, 2014).

In this research, the potential population is the students studying in Saudi state universities using LMS. The Saudi Arabian higher education system has more than fifty universities distributed around Saudi regions and provinces. Some of these institutions are under the supervision of the Ministry of Education (mainly state universities), while the rest are run by other government agencies and private organisations. The focus of this research is on state universities. The number of state registered universities is 30, with high absorptive capacity (Ministry of Education Saudi Arabia, 2017). These universities are geographically distributed in the different regions of KSA. According to the Ministry of Education statistic, the total students' population is 1,385,620 students of whom 657,990 (47%) are male and 727,630 (53%) are female (Ministry of Education Saudi Arabia, 2017). However, not all public universities implement or use LMS, therefore, the University of Hafr Albatin, the University of Bisha and Shaqra University were excluded. These exclusions reduced the number of public universities included in this study to 27, with 1,316,807 students, of whom 657,972 (48%) are male and 680,958 (52%) are female (Ministry of Education Saudi Arabia, 2017). Thus, the target population of this study is 1,316,807 students.

4.4.2 Sampling

It is important to consider how far the sample is representative of the total population. Due to time and financial constraints, decisions have to be made regarding the appropriate sampling technique, sample size and sample error (Bryman & Bell, 2015). All choices of sampling must be aligned with the nature of research problems and the study aim and objectives.

Cluster sampling is a probability sampling technique in which the population is subdivided into exclusive and exhaustive groups that represent the total population. A complete list of clusters represents the sampling frame. Then, a simple random technique is applied to these aggregations and the researcher conducts the analysis on data from the clusters. There are two types of clustering: single-stage cluster sampling and multi-stage cluster sampling. Researchers in the single-stage clustering employ all subjects in each group directly, whereas in the multi-stage cluster, a simple or systematic random sampling is applied to select a subset from each group in the sample (Bryman & Bell, 2015; Creswell & Creswell, 2018). The primary aim of using the clustering technique is the cost reduction in data collection while increasing the efficiency of sampling.

In this research, multi-stage cluster sampling is employed. The following discusses the choice rationale of the sampling technique.

4.4.3 Multi-stage Clustering Sampling Justification

The targeted population of the study comprises students studying in Saudi higher education. The sample frame is the total number of students in Saudi public universities who fits the research description (diploma, bachelor, master, doctorate) which is 1,316,807 students (Ministry of Education Saudi Arabia, 2017). The researcher targeted the students in Saudi public higher education with geographically dispersed universities. Hence, due to the large population and the time and financial constraints, the researcher is required to select a representative sample for detailed examination. The procedure involves the initial sampling of universities (clusters) followed by the selection of students within each of the selected clusters (Babbie, 2014). Many scholars recognise the importance of selecting a proper sample, as this has considerable influence on the reliability and authenticity of the results (Bryman & Bell, 2015).

To begin with, clustering sampling technique is suggested where it is difficult or infeasible to reach the total population due to geographical boundaries, time and budget constraints (Babbie, 2014; Saunders et al., 2012). Multi-stage cluster sampling is one of the most appropriate methods for area probability sampling (Fowler, 2014). As in this context with the limited time and budget, it is unlikely, even impractical, for the researcher to travel the length and breadth of Saudi to collect data for universities (from 1,316,807 students). A greater economy can be accomplished by grouping each geographical area into a cluster.

Secondly, the clustering method is ideal for the generalization of the results to the entire population (Babbie, 2014; Bryman & Bell, 2015). In a quantitative approach, researchers are usually concerned with the generalisability of the findings and conclusions to the population at large, which can be achieved primarily by using a representative sample (Bryman & Bell, 2015), in this research, geographical clustering.

Thirdly, even though cluster sampling is subject to sampling error, sampling error can be reduced the by two factors: an increase in the sample size and increased homogeneity of the subjects being sampled (Babbie, 2014). In the current research, all universities (clusters) are very much alike (state universities) and the sample of students in a given university is also homogenous. The clusters share similar characteristics, such as user type (students), educational levels, and gender balance and segregation. It is also useful in a homogenous large sample of Saudi students in a statistical population.

Finally, and from economical and feasibility perspectives, cluster sampling is both time and cost-efficient for the large geographical regions more than any other sampling plan (Babbie, 2014; Bryman & Bell, 2015). The researcher selects a sample of universities that fit the research criteria. In this research, the sample uses four cardinal directions to cover each part of Saudi provinces. Each cluster will represent a geographical province of Saudi Arabia. Primary data can be collected from each cluster (university) to represent the entire area population. The motive behind using clustering is to ensure that our sample is representative of the population and is not unique to the selected universities.

Thus, the most rigorous method of sampling is to use a probability sampling technique (Creswell & Creswell, 2018) and this remains the primary technique for selecting large and a representative sample (Babbie, 2014). Cluster sampling is ideal when it is impossible or impractical to list all elements or individuals of the population (Babbie, 2014). Hence, the study approaches this concern using geographical cluster sampling of Saudi universities.

In this research, the probability sampling method was used based on geographical clustering. Accordingly to Babbie (2014) Fowler (2014), Bryman & Bell (2015) and Saunders et al. (2012), there are several sampling procedures involve with multi-stage clustering sampling as follows.

- With the first stage of cluster sampling, the population is subdivided into groups (clusters) that represent the total population. All 27 state universities that use LMS represent the sampling frame for the study – the sampling clusters. Saudi Arabia was divided into five regions based on cardinal directions (Eastern, Western, Southern, Northern, Central). This grouping can be sampled as a first stage.
- From each region, a state university was chosen based on a simple random probability method, yielding five universities adapting LMS for student use. The selected university are King Khalid university from the southern district, Al Jawf university from the northern region, King Abdulaziz university from the western province, Saudi Electronic University from the central area and Imam Abdulrahman Bin Faisal University from the eastern region. These universities represent the samples for the study. The clusters share similar characteristics, such as user type (students), educational levels, and gender balance. To increase the representativeness of the population, Saunders et al. (2012) suggested maximising the number of areas to allow for variations in the population.
- Within each of these universities, the researcher selected samples of students using a simple random probability technique. The sample design made provision for obtaining a suitable number of males and females who use, or have used, the LMS in their studies.

4.4.4 Sample Size

Sample size determination involves the selection of the number of participants within the targeted population (Hair, Hult, et al., 2017). It is critical for any empirical study to specify the appropriate sample size to include in a statistical sample. It should be noted here, that a larger sample does not guarantee precision, but the increasing size is likely to increase precision, due to a decrease in sampling error (Bryman & Bell, 2015; Fowler, 2014). This is particularly true when PLS-SEM is applied in a large sample size to increase the precision and consistency of the PLS-SEM estimation (Hair et al., 2017). Hair et al. (2019) stressed that PLS-SEM works very well with large sample sizes. Moreover, using larger sample sizes in PLS-SEM is advantageous, since generalizability and out-of-sample prediction are often weak in small samples (Hair et al., 2017). Out of sample prediction assesses the extent to which a model will perform accurately in practice, using generated test data. Decisions about the sampling rely on a number of considerations: time and cost, non-response, sampling error and confidence interval (Bryman & Bell, 2015). Sampling error is incurred when the researcher estimates the study statistics from a subset of the population (Fowler, 2014). Therefore, the larger the sample size, the smaller the margin error to tolerate with larger interval confidence. Fowler (2014) suggests determining the sampling error, the confidence interval and the sample frame.

In this context, the total targeted population of the study is around 1,317,000 students and the calculated sampling error tolerated is 4% with a confidence interval of 95%. Taking previous estimates into consideration in Fowler's (2014) table, the sample size needed for the whole population is 600 participants. Alternatively, in multivariate modelling, Cohen (1992) reported that the minimum sample size for the PLS path model is 10 times the number of independent variables (in our case is 10 * 10 = 100 respondents) with a statistical power of 80% for detecting R^2 values of at least 0.25, assuming a significance level of 5%. While the 10 times rule provides a rough guideline, the researcher should consider the sample size against the background of the model and data characteristics (Hair et al., 2017). Although, PLS-SEM is robust when estimating small sample size, in such a large population it is important not to deal with small sample size where there is no need to do so. In this context, the researcher has followed Fowler's (2014) requirement and based on a sampling error of 4% and confidence interval of 95%, the sample size should be ≥ 600 in order for the sample to be representative of the total population. Overall, 605 complete responses were used for data analysis. This complies with the PLS-SEM guidelines and is considered sufficient to represent the concepts in the study of the online survey approach.

Having justified the clustering sampling technique and sample size, the next section discusses the instrument's development.

4.5 Instrumentation

This section provides detailed information about the instrument designed for this research, the validity and reliability established for the constructs and indicators, and the conducted pilot study.

4.5.1 Questionnaire Design Considerations

A well-designed questionnaire improves the validity and reliability of the measures and this also assists the respondents in the understanding of the developed questions (Neuman, 2013). An effective questionnaire requires two basics: clarity, and keeping the respondents' perspective in mind (Neuman, 2013). Questions or items that are misunderstood or are interpreted differently may result in biased responses which affect the validity and reliability of the questionnaire (Sekaran & Bougie, 2016). This may ultimately result in respondents' refusal to participate or leave incomplete or missing data which require further investigation. The low return rates might affect the generalizability of the results, as respondents may not represent the entire population. In this research and as discussed in subsection 4.3.2, an online-based questionnaire was employed.

Sekaran & Bougie (2016) highlights three design principles for questionnaire design and development: the wording of the questions, categorization of variables and their scales, and the general appearance of the questionnaire. Because of the tendency for an online survey to generate a lower response rate among the targeted students, a number of techniques have been considered in the study questionnaire design and development. In this research, issues regarding the survey presentation, questions wording and clarity and ambiguity, types and forms of questions, as well as the length of questions, have been considered (Bryman & Bell, 2015; Manfreda et al., 2006; Sekaran & Bougie, 2016). To increase the respondents' curiosity, the cover letter contains the reasons for the study and its importance, and guarantees the participants' confidentiality and anonymity. In the questionnaire design, the presentation and layout attractiveness and the clear and concise instructions were considered to boost the response rate. An attractive and neat questionnaire with clear instructions and well-arrayed set of questions not only eases answering questions but also tabulates participants' attitudes, perceptions and feelings (Sekaran & Bougie, 2016). Technical terms that are difficult and ambiguous to grasp were replaced with more frequent and simple items. Although the questionnaire contains more than 56 items, the researcher attempts to make the statements short and concise and avoid difficult and dull questions.

The questionnaire comprises closed questions which help the respondents to make quick decisions (Sekaran & Bougie, 2016). The researcher can also code and process the collected data easily for analysis (Sekaran & Bougie, 2016). According to Johnson and Christensen (2016), closed questions are appropriate when the constructs' indicators are fully understood and the participants respond to the same categories. This allows statistical analysis to be standardised.

The questionnaire items were measured using either nominal (e.g., gender and universities) or five-point Likert scale (e.g., usability variables) so as to facilitate the understanding of the questions. For accurate and more comprehensive results, it is appropriate to employ a Likert scale in measuring the individuals' beliefs, views, attitudes, BI and perceptions of concepts (Johnson & Christensen, 2016; McDaniel & Gates, 2013). Even though a seven-point Likert scale was employed in a few studies in user acceptance research, some researchers observed that a five-point Likert-type scale increases response rate and also response quality while reducing the respondents' frustration levels (Babakus & Mangold, 1992; Buttle, 1996). It has also been reported that it is possible to compare reliability coefficients with other similar literature using the five-point scale (Saleh & Ryan, 1991).

All question forms were positively formulated, and were all short and written in one sentence to encourage the participants to provide accurate, unbiased and complete results. The sequence of questions was organised from a general nature to more specific, and from easy to progressively more difficult questions. Demographic data were placed in the beginning of the questionnaire as a stimulus for respondents to take part in the study.

In the literature, the construct types of UTAUT theory appeared to share uniformity among studies. PE, EE, SI, FC, BI and AU have been single-category construct types in previous studies. Concerning the UTAUT constructs in e-learning studies, the survey items have been adapted extensively and were proven to yield high reliability and validity (for example, Almaiah & Alyoussef, 2019). The next subsection details the questionnaire, focussing on the constructs and indicators.

4.5.2 Questionnaire Development

A quantitative questionnaire survey was developed to collect the data required to meet the study's aims and objectives (Saunders et al., 2012). The research constructs were measured by indicators. Indicators are used to measure concepts that are less directly quantifiable (e.g., PE and EE) (Bryman & Bell, 2015). The questionnaire was disseminated using a web-based tool. The questionnaire items were adapted from reviewing the literature in technology acceptance and usability research. Specifically, UTAUT items initially used the original questions items of Venkatesh et al. (2003) as a foundation for the development of the survey instrument. Usability instruments were assembled from various studies of usability evaluation of e-learning systems (Holden & Rada, 2011; Junus et al., 2015; Khedr et al., 2011; Medina-Flores & Morales-Gamboa, 2015; Oztekin et al., 2010; Pituch & Lee, 2006; Zaharias & Poylymenakou, 2009). The indicators have been well-established in prior quantitative research, and performed well in terms of validity and reliability. From the past use of the instrument, UTAUT variables demonstrated high reliability and have positive consequences in e-learning system acceptance and use (Alshehri et al., 2019a). Internal consistency and correlations showed high scores in the use of e-learning systems across multiple studies (Khechine et al., 2016).

Many advantages have been highlighted in the use of a validated questionnaire. Using existing questions enables the researcher to draw a comparison with other research (Bryman & Bell, 2015). Using a well-validated instrument also benefits the research community regarding the replication of the base theory to a different context such as Saudi Arabia. However, the original validity and reliability may not hold for the existing study, due to the fact that the instrument has been modified and combined from components of various studies (Creswell & Creswell, 2018). Thus, the current research first re-established the validity and reliability of the instrument.

This research adapted a multiple-indicator measure for the model's constructs. From a statistical perspective, using multiple items to measure a construct, as opposed to single items, results in a more accurate representation of that construct (Hair et al., 2017). Even if there are many indicators and respondents have misclassified or misunderstood a particular question, it will be possible to offset its effect (Bryman & Bell, 2015). Even the scale was adapted from prior studies. It is suggested that employing a minimum of three to five indicators per construct might avoid problems in multivariate analysis (Kline, 2016). In this study, all the constructs were designed with four indicators or more. While there will be some degree of measurement error in the evaluation, the motive behind this claim is that multiple indicators are more likely to represent various aspects of a concept (Bryman & Bell, 2015). Furthermore, SEM is capable of identifying the measurement error and reporting that in the research results (Hair et al., 2017).

The process of conceptualization includes coming to some agreement about the meaning of the concept whereas operationalisation is the process of strictly defining variables into measurable factors (Sekaran & Bougie, 2016). This applies to abstract ideas such as feelings and attitudes (Sekaran & Bougie, 2016). The construct definition depends largely on the context, meaning that the construct definition can vary from one study to another, hence, its measurement dimension can also differ to reflect the object of interest. In principle, the construct definition will guide how the abstract idea will relate to observable quantities (Sarstedt et al., 2016). Nonetheless, construct representations do not escape from some ambiguity associated with them. Thus, all measurable quantities of a construct are approximations for the variables under investigation. Overall, and according to the literature, the selected items are characterised as having high reliability and validity for measuring the intended constructs.

The Novi survey tool, provided by Edinburgh Napier University, was selected for creating and disseminating the questionnaire to the audience. It is a web-based survey application to facilitate the gathering and analysis of data from different audiences, and fully supports the Arabic language. Novi is hosted on university resources, so it is more secure and reliable than other free utilities on the Internet. The Novi tool fully complies with the Data Protection Act 2018 (DPA) and the University's Data Protection Code of Practice. Appendices A and B include the English and Arabic versions of the developed survey. The sections of the scale utilised in this research are described, below:

The cover letter of the questionnaire briefly explains the purpose of the survey, the targeted population, guarantees respondent's anonymity and a consent form to participate in the research.

The body of the questionnaire was structured into four main segments for easy reading and completion. The first section included information about the respondents' characteristics, such as gender, age, educational level and academic discipline. Demographic data help to obtain descriptive statistics about the study sample and also to check that students from different universities and background have participated.

The second section included multiple choice questions to report additional information about the frequency with which they would use the e-learning system. It also garners data about students' previous experiences of e-learning systems, training and development modules received, and the taught modules using LMS.

UTAUT model statements were placed in the third section. This section served to measure each student's attitude and intention to use the LMS in Saudi higher education. This section comprises 25 items divided into seven subscales using a five-point Likert scale. The scale measures students' responses regarding UTAUT constructs based on LMS use in higher education

The last section elicited students' experiences and perceptions about the proposed usability variables that might affect the use of the e-learning system. This study focuses on e-learning systems, hence usability questions were derived mainly from the literature about usability of e-learning. It is noteworthy to mention that attempts were made to produce operationalisation of items that addressed the user as a learner, and those items have already been empirically validated and tested in e-learning contexts (Zaharias & Poylymenakou, 2009). This section comprised 31 items divided into six subscales.

All items in the third and fourth parts of the questionnaire were measured on a five-Point Likert scale, and respondents were requested to indicate their extent of agreement with the statements from 1 to 5, a mid-point (3) undecided representing the state of uncertainty (1= strongly disagree to 5= strongly agree). The constructs were measured with UTAUT scales previously validated and are available in the prior literature. Students' responses to the proposed scales formed the main part of this study.

The conceptualisation and operationalisation of the variables and their indicators are measured as follows.

Section (I): intends to gather information about the respondents' attributes.

- **Demographics characteristics**: It includes gender, age and educational level, field of study and university name. These attributes were asked in 5 questions in Part (1), age was measured based on a ratio scale and educational level measured on an ordinal scale while gender, field of study and university name were measured on a nominal scale.

Section (II): aims to explore the frequency with which students would use web-based learning systems.

- **E-learning system information:** This gathers data about the students' previous experience of the LMS, attended training and the taught modules using LMS. These moderators were structured into three questions and measured on a ratio scale.

Section (III): UTAUT Model Questions: This section includes UTAUT variables and the measurement scales. The questions initially used the original questions items of Venkatesh et al. (2003) as a foundation for the development of the survey instrument. However, the questions were modified to reflect the use of the LMS system (e.g., replacing information system with the Blackboard system) as follows.

- **Performance Expectancy (PE):** Is concerned with individuals' beliefs that the use of a system will enhance their job performance to perform various tasks (Venkatesh et al., 2003). PE is measured by the students' perceptions of using the Blackboard system in terms of its benefits, quickness, productivity and the software facilitation in achieving high academic achievements (Venkatesh et al., 2003).
- **Effort Expectancy (EE):** Is related to the degree of ease associated with the use of the system (Venkatesh et al., 2003). EE will be measured by the students' perceptions of the clarity of the system, the ease of use of the Blackboard services as well as the degree of ease associated with operating Blackboard functionalities (Venkatesh et al., 2003).
- **Social Influence (SI):** This construct relates to individuals' perceptions of whether important people (friends, colleagues and family members) believe that they should use the system (Venkatesh et al., 2003). In this study, this factor is assessed by the perceptions of how peers, instructors and university management influence students to use the LMS (Venkatesh et al., 2003).
- **Facilitating Condition (FC):** This factor refers to the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system (Venkatesh et al., 2003). In this context, FC measures whether individuals have personal knowledge and resources to use the system and whether the management support the use of the system

(Venkatesh et al., 2003). It also includes the technical supports staff available when there is a technical problem (Sánchez & Hueros, 2010).

- **Behavioural intention (BI):** BI is defined as the probability that individuals will perform the behaviour in question (Venkatesh et al., 2003). The BI construct is measured using the scale adapted originally from the TAM model of Davis (1989) and UTAUT model (2003). In the context of our study, the measurements of this variable comprised the students' intentions, predictions and the planned use of the Blackboard system.
- **Actual Use (AU):** It is the actual use behaviour and adoption of a web-based system (Davis, 1989). In this research, the factor is measured by the frequency with which Blackboard is used in the present and the past for learning activity. The measures were adapted from (Alshehri et al., 2019a; Binyamin et al., 2019a; Bouznif, 2018; Mohammadi, 2015).

Section (IV): Contains questions related to the usability constructs**:**

- **System Navigation (SN):** System navigation concerns the visible navigational structure such as menus, links and tabs that grant individuals many options over the system elements (Gilani et al., 2016). The navigation attribute is measured by the students' perceptions of the easiness of using Blackboard navigation, the correctness and reliability of Blackboard hyperlinks, the visibility of the navigation options, as well as the ability of students to leave whenever desired and return easily. The measurement scale was adapted from several studies that were conducted on e-learning systems (Binyamin et al., 2019a; Cheng, 2015; Gilani et al., 2016; Theng & Sin, 2012; Zaharias & Poylymenakou, 2009).
- **System Learnability (SL)**: The learnability dimension is related to the ease of learning; the degree to which students can learn how to use the LMS without difficulty (Holden & Rada, 2011; Nielsen, 1993; Orehovački et al., 2013). The learnability factor was measured by the ease of learning to perform tasks using the Blackboard system, the sufficiency of the system online help to support the learning process, the results of clicking buttons or links being predictable and

ease of learning the use of the system without a long introduction and the capability of the system to provide clarity of wording. These instruments were adapted from various sources (Holden & Rada, 2011; Horton, 2000; Lin et al., 1997; Scholtz et al., 2016; Zaharias & Poylymenakou, 2009).

- **Visual Design (VD)**: This attribute focuses on the aesthetic aspects of the system through considering the effects of images, colours, fonts and general layouts (Scholtz et al., 2016; Usability.gov, 2013). This factor comprises five indicators that relate to the visual structure and design Blackboard system. The measurements of this factor are whether the texts, fonts, colours are easy to read, whether the most important information on the screen is placed in the areas most likely to attract attention, if the Blackboard operates consistently throughout the modules and if students perceive that the Blackboard layout is attractive and follow a good structure. The items were adapted from several studies (Cho et al., 2009; Dringus & Cohen, 2005; Junus et al., 2015; Khedr et al., 2011; Oztekin et al., 2010; Zaharias & Poylymenakou, 2009)
- **Information Quality** (IQ): Information quality refers to the information and content that is provided by the e-learning system (Ameen et al., 2019; Aparicio et al., 2017). Information quality is measured by the students' perceptions of the ease of understanding of LMS information, the currency and accuracy of Blackboard content, the completeness of the system content as well as the sufficiency of the system content. All the measurements were validated in previous studies and adapted from (DeLone & McLean, 2003; Gable et al., 2008; Khedr et al., 2011; Mohammadi, 2015; Orehovački et al., 2013; Zaharias & Poylymenakou, 2009).
- **Instructional Assessment (IA):** This is concerned with e-learning system instructional assessment that facilitates the students' learning activities through the use of various useful tools including test, quizzes, surveys, electronic submission of assignments and the grade book (Zaharias & Poylymenakou, 2009). This is measured by the ease of using Blackboard assessment tools, whether the system assessment tools advance the students achievement, the

effectiveness of the tools to help understanding the materials, whether the system provides opportunities to access extended feedback from instructors and whether it provides students with informative feedback to online assessments. These indicators were adapted from (Junus et al., 2015; Oztekin et al., 2010; Reeves et al., 2002; Sun et al., 2008; Zaharias & Poylymenakou, 2009).

- **E-learning System Interactivity (ESI):** This dimension concerns the e-learning system's collaborative tools that facilitate the interaction among students and between students and instructors. It is measured by whether students perceive that the communicational tools (email, discussion board, chat room, etc.) in Blackboard are effective, the capability of the system to provide interactive communication between students themselves as well as between teachers and students, and whether the system makes the learning process more engaging for students. The measurement scale was adapted from studies that were conducted on e-learning systems (Cheng, 2012; Hassanzadeh et al., 2012; Moreno et al., 2017; Oztekin et al., 2010; Pituch & Lee, 2006).

4.5.3 Construct Validity

Construct validity is concerned with the degree to which the test measures what it claims to measure for the validity assessment of the measurement procedure (e.g., a questionnaire) (Bryman & Bell, 2015). The questionnaire contains hypothetical constructs that are not observable (latent variables) and are evaluated indirectly through the indicators (questions) (Kline, 2016). The aim is to ensure the questions present an accurate operationalization of the construct and that they reflect the operational definition of the construct. Thus, pre-testing the instrument is considered important for the reliability and validity of the research results. By doing so, issues raised will be considered to improve the construct validity as well as the questions, format, wording and the developed scales before the actual distribution of the questionnaire. The aim of construct validity is to test whether the measures appear to reflect the hypothetical construct being measured (face validity) and whether the measures sufficiently cover the domain they are intended to cover (content validity) (Creswell & Creswell, 2018; Kline, 2016; Sekaran & Bougie, 2016). It is important to mention that there is no single definitive test for construct validity, yet the importance is based on the content and context in which the study instrument is applied (Kline, 2016). In this research, all measurement scale items also have been previously validated in the literature.

However, two phases have been conducted to assess the survey before the actual distribution for data collection – one with experts in the field and the other with targeted participants. As Kline (2016) advised, the opinion of experts is the basis for establishing the construct validity, not the statistical analysis. The researcher sought the assistance of scholars in the field from the UK and Saudi Arabia to obtain construct validity. The academics involved in the questionnaire evaluation were 5 professors, 2 in a computing school in the Edinburgh Napier University, and 3 from different universities in Saudi Arabia. All experts have been published in the area usability and acceptance and aware of the current obstacles and opportunities of e-learning systems implementation in the Saudi context. In particular, experts were requested to describe how they believe each item is being measured. The majority of items were labelled consistent with the construct and their indicators. The received insights and suggestions were critical in questionnaire development design. Many useful comments and constructive feedback were offered regarding questionnaire length, terminologies, coverage of constructs as well as the items' significance, relevancy and accuracy. The refinement of the questionnaire resulted in modifying and rewording some measures especially those which might confuse the respondents. In fact, experts have conducted many revisions and adjustments until the attainment of final approval for producing the version of the instrument to the potential participants in the pilot testing phase.

4.5.4 Translation

Given the fact that this research collected data from Saudi Arabia, it was important to ensure that the translation of the instrument to Arabic matched accurately the original language of English as suggested by Sekaran and Bougie (2016). Thus, all survey items were translated from the English version of the original survey into Arabic version using the Brislin (1986) back-translation method. The items were converted into Arabic by bilingual professors to ensure linguistic equivalence and also all translated scales remained accurate. Furthermore, attention was given to the cultural nuances, colloquial phrases, grammatical errors and jargon. For instance, the literal translation of the facilitating conditions factor yielded an interpretation beyond the original phrase, so the Arabic meaning was revised to reflect the meaning of the term in the source version. Furthermore, the scale was also rechecked with technology acceptance and usability experts to ensure the instrument terminologies were appropriate for students in Saudi tertiary education. In particular, there was an emphasis on the validity of the translated questions and whether they measured the phenomena that they intended to represent. The researcher also considered how the respondent might interpret the questionnaire items. A group of students were gathered to evaluate the questionnaire and to ensure that the meaning was consistent with the conceptual value of the construct.

4.5.5 Pilot Study

The pilot study is a crucial element in the research design before the main survey is conducted as the testing establishes the content validity and reliability of scores on an instrument and improves questions, format, and scales and whether instruments are too complicated or long to complete (Creswell & Creswell, 2018). In our study, the employed instrument has been tested extensively in the prior literature and yielded high reliability and validity (Holden & Rada, 2011; Junus et al., 2015; Khedr et al., 2011; Medina-Flores & Morales-Gamboa, 2015; Oztekin et al., 2010; Pituch & Lee, 2006; Zaharias & Poylymenakou, 2009). However, the reliability will be expected to fluctuate from sample to sample. Thus, the researcher needs to estimate the reliability of the study sample.

All the items were pre-tested using a pilot test conducted on 55 undergraduate students who trialled the questionnaire before it was distributed to the study sample. The purpose was to check the questionnaire's clarity, validity and reliability as well as the length and complexity of the questionnaire to ensure the questionnaire is more likely to obtain the sufficient number of responses from prospective respondents. The pilot study was carried out with students from two universities, King Khalid University and King Abdulaziz University . The students were selected randomly and were asked to fill out a paper-based questionnaire during class time so the non-response problem was absent.

There was a high degree of consistency among students about the constructs and their measurement items. An issue that merits attention in this regard was the frequent comment about the length of the questionnaire from several professors and expert students in the e-learning system. Thus, the researcher had to reduce the overall number of items in the questionnaire without affecting the research aim and objectives. To be specific:

- In the demographic data, researcher eliminated the items of field of study, year of study and the GPA. These data were less relevant to the research aim and objectives. Besides, some students in their first year have not received grades and their overall GPA were undetermined.
- In the visual design variable, two items were removed "Fonts, colours and sizes are consistent throughout Blackboard" and the statement " The activity, icon, button, label, and links actually lead to the content they promise to lead to". The reason for removal was that these items were redundant and already covered in the variable operationalization.
- In the instructional assessment variable, an item was removed "I receive regular feedback about my performance in a timely manner". Students appeared to be uncertain about the meaning of 'in a timely manner'.
- In the interactivity dimension, an item was removed " Interacting with other students and the instructor using Blackboard became more natural as the module progressed". There was some confusion about the phrase 'Blackboard became more natural as the module progressed'. Further, the remaining questions cover the interactive features of Blackboard.

- The questions were also modified to reflect the use of the Blackboard system, rather than a learning management system.

All other 56 indicators were retained for the final questionnaire as they show satisfactory validity. The pilot study showed that the expected average time for filling in the questionnaire was 10-15 minutes. To check the reliability of the instrument, the scale should have a Cronbach's coefficient α of above 0.7 (Hair et al., 2014; Straub et al., 2004). It is important to check the reliability since if the scale is not reliable, the research will not yield useful information. In this research, the α scores for all the sub-scales ranges from 0.72 to 0.86 which are above the cut-off point of 0.70, as illustrated in Table 4.3. It should be noted that the pilot study was conducted on the Arabic version of the instrument (refer to Appendix E).

Table 4.3 The Cronbach's α of the Pilot Study

Constructs	Number of Indicators	Cronbach's Alpha
PE	4	0.810
EE	4	0.790
SI	4	0.801
FC	5	0.786
BI	4	0.722
AU	4	0.719
SN	5	0.839
SL	5	0.738
VD	6	0.842
IQ	5	0.862
IA	6	0.809
ESI	4	0.763
Overall	56	

4.5.6 Ethical consideration

As this research involves human participants, a consent form was obtained from all participating students. The consent form explained the title and the purpose of the study, the targeted population and the length of time required to complete the survey. Furthermore, the students were aware that participation in this investigation was voluntary and they did not gain module credits or extra grades for participating. Financial incentives were also not offered in this research. The study guaranteed the informant's anonymity and confidentiality that all personal details (e.g., name, email, and IP address) would not be collected. A source of information about the researchers was provided for further clarification or any concerns regarding the ethics of the study. During the students' active involvement, they had the right to withdraw from the study at any time without giving reasons and they were free to decline to answer any particular question. Before answering the questions, all participants were requested to tick a box as an indication of their consent to participate in the survey. Finally and in accordance with the university code of ethics, approval was granted by the School of Computing at Edinburgh Napier University to begin the data-collection phase (see Appendix C).

4.5.7 Study Procedure

Once the content and face validity of the online questionnaire had been established, the data collection procedures began. The current research employed a questionnaire for data collection. Three thousand emails, each providing a hyperlink to the web-based survey, were distributed to students registered in different academic programmes. Around 600 emails were sent to students in each university by the deanships of Information Technology. The communication with universities is conducted through the Vice Presidency for Graduate Studies and Scientific Research. In this email, the research title and purpose were stated and the students were asked to participate in the study, and the link to the online survey was included. More specifically, an online survey was employed to reach the wider population of female colleges, as female students study in gender-segregated campuses. The selected five universities were King Khalid University, Al Jawf University, King Abdulaziz University, Saudi Electronic University, and Imam Abdulrahman Bin Faisal University. The universities were randomly selected based on the cardinal directions (north, south, east, west and central). The link to the online survey was available for three months during the autumn semester starting from 1st September 2018.

However and as with the Internet surveys, a low response rate was expected. Sekaran and Bougie (2016) stated that online questionnaires usually have a low response rate.

Therefore, the researcher had to visit the five selected universities. The main strategy was to contact instructors to disseminate the questionnaire and to encourage their students to participate in the research. There were no specific targeted programmes. The instructors were informed about the study aim objectives and the questions were formulated based on the overall experience with the Blackboard modules rather than a specific module. Also it was clarified that all the data provided by the participants would be treated confidentially. For those who agreed to disseminate the survey online, the web link to the online survey was given to them to email it to their students. Specifically, the WhatsApp and Telegram applications were utilised to disseminate the online survey to female students in the segregated colleges. In some universities, the link was sent to the representatives of the e-Learning Deanship who can distribute the link to faculty members who teach online modules. A total of 186 responses were received from King Abdulaziz University, 257 from King Khalid University, 106 from Al Jawf University, 143 Saudi Electronic University, and 169 responses from Imam Abdulrahman Bin Faisal University. After the preliminary data analysis using SPSS (see CHAPTER 5:), 605 usable responses were used for inferential analysis and are considered sufficient and acceptable to represent the concepts in the study.

Having explained the instrumentation and the study procedure for this research, the next section will introduce and justify the data analysis technique employed to validate and test the instrument

4.6 Data analysis

The data were analysed using SPSS version 24 and SmartPLS 3 Partial Least Squares Structural Equation Modelling PLS-SEM. The SPSS 24 package was employed to perform the preliminary examination including missing data, outliers, normality and unengaged responses (chapter 5). SmartPLS 3 software was used to analyse and test the research proposed model (chapter 6). PLS-SEM is convenient when the primary objective of the research is to extend an existing theory or identify key drivers (Hair et al., 2017). Since the goal was to identify the key drivers for student's acceptance of an LMS, PLS-SEM was used. A more detailed account of the statistical technique

(SEM) is given in the following section, focusing on the rationale and the benefits of PLS-SEM, as opposed to CB-SEM approaches.

4.6.1 Structural Equation Modelling (SEM)

As there has been a data explosion from different sources, the world is pushed toward data-driven discovery and in particular, techniques for analysis. Thus, a sophisticated statistical analysis such as SEM was introduced to compensate for previous inadequacies in technique. Second-generation statistical techniques like SEM have been beneficial in that they have substantially advanced the scientific community (Hair et al., 2014). SEM is a multivariate technique that amalgamates factor analysis, canonical correlation and multiple regression analysis, enabling the researcher to simultaneously estimate the relationships between independent and dependent variables, as well as between latent variables (Hair, Hult, et al., 2017; Tabachnick & Fidell, 2013). SEM is capable of handling multiple dependent variables within a single model, which is an advantage over linear regression (Tabachnick & Fidell, 2013). It also allows researchers to perform a single analysis of a model, rather than a series of univariate or bivariate analyses (Tabachnick & Fidell, 2013). It is considered one of the most sophisticated statistical analyses, as it evaluates the model fit to the data (Hair, Hult, et al., 2017; Tabachnick & Fidell, 2013).

Covariance-based structural equation modelling (CB-SEM) and partial least squares structural equation modelling (PLS-SEM) are the two main approaches that the researcher draws on when estimating structural models. Software packages such as AMOS and LISREL are used for CB-SEM estimation whereas applications such as SmartPLS and PLS-Graph are used for PLS-SEM analysis. While CB-SEM is the most wildly applied method, the variance-based PLS-SEM approach has become a key research method (Hair et al., 2017; Hair et al., 2019). The use of the PLS-SEM algorithm has increased exponentially in recent years as a distinctive and evolving methodological method, especially in social science studies (Henseler et al., 2009). More specifically, in recent years, there has been an increasing interest in the use of PLS-SEM in information system studies (Hair et al., 2017).

PLS-SEM estimates the path coefficients in which the explained variance of the dependent variable is maximized (i.e. the R^2 value) (Hair et al., 2017). The algorithm computes measurement and structural model relationships separately. PLS-SEM has many benefits over CB-SEM including the capability to handle small sample sizes efficiently, work well with non-normally distributed data, handle reflective and formative measurement models, and also handles complex models with many indicators and relationships (Hair et al., 2019; Hair et al., 2017). However, the two approaches complement each other, and the selection is based on the study goal. For instance, CB-SEM is recommended when the objective is model confirmation – that is, how well the model fits the data. However, a good fit may not imply prediction. Conversely, PLS-SEM is preferred when the research goal is the prediction of constructs, focusing more on exploration than confirmation, with little prior knowledge about the structural model relationship, as in the case of this study. In a complex model, where many latent variables and indicators are present, CB-SEM is often impossible to estimate (Chin, 1998; Hair et al., 2017). Overall, the reason for the selection of PLS-SEM is grounded on the following.

- CB-SEM is primarily used to confirm or reject theories where research model variables are correctly chosen and linked together (the prior theory is strong) (Ken, 2013) whereas PLS-SEM is used when theory is less developed as pointed by Hair et al. (2017) and Hair et al. (2019)
- Researchers use PLS-SEM where the focus is on prediction, testing complex models with little theoretical substantiation (Hair et al., 2017; Stieglitz et al., 2014).
- In terms of model complexity, the path model is relatively complex as evidenced in many constructs per model (six or more) and indicators per construct (four or more indicators) (Hair et al., 2019; Hair et al., 2017; Sarstedt et al., 2017). PLS-SEM is preferred when the structural model is complex and has many variables with a large number of indicators (i.e., extends existing theory). In fact, using this technique is considered useful in minimizing PLS-SEM bias (Hair et al., 2019).

- The primary aim of this research is the prediction and explanation of Saudi students' use behaviour; therefore, PLS-SEM is an attractive alternative to CB-SEM given that the entire aim of CB-SEM is supposed to be theory testing, testing whether the model fits the data. It is not suited for prediction (Chin, 1998; Hair et al., 2019; Hair et al., 2017).
- The PLS-SEM goal is to maximise the explained variance of the endogenous latent constructs (as the goal of this research is) whereas the objective of CB-SEM is to reproduce the theoretical covariance matrix without focusing on the explained variance (Hair et al., 2017).
- PLS-SEM allows researchers to predict the key driver variables or predict key target constructs by focusing on explaining the variance in the dependent variable. PLS-SEM estimates the path relationship with the objective of minimizing the error of the dependent variable and maximizing the R^2 value of the target variable (Hair et al., 2017; Ken, 2013).
- Unlike CB-SEM, the technique is characterised by a high efficiency in parameter estimation, resulting in a greater statistical power of the target relationship that reflects the significance in the population. This means that trust in PLS-SEM is high, reflecting the studied phenomena in the population (Hair et al., 2018).
- The goal of this study is exploration rather than confirmation. Thus, PLS-SEM appears to be the most appropriate (Hair et al., 2017)
- PLS-SEM has a robust model estimation with both normal and non-normal distributions (Hair et al., 2019; Reinartz et al., 2009).
- The researcher can use PLS in a composite-based approach to SEM where indicators linearly form composite variables – proxies for the theoretical concept under examination (Sarstedt et al., 2016).

Nevertheless, the strategy has not escaped criticism from several academics. There is, for example, no estimation of global goodness-of-fit criteria in PLS-SEM (Hair et al., 2017). Furthermore, its use for theory testing confirmation is limited (Hair et al., 2017). PLS-SEM cannot be applied to models containing circular relationships between the latent variables (Hair et al., 2017). The technique cannot measure undirected correlations since arrows are always single-headed (Ken, 2013). Overall, some researchers did not draw a definitive conclusion about the difference between CB-SEM and PLS-SEM as there are subtle variations in variance estimates between them, especially with a large dataset (e.g., N=250) (Hair et al., 2017; Reinartz et al., 2009). The techniques complement each other and the selection is based primarily on the research aim. Drawing upon this discussion, the PLS-SEM technique seems to suit the research objective, data characteristics and model setup, and hence it is selected.

4.7 Summary

This chapter has described the methods used in this investigation. The positivist paradigm was chosen, whereby a quantitative, survey method was used to collect empirical data. As the goal of this research is to examine and validate the conceptual framework, quantitative analysis was used for the collected data. A survey research was the most appropriate technique, as it fits with the causality approach adopted in this study. The survey is a common method to use in usability and technology acceptance studies, and can yield direct information of users' experiences, considering the large sample size (Saudi students in higher education). A brief description was given of the target population and the sampling techniques where a multi-stage cluster-sampling technique was selected and justified for the data collection from five universities in Saudi higher education. Based on the geographical clustering sampling, the results can also be generalised to the population. A more detailed account of questionnaire considerations and development was given, focusing on construct validity, translation, pilot study and ethical guidelines that were assured. With respect to the statistical technique employed in this research, a comparison between PLS-SEM and CB-SEM was provided, highlighting the relevance of PLS-SEM technique to test the model in this research.

CHAPTER 5: DATA ANALYSIS

5.1 Introduction

This chapter deals with a set of issues after the data collection process and before multivariate analysis is conducted. It is considered essential to carefully examine the accuracy and validity of the data before the main analysis as inaccurate data could produce distorted correlation (Hair et al., 2014; Kline, 2016; Tabachnick & Fidell, 2013). This stage is particularly important in the application of PLS-SEM to ensure the results are valid and reliable (Hair et al., 2017). Hence, the chapter begins with presenting the issues concerned with the preliminary data analysis that include data screening, missing data, outliers and normality for UTAUT and usability variables. While distributional assumptions are of less concern in the PLS-SEM technique, it is worthwhile performing it to ensure the data are not too far from a normal distribution. That was conducted to ensure the data fit the assumptions underlying the multivariate analysis. The chapter also reports the descriptive statistics of the main study, including frequencies and percentages related to respondents' profiles as well as the e-learning system experience, use frequency and the training received.

5.2 Data Screening and Management

Data screening is an essential step before any statistical procedure to ensure data integrity. The process includes handling the missing values, patterns, outliers, and identifying data normality (Hair et al., 2014; Tabachnick & Fidell, 2013). The ultimate purpose is to minimise the data noise and ensure the data accuracy and validity by fixing and removing the errors in the raw data before any inferential analysis. By doing so, not only does the researcher gain a basic understanding of the data but also ensures that the data meet all the requirements for multivariate analysis (Hair et al., 2014). In this study, pre-analysis data screening was conducted on the raw data before the multivariate analysis. In a data examination, all raw data were coded, edited and transferred into IBM SPSS version 24. Descriptive statistics and visual representations of the measures were obtained to check and ensure the data accuracy. This process detects and corrects any illogical or illegal entry by the participants. For instance, Arabic numerals were transformed into Western numerals as SPSS only accepts the latter form of number expression. Univariate descriptive statistics for each categorical and continuous variable were confirmed to be plausible, including frequency, means, ranged values, and standard deviations. In total, all responses of the questionnaire items were screened to identify, and fix, missing values, normality of each variable, and outliers. In the following subsections, the data missing values, normality and outliers will be further discussed.

5.2.1 Missing Data

Missing data often happen when a respondent fails to answer one or more items in a questionnaire (Hair et al., 2014). Missing data are a challenging and common concern in data analysis particularly those of a multivariate nature (Tabachnick & Fidell, 2013). It is a nuisance to researchers and even with well-designed and controlled research, missing responses can occur especially because of data entry errors or respondents' refusals to answer. It has adverse consequences on the study results as inaccurate inferences and biased estimates might arise. Furthermore, the problem is exacerbated with structural equation modelling as some computation measurements such as the bootstrapping procedure require complete data on all variables and cannot be estimated if any missing data in the sample is identified. Thus, it is important to classify and deal with missing data before conducting any statistical analysis (Hair et al., 2014).

As seen in the earlier discussions, it is crucial to identify the presence of the missing data and then apply the appropriate solution. In this study and during the design of the data collection instrument, all sections in the questionnaires were set to be mandatory so respondents cannot move to the next section until the previous section is completed. It can be inferred that if a respondent stops half-way through the survey, then all next items will be shown as missed and the questionnaire will be incomplete. The researcher identified the respondents who failed to complete the entire questionnaire. The researcher discarded all incomplete observations related to UTAUT and usability variables. The reasons for ignoring the missing values were 1) the number of cases with no missing values on any variables satisfies the required sample size for analysis, 2) substituting values for the missing data can create a bias in the results, 3) fit measures such as the bootstrapping function of SEM techniques required complete answers, and 4) missing values appeared to be a random subsample of the data. In these circumstances, the deletion of missing values can be a good alternative (Tabachnick & Fidell, 2013). Besides, Hair et al. (2014) emphasised that missing values can be ignored if the number of cases with no missing values is sufficient for analysis. In many instances where a non-pattern occurs and a large amount of data are available, the deletion of cases with missing values might be the most efficient approach (Hair et al., 2014; Hair et al., 2017; Sekaran & Bougie, 2016).

Overall, more than 3000 questionnaires were distributed randomly among students in Saudi higher education in the five different regional universities. From 3000 questionnaires, 861 (29%) were returned and of these, 256 (30%) questionnaires were incomplete and considered unusable due to the excessive missing data (more than 50% missing values). To be specific, 100 participants had only agreed to participate but did not go further to demographic information while the remaining 142 had only completed the first part of the UTAUT variables (more than 50% were missing). There were 14 suspicious response patterns removed as evidenced by marking the same response for every single item. It is justifiable to remove all unengaged response patterns from the dataset (Hair, Hult, et al., 2017).

The remaining 605 cases have full data on all of the variables and an adequate sample size for the multivariate analysis. Even though online surveys are less likely to achieve response rates as high as paper-based surveys, 605 is considered sufficient and acceptable to represent the concepts in the study in the online survey approach. Sekaran and Bougie (2016) stated that 30% is considered acceptable in surveys, and in many cases even exceptional.

5.2.2 Outliers

Outliers are observations that are substantially different from other observations (Hair et al., 2014). The decision to label a data point an outlier is based on it having an extremely high or low value on a variable or number of variables and which therefore stands out in the study sample (Hair et al., 2014; Tabachnick & Fidell, 2013). An outlier can have a large impact on the data normality and ultimately the research results (Sekaran & Bougie, 2016; Tabachnick & Fidell, 2013). Thus, identifying and correcting outliers is a fundamental step before preceding to multivariate analysis as they can seriously distort the data analysis. According to Hair et al. (2014) and Kline (2016), outliers can be examined from univariate and multivariate perspectives.

In this study, the univariate outliers were tested using frequency distributions of zscores as suggested by Kline (2016). The zscores are standardized scores that have a mean of zero and a standard deviation of one (Kline, 2016; Tabachnick & Fidell, 2013). It measures the number of standard deviations above or below the mean of the score. A case can have a univariate outlier if an unusual value is detected on a single variable (Kline, 2016). Thus, the distributions of responses for each variable have to be examined. While there is no consensus on the extreme value in the literature, large sample sizes can accept the value of ± 3.29 (Tabachnick & Fidell, 2013). Using SPSS, the mean composites were standardized and instances exceeding the absolute value of 3.29 were regarded as potential outliers (Tabachnick & Fidell, 2013). In this study, the result indicated that all variables ranged between the standardized values of ±3.29 and there was no univariate outlier instance in the study sample.

Multivariate outliers occur when multiple cases have extreme scores in the data. It is a measure of the multidimensional position of each case and can be addressed using the Mahalanobis D^2 measure. D^2 is distributed as a central chi-square (chi^2) with the degree of freedom (*Df*) equal to the number of independent constructs, in this case 10. This technique computes each observation's distance from the sample means for all variables (centroid) (Kline, 2016). Thus, a higher D^2 value of observations indicates a higher distance from the centroid of remaining cases. In this study, SPSS was used to measure the Mahalanobis D^2. The D^2 is a chi-squared distributed value and can be computed using the regression function in SPSS. Then P1-value was computed for D^2 for each case. As suggested by Tabachnick and Fidell (2013), the probability value of 0.001 is used as the threshold value for designation as an outlier. The observations whose p value < 0.001 would be considered potential outliers in the dataset. With this threshold, 22 cases were found to be different (refer to Table 5.4). However, those instances are not unique on any single variable but unique in combination. Furthermore, Tabachnick and Fidell (2013) projected that it is expected to have outliers on a large sample size which should only be deleted if they are truly influencing the results. Thus, since the potential outliers are limited compared to the complete dataset (3%), the researcher decided to retain the 22 cases for further multivariate analyses as suggested by Hair et al. (2014). Besides, outliers were absent in the use of diagnostics by means of box plots using IBM SPSS statistics as advised by Tabachnick and Fidell (2013).

Table 5.4 Multivariate Outliers

Case ID	**Mahalanobis D2**	**p.value < 0.001**
487	50.77913	0.00001
345	41.58642	0.00001
225	39.08092	0.00002
237	38.97444	0.00003
99	37.90946	0.00004
230	37.78005	0.00004
182	37.71237	0.00004
369	34.50417	0.00015
510	34.34852	0.00016
293	34.31626	0.00016
549	33.97258	0.00019
38	33.24559	0.00025
394	33.01729	0.00027
86	32.43848	0.00034
19	31.99757	0.0004
28	31.80776	0.00043
401	31.36651	0.00051
43	30.75663	0.00064
124	30.66619	0.00067
573	30.43426	0.00073
364	30.27257	0.00077
392	29.83528	0.00091

5.2.3 Normality Assumption

Normality is the most essential assumption in the multivariate analysis (Tabachnick & Fidell, 2013). The term normality refers to the shape of the sample data distribution for each variable and its correspondence to the normal distribution (Hair et al., 2014). If the data are not normally distributed, the results of statistical analysis are invalid and the large values are enough to warrant attention (Hair et al., 2014). However, Hair et al. (2014) highlighted that the impact of non-normality effectively diminishes in a large sample size (200 responses or more). This view is also supported by Tabachnick and Fidell (2013) in which skewness will not make a substantive difference in the analysis for a large sample size. Importantly, PLS-SEM makes no assumptions about the data distribution (Hair et al., 2018; Hair et al., 2017). In all circumstances, it is worthwhile to test normality and how the data are well-modelled by the normal distribution. It is also worth mentioning that the severity of non-normality is grounded on two assumptions, the shape of the offending distribution and the sample size (Hair et al., 2014). In this study, the univariate normality was tested from statistical and graphical perspectives. Statistical normality was measured by kurtosis and skewness. While Kurtosis is concerned with distribution height, the skewness refers to the balance of the distributions, i.e., the symmetry. A negative skew denotes a distribution is shifted to the right, whereas positive skew indicates a leftward shift. According to Hair et al. (2014), in a normal distribution, the skewness and Kurtosis z-values should be between the critical value of ±2.58 (.01 significance level). Following this guideline, the dataset falls between the specified critical values of ±2.58 at significant level 0.01 (refer to Table 5.5). These results assumed that the data are approximately normally distributed for each variable. Graphical representation was also examined visually using a histogram that compares the observed data values with a distribution approximating the bell curve of a normal distribution. In this research, the visual representation of the histogram for all variables indicated that the data are approximate the bell-shaped curve of the normal distribution. It can be concluded that the statistical calculation and visual assessment demonstrate that the data distribution is acceptable and there are no major issues in non-normality.

Table 5.5 Skewness and Kurtosis Statistics for the Study Variables

Construct	Skewness Statistic	Kurtosis Statistic
PE	-0.806	0.307
EE	-1.122	1.296
SI	-0.797	0.626
FC	-0.335	-0.043
BI	-0.965	0.317
AU	-0.836	0.875
SN	-0.689	0.168
SL	-0.835	0.866
VD	-0.682	0.105
IQ	-0.674	0.242
IA	-0.768	0.615
ESI	-0.394	-0.479
Note: Std. Error for Skewness Statistic = 0.1. Std. Error for Kurtosis Statistic = 0.2		

Overall, this section has discussed the data screening approaches of the study's sample. The issues of missing data, outliers and normality were examined. Based on the results of data screening assumptions, it can be concluded that the data are valid and reliable for multivariate analysis. The section that follows moves on to consider the descriptive statistics for the respondent demographics.

5.3 Descriptive Statistics of Demographic data

Descriptive statistics, unlike inferential statistics, are a summary of the basic features that describe the dataset. This includes the generating of tables of the respondents' demographic, general characteristics, and the information about the measures.

In this study, the target sample for this study was taken from students in Saudi higher education. A total of 3000 questionnaires were distributed to five universities in different regions in Saudi Arabia. As detailed above, 605 final questionnaires were used for data analysis. All of these respondents are Saudi Arabian students from various backgrounds, region and educational specialities. The target sample consists of full-time students, either undergraduate or postgraduate, from five universities in

Saudi Arabia geographically dispersed across Saudi Arabia. They are all users of the Blackboard LMS provided by the university.

Frequency distributions were obtained for all profiles of the participants. The descriptive analysis of this study is presented in Table 5.6. The table shows the distribution of respondents' characteristics including gender, age, educational level, e-learning system experience, use frequency, registered modules, and the training received about the system. The following sections will illustrate each category and provide the results of the analysis using SPSS software version 24.

Table 5.6 Demographics Analysis of Respondents

	Frequency	**Percentage**
Gender		
Male	279	46.1
Female	326	53.9
Educational Level		
Undergraduate	573	94.7
Postgraduate	32	5.3
System Experience		
Less than 1 year	68	11.2
1 – 2 years	324	53.6
> 2 years	213	35.2
Blackboard Enrolled Modules		
1-3 modules	246	40.7
4-5 modules	194	32.1
More than 6 modules	159	26.3
I do not Use Blackboard in any module	6	1
Use Frequency		
Daily	390	64.5
Weekly	174	28.8
Monthly	38	6.3
I do not Use Blackboard	3	0.5
System Training		
1-3 hours	263	43.5
4 -6 hours	36	6
More than 6 hours	17	2.8
None	289	47.8

5.3.1 Gender and Educational Level

As Table 5.6 outlines, a total of 605 students fully completed their responses. Of the 605 completed questionnaires, males represent 46.1% (279 participants) and females 53.9% (326 participants). The proportion of females is slightly higher than males which may be related to the fact that females' enrolment in the Saudi universities is higher than that of males (Ministry of Education Saudi Arabia, 2017).

Regarding the educational level, undergraduates represent 94.7% (573 respondents), while postgraduates constitute only 5.3% (32 respondents). Thus, the results of the educational level were anticipated, as undergraduates constitute the majority in Saudi tertiary education (Ministry of Education Saudi Arabia, 2017).

5.3.2 Age

Age was measured based on a ratio scale. As Table 5.7 illustrates, the dominating age group ranges from 18 to 25 years old, representing 87.7% (531 respondents) of the total study sample. The remaining 12.3% corresponds to the more senior age group, 26-36 years old. The mean score for age is 22.07 with a standard deviation of 4.8 years. These findings appear to be reasonable and indicate that most of the respondents are undergraduates.

Table 5.7 Age Distribution of Respondents

Age	Frequency	Percent %	Mean	Standard Deviation
17	2	0.3	22.07	4.75
18	81	13.1		
19	99	16.4		
20	101	16.7		
21	84	13.9		
22	70	11.6		
23	45	7.4		
24	29	4.8		
25	22	3.6		
26	9	1.5		
27	8	1.3		
28	1	0.2		
29	4	0.7		
30	12	2		
31	3	0.5		
32	7	1.2		
33	2	0.3		
34	3	0.5		
35	7	1.2		
36	2	0.3		
37	2	0.3		
38	3	0.5		
39	3	0.5		
40	3	0.5		
43	1	0.2		

45	2	0.3		
46	1	0.2		
53	1	0.2		
Total	605	100		

5.3.3 System Experience

In terms of e-learning system experience, the majority of respondents have had some experience in using the Blackboard system. The objective is to elicit students' views about their proficiencies in using Blackboard. The study shows that experience up to one year comes as the minority (11.2%) since they have recently started using Blackboard. It also demonstrates that the majority arrive with 1-2 years of experience, with more than half of respondents (53.6%), whereas more than a third of those who responded (35.2%) indicated more than 2 years of experience in using the system.

5.3.4 Blackboard Enrolled Modules

Data for several groups who have enrolled in the Blackboard module were gathered. The largest percentage represents those who are registered in 1-3 modules (40.7%); 4-5 modules (32.1%); more than 6 modules (26.3%) and a small percentage of the students, only 1%, are not enrolled in any module in the current academic year.

5.3.5 System Training

The descriptive statistics, presented in Table 5.6, also show that the majority of students had no previous training in the use of Blackboard (47.8%) while a minority (43.5%) reported some training (1-3 hours). The remaining slots accounted for students who received 4-6 hours (6%) and those who acknowledged training for more than 6 hours (2.8%).

5.4 Descriptive Statistics of Construct Items

Table 5.8 shows the descriptive statistics for the observations. This includes means and standard deviations for each item of the predictor and the outcome variables. The objective is to appraise how respondents have reacted to each item in the survey. By doing so, not only does the researcher identify whether the responses range satisfactorily over the scale but also the variability and dispersion for every question of the construct (Sekaran & Bougie, 2016).

Table 5.8 shows the means of standard deviations for each item in the questionnaire. Overall, the means ranged between 3.01 and 4.4 and the standard deviations between 0.837 and 1.383. It can be seen that the majority of respondents exhibited a positive overall reaction for the proposed input constructs. All means for all the factors are above 3.01 and the standard deviations are generally around 1 which denotes higher levels of agreement for the questionnaire questions. It also indicates a narrow spread around the mean and illustrates that students have similar perceptions of the advantages of the LMS in Saudi higher education. In the following section, descriptive statistics will be discussed.

Table 5.8 Descriptive Statistics of the Scale Construct

Construct	Item	Mean	Std deviation
Performance Expectancy (PE)	PE1	4.03	1.009
	PE2	3.96	1.081
	PE3	3.54	1.147
	PE4	3.62	1.253
Effort Expectancy (EE)	EE1	3.90	1.031
	EE2	4.08	0.936
	EE3	4.16	0.912
	EE4	4.07	0.961
Social Influence (SI)	SI1	3.01	1.100
	SI2	3.33	1.143
	SI3	4.09	0.984
	SI4	4.08	1.067
Facilitating Conditions (FC)	FC1	4.05	0.939
	FC2	4.02	0.928
	FC3	3.21	1.153
	FC4	3.21	1.255
	FC5	3.32	1.199
Behavioural Intention (BI)	BI1	3.77	1.158
	BI2	3.86	1.168
	BI3	3.69	1.324
	BI4	3.93	1.103
Actual Use (AU)	AU1	4.40	0.837
	AU2	3.56	1.383
	AU3	3.99	1.056
	AU4	4.00	1.051
System Navigation (SN)	SN1	3.86	1.077
	SN2	3.40	1.180
	SN3	3.56	1.117

	SN4	3.72	1.055
	SN5	3.94	1.152
System Learnability (SL)	SL1	3.93	0.975
	SL2	3.76	0.995
	SL3	3.79	1.026
	SL4	4.09	0.912
	SL5	3.52	1.136
Visual Design (VD)	VD1	3.88	1.015
	VD2	3.60	1.124
	VD3	3.45	1.171
	VD4	3.55	1.126
	VD5	3.63	1.140
	VD6	3.52	1.201
Information Quality (IQ)	IQ1	3.68	1.067
	IQ2	3.53	1.160
	IQ3	3.53	1.136
	IQ4	3.72	1.055
	IQ5	3.45	1.136
Instructional Assessment (IA)	IA1	3.95	1.015
	IA2	3.73	1.116
	IA3	3.66	1.062
	IA4	3.58	1.094
	IA5	3.67	1.128
	IA6	3.51	1.162
E-learning System Interactivity (ESI)	ESI1	3.19	1.248
	ESI2	3.30	1.258
	ESI3	3.06	1.283
	ESI4	3.49	1.191

5.5 Summary

The chapter has presented the results of the preliminary data analysis for the collected data before the main data analysis was conducted. The researcher began with the data screening of the dataset. Missing data, outliers and normality were examined through various statistical analysis for accuracy. Responses with missing data were deleted as they fell below 50% completion rate. Univariate and multivariate outliers were assessed and dealt with. The normality assumption was tested and the data found to approximate the normal data distribution. It is considered fundamental to deal with these potential problems before running the multivariate analysis as failure to do so might produce inaccurate and invalid results.

The researcher then explored the respondents' characteristics from the questionnaire of students in Saudi tertiary education. Demographic details about gender, age, educational level, students' system experiences, registered modules, and the training received about the system were presented. Furthermore, mean and standard deviations were obtained for each item of the constructs. While there was a variety of perspectives regarding the system throughout Saudi institutions, the majority of students expressed a positive response across the UTAUT and usability variables.

The data are therefore eligible for further analysis including PLS-SEM. The next chapter will discuss the model analysis, the measurement model and the structural model along with the analysis of moderating effects.

CHAPTER 6: MODEL ANALYSIS

6.1 Introduction

This section describes the analysis of the data. Using the SmartPLS software to estimate the relationship between the constructs, two sub-models emerge: the measurement model and the structural model. In the measurement model, the emphasis is on the relationship between the constructs (UTAUT and Usability variables) and their corresponding indicators. An indicator, also called a measurement item, is a particular questionnaire question. A UTAUT and usability construct can be measured by group of questions (multiple indicators). In the measurement model estimation, the criteria of internal consistency, convergent validity and discriminant validity are established to prove statistically the validity and reliability of the constructs and their indicators (Hair et al., 2019). The reliability and validity of the model are prerequisites of the structural model estimation in which the measurement model provides evidence of the construct quality (Hair, Hult, et al., 2017).

In contrast, the structural model analysis represents the research hypotheses. The emphasis of this phase is on the path model – the relationship between constructs. PLS-SEM examination of the structural model involves the assessment of criteria of the coefficients of determination (R^2 values), the predictive relevance (Q^2) as well as the size and significance of the path coefficients (Hair, Hult, et al., 2017). R^2 values represent the combined effects of independent variables on the outcome variables while Q^2 is an indicator of the model's out-of-sample predictive power (Hair, Hult, et al., 2017). Thus when a PLS path model exhibits predictive relevance, it accurately predicts data not used in the model estimation (Hair, Hult, et al., 2017). The next section describes the measurement model analysis.

6.2 Measurement Model Analysis

The assessment of the measurement model includes the estimations of internal consistency, indicator reliability, Average Variance Extracted (AVE), and convergent validity and discriminant validity. Using the PLS algorithm, the measurement model was estimated. It is the relationship between the construct and the corresponding indicators. Most research on IS has reported the composite reliability and Cronbach's α and AVEs for the assessment of the measurement model as well as Fornell-Larcker and cross-loadings for the assessment of discriminant validity (Hair, Hollingsworth, et al., 2017). Using the PLS algorithm, the researcher estimated the measurement model, including outer loadings, composite reliability, Cronbach's α (CA), AVE, and discriminant validity. Table 6.9 summarises the criteria used for evaluating the measurement model. In the following sections, each criterion will be addressed for the evaluation of reflective measurement models.

Table 6.9 The Criteria Used to Evaluate the Measurement Model

Assessment Type	**Criterion**	**Guidelines**	**References**
Measurement model	Indicator reliability	Factor Loading ≥ 0.70 (or ≥ 0.60 in exploratory research)	(Chin, 1998; Hair et al., 2019)
	Construct reliability	CA ≥ 0.70 (or ≥ 0.60 in exploratory research)	(Cronbach, 1951; Hair et al., 2014, 2019; Nunnally & Bernstein, 1994)
		CR ≥ 0.70	(Hair et al., 2014; Sarstedt et al., 2017)
	Convergent validity	AVE ≥ 0.5	(Fornell & Larcker, 1981; Hair et al., 2019)
	Discriminant validity	AVE > correlation with other constructs	(Fornell & Larcker, 1981)
		For conceptually similar constructs: HTMT < 0.90 For conceptually different constructs: HTMT < 0.85	(Hair et al., 2019; Henseler et al., 2015; Sarstedt et al., 2017)

CA: Cronbach's alpha, CR: Composite reliability, AVE: Average variance extracted

6.2.1 Construct Reliability

The first criterion to be evaluated is internal consistency reliability. Reliability measures the extent to which a factor is consistent with what it is supposed to measure (Hair et al., 2014). That is, if the results of a study are replicated consistently, measures will show greater consistency and the items exhibit a high positive correlation within a measure. If the measurement random error occurrence is high, the data are distorted and further multivariate analysis may yield marginal results (Kline, 2016). The

Cronbach's α (also called coefficient α) measure is the traditional criterion for reliability (Hair, Hult, et al., 2017; Pallant, 2016). It computes the internal consistency, the degree to which responses are consistent across items within variable (Kline, 2016; Pallant, 2016). The coefficient α assumes that factor loadings are the same for all items. The score of Cronbach's α ranges from 0 to 1, with higher values indicating higher reliability and the value of .70 is the lower limit of acceptability (Hair et al., 2014, 2019; Pallant, 2016). However, in order to address Cronbach's α sensitivity to item number in the scale, it is sensible to apply composite reliability, a more conservative measure of internal consistency reliability where varying factor loadings are taken under consideration (Hair, Hult, et al., 2017). The items in the composite reliability are weighted based on the constructs' indicators loadings so the reliability is higher than Cronbach's α (Hair et al., 2019). Overall, prior studies have demonstrated that the constructs constituting UTAUT have a good internal consistency, with a Cronbach's α coefficient reported of 0.70 (Venkatesh et al., 2003).

Table 6.10 Cronbach's α and Composite Reliability Results

	Cronbach's α	**rho_A**	**Composite Reliability**
PE	0.83	0.86	0.89
EE	0.89	0.90	0.93
SI	0.77	0.79	0.86
FC	0.79	0.81	0.85
BI	0.90	0.93	0.93
AU	0.75	0.77	0.84
SN	0.85	0.86	0.90
VD	0.90	0.92	0.93
SL	0.88	0.88	0.91
IQ	0.90	0.93	0.93
IA	0.90	0.91	0.93
ESI	0.88	0.93	0.91

For the measurement of the internal consistency, a reliability coefficient of Cronbach α was utilised to determine the reliability of the questionnaire. As is shown in Table 6.10, the reliability assessment of the measurement model ranges between 0.75 and 0.90 in which all variables were greater than the recommended benchmark value of 0.70 (Churchill, 1979). The overall reliability statistic for the scale is 0.973 which suggests that the UTAUT and usability variables are robust in terms of their internal consistency (see Table 6.10).

Along with that, the composite reliability was estimated. As Table 6.10 outlines, the composite reliability values demonstrate that all constructs have high levels of internal consistency reliability. The factor loadings might be very similar in that the discrepancy between the construct reliability value is diminished. Thus, all latent variables exceed the adequate values in which internal consistency is established. This means that the indictors within the construct correlate highly and hence, are representative of the variable.

6.2.2 Indicator Reliability

Indicator reliability (also called factor loading) is the correlation between the construct and its corresponding indicators, with higher loadings making the indicator representative of the construct (Hair et al., 2014). The assessment of items' factor loadings was employed to examine the variability among correlated constructs. The factor loadings of all individual indicators were calculated using the PLS algorithm in SmartPLS3. Hair et al. (2019) outlined that guidelines for interpreting the results vary based on the context. The rule of thumb is that standardized loading of 0.50 is considered, in most instances, acceptable while 0.70 or higher is ideal (Hair et al., 2014). In exploratory research, the reliability should be a minimum of 0.60 whereas in established measures, the reliability should be equal to or more than 0.70 (Hair et al., 2019). It is important to observe that the researcher should be careful of deletion factor with outer loading of less than 0.5. Instead, indicators with factor loadings between 0.40 and 0.70 should be considered for removal only if the deletion leads to an increase in composite reliability and AVE above the suggested threshold value (Hair, Hult, et al., 2017). As it can be shown in Table 6.11, most of the factor loadings of the reflective constructs are well above the threshold value of 0.70 (Hair, Hult, et al., 2017). Besides, a number of researchers advised that values of 0.60 to 0.70 are acceptable in exploratory research, as of the case of this research (Hair et al., 2019; Hair, Hult, et al., 2017). In this research, few loadings estimate fall just below the 0.70 ideal standard. Two indicators which are ≥ 0.60 (e.g. FC3, AU2) are retained for further analysis as is the case for exploratory research. Furthermore, these two are considered significant and they are retained for further analysis on the basis of their contribution to construct content validity. From another perspective, the t statistics show that all factors are above 1.96, therefore, there all significant indicators. From Table 6.11, it can be seen that AU2 has the smallest indicator reliability with a value of 0.60 while the BI4 indicator has the highest reliability with a value of 0.92.

Table 6.11 Factor Loadings and AVE

Indicators	Factor Loading	AVE
Performance Expectancy		0.67
PE1	0.84	
PE2	0.86	
PE3	0.88	
PE4	0.70	
Effort Expectancy		0.76
EE1	0.85	
EE2	0.90	
EE3	0.87	
EE4	0.88	
Social Influence		0.60
SI1	0.76	
SI2	0.84	
SI3	0.77	
SI4	0.72	
Facilitating Conditions		0.54
FC1	0.72	
FC2	0.76	
FC3	0.66	
FC4	0.73	
FC5	0.79	
Behavioural Intention		0.81
BI1	0.90	
BI2	0.92	
BI3	0.88	
BI4	0.91	
Actual Use		0.57
AU1	0.75	
AU2	0.60	
AU3	0.88	
AU4	0.77	
System Navigation		0.63
SN1	0.84	
SN2	0.78	
SN3	0.83	
SN4	0.75	
SN5	0.77	
System Learnability		0.67
SL1	0.84	
SL2	0.81	
SL3	0.87	
SL4	0.81	
SL5	0.76	

Visual Design		0.70
VD1	0.73	
VD2	0.77	
VD3	0.88	
VD4	0.90	
VD5	0.86	
VD6	0.88	
Information Quality		0.77
IQ1	0.87	
IQ2	0.90	
IQ3	0.89	
IQ4	0.88	
IQ5	0.86	
Instructional Assessment		0.69
IA1	0.79	
IA2	0.85	
IA3	0.88	
IA4	0.86	
IA5	0.79	
IA6	0.80	
E-learning System Interactivity		0.73
ESI1	0.84	
ESI2	0.87	
ESI3	0.84	
ESI4	0.86	

It can be interpreted that the assessed latent variables are more reliable, confirmed by the absolute contribution of the factors to the definition of the construct (see Table 6.11).

6.2.3 Convergent Validity

Convergent validity evaluates the extent to which two measures of the same construct yield results that are highly correlated and whether the items can effectively reflect the corresponding constructs (Hair et al., 2014; Hair, Hult, et al., 2017). High correlation indicates the scale is measuring the underlying concept. The indicators of the construct should share a high proportion of variance. In this study, the researcher begins with the evaluation of the convergent validity, the criterion of the AVE (Fornell & Larcker, 1981).

The AVE is the mean value of the squared loadings of the item in a construct (Hair et al., 2014, 2019; Hair, Hult, et al., 2017). The AVE calculates the amount of variance that each construct captures from its indicators relative to the variance contained in the measurement error. The measurement of the AVE for each construct should exceed the cut-off of 0.50 as recommended by Fornell and Larcker (1981). A value of 0.50 denotes that, on average, the construct explained half of the variance of its corresponding indicators where the other half being the error variance.

Table 6.11 the AVE values of the all constructs lie within the 0.54 to 0.81 range and are able to satisfy the explaining criteria of 50% of the variance, as suggested by Fornell and Larcker (1981) and Hair et al. (2014). This indicates that the model constructs explain more than half of the variance of its indicators which signifies that all constructs are valid measures of unique concepts. In other words, all measurement items converge highly on their own corresponding construct. Hence, adequate evidence of convergent validity is established.

6.2.4 Discriminant Validity

Discriminant validity measures whether the items of the same construct are statistically different from other similar concepts (Anderson & Gerbing, 1988; Kline, 2016). Low correlation implies the summated scale is different from other factors. Thus, estimating discriminant validity implies that a variable is unique and captures the concept not represented by other constructs in the model. The measure can be evaluated using three approaches – cross-loadings, Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT) – (Hair, Hult, et al., 2017; Henseler et al., 2015).

For the first measure, cross-loadings are obtained by correlating each variable's component scores with all the other items (Chin 1998b). Cross-loading is the first approach to assess discriminant validity. The term cross-loadings denotes the inter-construct covariance, the correlations (Hair et al., 2014; Urbach & Ahlemann, 2010). Indicator loadings on the corresponding construct should be higher than all of its loadings on other constructs (Hair, Hult, et al., 2017), thus the different constructs' indicators are not interchangeable (Urbach & Ahlemann, 2010). The presence of cross-loadings that exceed the factor loadings violates the discriminant validity, for which it becomes a candidate for deletion (Hair et al., 2014). In this research, each indicator has the highest loading value (in bold) with the construct to which it has been assigned to as illustrated in Table 6.12. For instance, the Behavioural Intention indicators (questions) yield student responses that correlate well together and do not correlate so well with other constructs, for example, with responses for Actual Use. This means that factors load well on their intended constructs. Thus, discriminant validity is established regarding the cross-loadings.

Table 6.12 Cross Loadings

	AU	ESI	BI	EE	FC	IA	IQ	SL	SN	PE	SI	VD
AU1	**0.75**	0.27	0.42	0.40	0.47	0.35	0.34	0.41	0.37	0.40	0.49	0.28
AU2	**0.61**	0.18	0.35	0.30	0.30	0.28	0.25	0.32	0.32	0.30	0.23	0.28
AU3	**0.88**	0.32	0.50	0.40	0.46	0.42	0.41	0.47	0.44	0.48	0.51	0.39
AU4	**0.77**	0.41	0.43	0.37	0.43	0.45	0.40	0.45	0.41	0.47	0.49	0.38
ESI1	0.34	**0.84**	0.39	0.33	0.47	0.58	0.46	0.48	0.51	0.44	0.32	0.46
ESI2	0.32	**0.87**	0.39	0.31	0.42	0.59	0.44	0.46	0.51	0.41	0.35	0.47
ESI3	0.27	**0.84**	0.35	0.29	0.36	0.55	0.41	0.44	0.43	0.37	0.28	0.44
ESI4	0.39	**0.86**	0.61	0.43	0.49	0.60	0.59	0.55	0.55	0.61	0.39	0.50
BI1	0.53	0.48	**0.90**	0.54	0.53	0.49	0.51	0.55	0.50	0.71	0.47	0.39
BI2	0.47	0.47	**0.92**	0.53	0.50	0.46	0.48	0.52	0.49	0.69	0.44	0.38
BI3	0.47	0.45	**0.88**	0.48	0.46	0.41	0.42	0.48	0.45	0.66	0.38	0.36
BI4	0.57	0.53	**0.91**	0.54	0.54	0.52	0.52	0.55	0.50	0.74	0.54	0.41
EE1	0.46	0.40	0.54	**0.85**	0.55	0.49	0.48	0.65	0.61	0.52	0.34	0.45
EE2	0.42	0.37	0.52	**0.90**	0.55	0.51	0.47	0.68	0.56	0.52	0.37	0.43
EE3	0.37	0.31	0.47	**0.87**	0.53	0.44	0.43	0.63	0.48	0.44	0.32	0.36
EE4	0.44	0.37	0.51	**0.88**	0.55	0.46	0.46	0.67	0.55	0.49	0.38	0.43
FC1	0.46	0.33	0.44	0.45	**0.72**	0.41	0.39	0.51	0.48	0.44	0.37	0.33
FC2	0.53	0.36	0.56	0.70	**0.76**	0.49	0.44	0.62	0.55	0.52	0.38	0.41
FC3	0.29	0.39	0.29	0.27	**0.66**	0.38	0.41	0.42	0.46	0.30	0.34	0.43
FC4	0.30	0.42	0.31	0.33	**0.73**	0.46	0.43	0.47	0.43	0.36	0.37	0.40
FC5	0.35	0.44	0.36	0.37	**0.79**	0.51	0.45	0.53	0.48	0.38	0.38	0.45
IA1	0.43	0.51	0.41	0.42	0.48	**0.79**	0.53	0.51	0.50	0.45	0.39	0.50
IA2	0.41	0.51	0.45	0.54	0.51	**0.85**	0.54	0.60	0.54	0.48	0.37	0.51
IA3	0.40	0.56	0.45	0.48	0.52	**0.88**	0.61	0.59	0.58	0.50	0.38	0.55
IA4	0.43	0.54	0.46	0.49	0.53	**0.86**	0.57	0.56	0.55	0.49	0.44	0.53
IA5	0.40	0.65	0.43	0.38	0.52	**0.79**	0.51	0.50	0.51	0.45	0.39	0.51
IA6	0.41	0.64	0.40	0.38	0.51	**0.80**	0.54	0.50	0.51	0.44	0.39	0.50
IQ1	0.43	0.54	0.50	0.52	0.56	0.62	**0.87**	0.67	0.60	0.59	0.43	0.59
IQ2	0.38	0.50	0.47	0.43	0.48	0.58	**0.90**	0.58	0.53	0.54	0.42	0.56
IQ3	0.42	0.51	0.48	0.46	0.49	0.57	**0.89**	0.60	0.51	0.56	0.44	0.55
IQ4	0.41	0.49	0.47	0.49	0.52	0.58	**0.88**	0.61	0.54	0.53	0.43	0.53
IQ5	0.41	0.50	0.44	0.42	0.48	0.57	**0.86**	0.58	0.53	0.50	0.48	0.56
SL1	0.46	0.47	0.50	0.69	0.56	0.55	0.54	**0.84**	0.65	0.51	0.40	0.52
SL2	0.42	0.45	0.44	0.54	0.57	0.50	0.53	**0.81**	0.63	0.45	0.38	0.55
SL3	0.49	0.51	0.53	0.64	0.60	0.60	0.64	**0.87**	0.70	0.53	0.44	0.64
SL4	0.45	0.37	0.49	0.70	0.52	0.49	0.51	**0.81**	0.57	0.48	0.35	0.46
SL5	0.43	0.56	0.45	0.49	0.65	0.56	0.62	**0.76**	0.63	0.48	0.41	0.58
SN1	0.45	0.51	0.48	0.64	0.57	0.56	0.52	0.69	**0.84**	0.49	0.38	0.56
SN2	0.34	0.51	0.42	0.39	0.51	0.46	0.47	0.52	**0.78**	0.41	0.28	0.53
SN3	0.39	0.52	0.38	0.46	0.53	0.54	0.55	0.64	**0.83**	0.42	0.34	0.68

SN4	0.42	0.41	0.41	0.49	0.48	0.51	0.46	0.59	**0.75**	0.40	0.33	0.51
SN5	0.42	0.42	0.45	0.50	0.54	0.48	0.46	0.63	**0.77**	0.45	0.38	0.51
PE1	0.50	0.45	0.71	0.57	0.53	0.50	0.52	0.56	0.51	**0.84**	0.49	0.35
PE2	0.49	0.50	0.68	0.52	0.49	0.46	0.49	0.52	0.48	**0.86**	0.50	0.38
PE3	0.46	0.48	0.67	0.41	0.46	0.46	0.56	0.48	0.44	**0.88**	0.42	0.40
PE4	0.34	0.41	0.45	0.32	0.37	0.44	0.47	0.39	0.35	**0.70**	0.37	0.37
SI1	0.37	0.29	0.34	0.26	0.30	0.32	0.36	0.33	0.27	0.39	**0.76**	0.28
SI2	0.45	0.32	0.47	0.31	0.32	0.39	0.43	0.36	0.31	0.50	**0.84**	0.34
SI3	0.49	0.26	0.38	0.30	0.39	0.33	0.38	0.36	0.32	0.40	**0.77**	0.26
SI4	0.50	0.37	0.39	0.37	0.56	0.42	0.37	0.46	0.44	0.39	**0.72**	0.39
VD1	0.35	0.35	0.27	0.41	0.43	0.47	0.43	0.53	0.52	0.29	0.33	**0.73**
VD2	0.39	0.47	0.34	0.35	0.46	0.49	0.55	0.53	0.53	0.39	0.36	**0.77**
VD3	0.36	0.48	0.36	0.36	0.42	0.50	0.51	0.53	0.59	0.37	0.31	**0.88**
VD4	0.37	0.50	0.36	0.42	0.45	0.55	0.55	0.59	0.61	0.39	0.32	**0.90**
VD5	0.40	0.47	0.38	0.45	0.52	0.58	0.60	0.61	0.61	0.40	0.39	**0.86**
VD6	0.36	0.50	0.41	0.43	0.46	0.53	0.53	0.57	0.64	0.42	0.36	**0.88**

Note: an indicator has the highest loading value (in bold) with the construct to which it has been assigned.

The Fornell-Larcker criterion is the second method for evaluating discriminant validity (Chin, 1998; Hair et al., 2014; Urbach & Ahlemann, 2010). Fornell-Larcker criterion assessment compares the square root of the AVE values with the latent variable correlation (Chin, 1998; Hair, Hult, et al., 2017). Successful evaluation of discriminant validity can be verified by comparing the correlation variances between any pair of variables with an AVE square root in which the value of the AVE square root should exceed the correlation coefficients among any pair of latent constructs (Fornell & Larcker, 1981). The motive for this assessment is that a construct shares more variance with the associated indicators than any of its correlations with another construct. The elements in the matrix diagonals, presented in Table 6.13, indicate the square roots of the average variance extracted. The diagonal bold values confirmed that all the AVEs are higher than any other correlation. This indicates that for any variable in the model, the variance shared with its block of factors is greater than the variance it shares with any other variable. Therefore, the discriminant validity of the constructs is established.

Table 6.13 The Fornell-Larcker Criterion Result

	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**	**VD**
AU	**0.76**											
BI	0.57	**0.90**										
EE	0.49	0.58	**0.87**									
FC	0.55	0.56	0.62	**0.73**								
IQ	0.47	0.54	0.53	0.58	**0.88**							
IA	0.50	0.52	0.54	0.62	0.67	**0.83**						

ESI	0.40	0.54	0.42	0.52	0.58	0.69	**0.85**					
SL	0.55	0.59	0.75	0.65	0.69	0.66	0.57	**0.82**				
SN	0.51	0.54	0.63	0.66	0.62	0.64	0.60	0.70	**0.79**			
PE	0.55	0.78	0.57	0.57	0.62	0.57	0.56	0.60	0.55	**0.82**		
SI	0.58	0.51	0.40	0.51	0.50	0.48	0.40	0.49	0.43	0.55	**0.77**	
VD	0.44	0.43	0.48	0.54	0.63	0.62	0.56	0.67	0.70	0.45	0.41	**0.84**

While the previous methods have grown in popularity in the assessment of discriminant validity, such approaches, however, have been in question regarding reliably detecting discriminant validity issues (Henseler et al., 2015). Thus, to compensate for the previous approaches' contended inadequacies, Henseler et al. (2015) proposed an alternative approach: the HTMT ratio assessment of correlations in variance-based SEM. The technique achieves high specificity and sensitivity rates across all simulation considering compared with cross-loadings and the Fornell-Larcker criterion (Henseler et al., 2015). The HTMT estimates the average heterotrait-heteromethod correlations relative to the average of monotrait-heteromethod correlations. Monotrait-heteromethod estimates the correlations of indicators measuring the same construct, whereas heterotrait-heteromethod estimates correlation of indicators across constructs measuring different phenomena (Hair, Hult, et al., 2017; Henseler et al., 2015). Specifically, the techniques measure the average of correlations of indicators across constructs measuring different phenomena relative to the average the correlations of indicators within the same construct (Henseler et al., 2015). To this end, HTMT measures the true correlations between two variables on the basis of these variables were perfectly measured (Hair, Hult, et al., 2017; Henseler et al., 2015). An HTMT value close to 1 indicates a lack of discriminant validity. The exact threshold level of the HTMT is debatable; some suggest a more liberal threshold of 0.90 when the constructs are conceptually similar, others propose a more conservative threshold value of 0.85 when the path model construct is conceptually more distinct (Hair et al., 2019; Hair, Hult, et al., 2017; Henseler et al., 2015). PLS-SEM was used to assess the HTMT criterion for discriminant validity.

In this research, the calculation of the HTMT ratio of the correlations was used, applying the more conservative threshold value of 0.85. It can be seen from the data in Table 6.14 that, all the values are below the threshold of HTMT, hence, the discriminant validity is established. Besides, Hair et al. (2017) suggested using an alternative procedure for discriminant validity called bootstrapping using inferential statistics in PLS-SEM. Bootstrapping subsamples are randomly drawn from the original set of data with replacement. In this test, 5000 bootstrap samples are applied as recommended by Hair et al. (2017). In Table 6.15, the columns labelled 2.5% and 97.5% show the lower and upper bounds of the 95% confidence interval. The bootstrap confidence interval for both lower and upper values should be below the threshold of 1. The confidence interval is the range into which the true HTMT population value will fall, assuming the 0.95 level of confidence (Hair, Hult, et al., 2017). As illustrated in Table 6.15, all values of the confidence interval of the upper bound of 97.5 and the lower bound 2.5 are below the threshold value of one. Since the conservative HTMT threshold of 0.85 already supports discriminant validity (refer to Table 6.14), the bootstrap confidence interval results of the HTMT criterion also clearly speak in favour of the discriminant validity of the constructs (see Table 6.15).

Table 6.14 The HTMT Results

	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**
AU											
BI	0.683										
EE	0.593	0.637									
FC	0.668	0.614	0.678								
IQ	0.557	0.577	0.575	0.666							
IA	0.604	0.567	0.597	0.721	0.723						
ESI	0.468	0.559	0.447	0.62	0.617	0.762					
SL	0.678	0.648	0.845	0.827	0.767	0.739	0.641				
SN	0.636	0.604	0.710	0.786	0.693	0.728	0.675	0.795			
PE	0.684	0.771	0.638	0.660	0.703	0.652	0.624	0.694	0.638		
SI	0.753	0.597	0.481	0.642	0.586	0.566	0.474	0.593	0.532	0.671	
VD	0.537	0.460	0.529	0.643	0.686	0.684	0.608	0.751	0.793	0.519	0.491

Table 6.15 HTMT-based Assessment Using a Confidence Interval

Relationships	**Lower Confidence Interval of 2.5%**	**Upper Confidence Interval of 97.5%**
BI -> AU	0.610	0.757
EE -> AU	0.505	0.673
EE -> BI	0.563	0.702
FC -> AU	0.590	0.737
FC -> BI	0.536	0.687
FC -> EE	0.602	0.742
IQ -> AU	0.479	0.634

IQ -> BI	0.491	0.647
IQ -> EE	0.484	0.649
IQ -> FC	0.595	0.732
IA -> AU	0.519	0.685
IA -> BI	0.484	0.642
IA -> EE	0.516	0.672
IA -> FC	0.654	0.779
IA -> IQ	0.650	0.785
SI -> AU	0.378	0.553
ESI -> BI	0.478	0.630
ESI -> EE	0.358	0.530
ESI -> FC	0.541	0.691
ESI -> IQ	0.545	0.684
ESI -> IA	0.710	0.809
SL -> AU	0.596	0.750
SL -> BI	0.564	0.718
SL -> EE	0.801	0.841
SL -> FC	0.776	0.830
SL -> IQ	0.708	0.815
SL -> IA	0.676	0.793
SL -> ESI	0.574	0.703
SL -> AU	0.553	0.712
SN -> BI	0.521	0.676
SN -> EE	0.646	0.766
SN -> FC	0.724	0.839
SN -> IQ	0.625	0.752
SN -> IA	0.664	0.782
SN -> ESI	0.607	0.735
SN -> SL	0.824	0.840
PE -> AU	0.599	0.763
PE -> BI	0.827	0.837
PE -> EE	0.564	0.708
PE -> FC	0.583	0.729
PE -> IQ	0.636	0.764
PE -> IS	0.579	0.715
PE -> ESI	0.551	0.691
PE -> SL	0.624	0.756
PE -> SN	0.563	0.709
SI -> AU	0.670	0.826
SI -> BI	0.499	0.677
SI -> EE	0.372	0.576
SI -> FC	0.558	0.716
SI -> IQ	0.490	0.671
SI -> IA	0.465	0.654
SI -> ESI	0.380	0.561
SI -> SL	0.494	0.683
SI -> SN	0.435	0.624
SI -> PE	0.573	0.753
VD -> AU	0.454	0.618
VD -> BI	0.37	0.543
VD -> EE	0.44	0.611
VD -> FC	0.572	0.709
VD -> IQ	0.616	0.747
VD -> IA	0.612	0.744

VD -> ESI	0.537	0.677
VD -> SL	0.693	0.804
VD -> SN	0.736	0.841
VD -> PE	0.437	0.601
VD -> SI	0.398	0.582

Based on the results of the assessment of cross-loadings, Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT), the discriminant validity of the models' constructs is established. Overall, all mentioned constructs and measurement items exhibited sufficient reliability and convergent and discriminant validity hence the data are eligible for estimating the structural model.

In summary, this section demonstrated the analysis of the three main criteria for evaluating the measurement model: internal consistency (Cronbach's alpha, composite reliability), convergent validity (indicator reliability, average variance extracted) and discriminant validity (cross-loadings, Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT)). Convergent validity means that the construct includes more than 50% of the indicator's variance while discriminant validity means that every construct must share more variance with its own indicators than with other constructs in the path model (Hair, Hult, et al., 2017). Essentially, these measurements were used to evaluate the reliability and the validity of the construct indicators (the relationship between constructs and their indicators), therefore providing support for the suitability of their inclusion in the path model. In this research, the results confirm that all 56 indictors used are valid and reliable measures for the UTAUT and usability variables. Therefore, the analysis of the measurement model showed evidence that the measurement model fulfilled the desired quality criteria. It is important to note that satisfactory outcomes for the measurement model are a prerequisite for evaluating the relationships in the structural model (Hair, Hult, et al., 2017). The next step is to evaluate the structural model.

6.3 Structural Model Estimation

Since the measurement model reliability and validity have been confirmed, the next stage is to estimate the structural model (Hair et al., 2019; Hair, Hult, et al., 2017). This section focuses on the estimation of a structural model which represents the underlying structural concepts of the path model. The path model is the structural model for the observed variables; the hypothesis (Kline, 2016). SmartPLS3 was used to estimate the path model. The bootstrapping procedure is employed. The number of bootstrap samples should be larger than the number of valid observations (Hair, Hult, et al., 2017). The key measures for assessing the structural model in PLS-SEM are the model fit, the collinearity assessment, the significance of the path coefficients, the level of the R^2 values and the predictive relevance Q^2 (Hair et al., 2019; Hair, Hult, et al., 2017). Table 6.16 summarises the criteria and guidelines used to evaluate the structural model. This part begins by assessing the model fit followed by the hypotheses testing.

Table 6.16 The Criteria Used to Evaluate the Structural Model

Assessment Type	**Criterion**	**Guidelines**	**References**
Structural model	Collinearity	Variance Inflation Factor (VIF) < 5	Hair, Hult, et al., 2017
	Path coefficients	Use bootstrapping with 5,000 sub-samples Significance: $p \leq 0.05$	Hair, Hult, et al., 2017
	Coefficient of determination (R^2)	Weak effect: $R^2 = 0.19$ Moderate effect: $R^2 = 0.33$ High effect: $R^2 = 0.67$	Chin, 1998
	Q^2 value	Values larger than zero are meaningful Values higher than 0, 0.25 and 0.50 depict small, medium and large	Hair et al., 2019; Hair, Hult, et al., 2017

6.3.1 Model Fit

Although the objective of PLS-SEM is the prediction, other people have sought to expand the technical capability for theory testing using various model fit criteria. Model fit provides insight into how well the hypothesized model fits the empirical data (Hair, Hult, et al., 2017). The standardized root mean square residual (SRMR) criterion was used to assess the model fit in SmartPLS3. The SRMR is defined as the root mean square discrepancy between the observed correlations and the model-implied correlations (Henseler et al., 2014). The recommended value of less than 0.08 is generally considered a good fit (Hu & Bentler, 1995). In this study, the SRMR for the estimated composite factor model is 0.065 which is less than the recommended value.

Hence, the model fits the empirical data. That said, some researchers acknowledged that these model fit measures lack a comprehensive assessment in PLS-SEM (Hair et al., 2019). In general, the objective of PLS-SEM is to maximise the explained variance of the dependent variables, so scholars have questioned whether the concept of model fit is of value to PLS-SEM (Hair et al., 2019). However, the structural model in PLS-SEM was assessed in terms of the model's predictive power; how well the model predicts the outcome constructs (Hair, Hult, et al., 2017).

6.3.2 Collinearity Assessment

Collinearity occurs when there are high correlations among two predictor variables. If more than two constructs are involved, it refers to multicollinearity. Bias will arise on the path coefficients involving critical levels of collinearity, leading to unreliable and unstable estimates of structural models. Collinearity can be assessed using the variance inflation factor (VIF), estimating how much the variance of a regression coefficient is inflated as a result of collinearity (Hair, Hult, et al., 2017). A VIF value of 5 or higher (tolerance value of 0.20 or lower) indicates high collinearity (Hair, Hult, et al., 2017). Using SmartPLS3, each of the predictor variables was checked for collinearity as indicated by the tolerance and VIF. Table 6.17 provides the VIF values of all combinations of dependent variables (columns) and corresponding independent variables (rows). It can be seen from the data in Table 6.17 that all predictors variables exhibited VIF value less than the value of 5.00 which indicated that the sample has no critical level of collinearity between the variables (Hair et al., 2019; Hair, Hult, et al., 2017). This indicates that each predictor in the model independently predicts the value of the outcome variable. Thus, the data are eligible for proceeding to the report examination.

Table 6.17 VIF Values in the Structural Model

	Actual Use	**Behavioural Intention**	**Effort Expectancy**	**Performance Expectancy**
AU				
BI	1.625			
EE		2.603		2.429
FC	1.632	2.453		
IQ		2.609	2.394	2.394

IA		2.761	2.637	2.677
ESI		2.207	2.078	2.098
SL		3.990	3.225	4.027
SN		3.255	3.113	3.172
PE		2.227		
SI	1.507	1.615		
VD		2.429	2.372	2.402

6.3.3 Hypothesis Testing

In running the PLS-SEM algorithm, the hypothesized relationship among variables will be estimated based on a series of regression equations (Hair et al., 2019). The path coefficient has standardized values between +1 and -1 whereas values close to +1 represent significant positive correlation and value close to -1 represent significant negative relationships (Hair et al., 2014; Hair, Hult, et al., 2017; Kline, 2016). The closer the estimated path coefficient to zero, the weaker is the correlation (Hair et al., 2014; Hair, Hult, et al., 2017; Kline, 2016).

To assess the model's path coefficients, the researcher ran the bootstrapping technique. Using SmartPLS3, 5000 bootstrap samples were set as recommended by Hair et al. (2017). The critical *t* value should be above 1.96 with p-value of 0.05 as the cut-off for significance (Hair, Hult, et al., 2017). The *t* value measures the size of the difference between the estimated mean value and hypothesized value of a variable, represented by a difference in units of standard error (Hair, Hult, et al., 2017). The greater the magnitude of *t*, the greater the evidence against the null hypothesis. In contrast, the p-value represents the statistical significance, the probability of erroneously rejecting a true null hypothesis (Hair, Hult, et al., 2017). Thus, the p-value smaller than 0.05 indicates that the relationship under investigation is significant at a 5% level.

Table 6.18 The Result of Hypothesis Testing

Hypothesis number	Path	Path Coefficient β	T Value	P-value	Study Results
H1	PE -> BI	0.571***	13.574	0.001	Supported
H2	EE -> BI	0.159***	3.718	0.001	Supported
H3	EE -> PE	0.245***	5.021	0.001	Supported

H4	SI -> BI	0.081**	2.524	0.012	Supported
H5	SI -> AU	0.340***	8.312	0.001	Supported
H6	FC -> BI	0.065	1.814	0.070	Not Supported
H7	FC -> AU	0.229***	6.210	0.001	Supported
H8	BI -> AU	0.266***	6.414	0.001	Supported
H9	SN -> PE	0.05	0.895	0.371	Not Supported
H10	SN -> EE	0.157**	3.127	0.002	supported
H11	SN -> BI	0.037	0.792	0.428	Not Supported
H12	VD -> PE	-0.102**	2.153	0.031	Not Supported
H13	VD -> EE	-0.111**	2.240	0.025	Not Supported
H14	VD -> BI	-0.033	0.832	0.406	Not Supported
H15	SL -> PE	0.056	0.874	0.382	Not Supported
H16	SL -> EE	0.673***	13.376	0.001	Supported
H17	SL -> BI	0.009	0.155	0.877	Not Supported
H18	IQ -> PE	0.309***	5.852	0.001	Supported
H19	IQ -> EE	0.003	0.071	0.944	Not Supported
H20	IQ -> BI	-0.029	0.673	0.501	Not Supported
H21	IA -> PE	0.068	1.295	0.196	Not Supported
H22	IA -> EE	0.129**	2.749	0.006	Supported
H23	IA -> BI	-0.034	0.788	0.431	Not Supported
H24	ESI -> PE	0.228***	5.225	0.001	Supported
H25	ESI -> EE	-0.092**	2.187	0.029	Not Supported
H26	ESI -> BI	0.112**	2.375	0.018	Supported
**P <0.1, **p<0.05, ***P<0.001*					

Table 6.18 illustrates all the study hypotheses, the path coefficients, *t* values and p-values. Among the factors influencing BI, PE (β = 0.571) exhibited the highest positive effect on students' intention towards using the LMS, followed by EE (β = 159), ESI (β = 0.112), SI (β = 0.081) and supporting, H1, H2, H26 and H4. It can be observed that all *t* values for these relationships are above the threshold of 1.96 with the significance level less than 0.05 (see Table 6.18). The other hypotheses that were proposed to have a direct influence on BI did not prove to be a significant determinant of the construct, hence H6, H11, H14, H17, H20 and H23 are not supported (p > 0.05).

Moving to the students' actual use of the e-learning system, the findings also reveal that usage behaviour is influenced positively by SI (β = 0.340) followed by BI (β = 0.266) and FC (β = 0.229). These results provide support for hypotheses H5, H7 and

H8. Figure 6.13 provides a graphical representation of the path modelling results along with R^2 values.

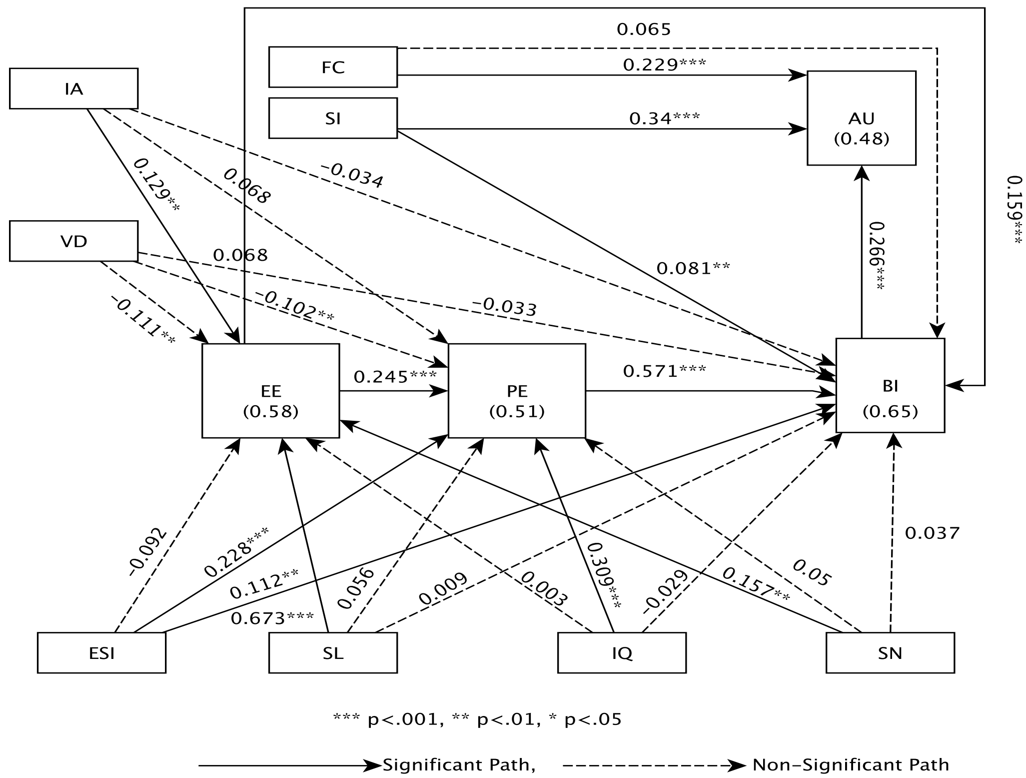

Figure 6.13 The results of Path modelling and R^2 values.

Regarding the dependent variable of PE, the variable IQ displayed the primary positive correlation with PE of the e-learning system (β = 0.309), followed by EE (β = 0.245) and ESI (β = 0.228) with the t value greater than 1.96 and the p-value less than 0.05. Hence, H18, H3 and H24 were supported. Since there was negative evidence of the relationship between visual design and performance expectancy (β = -0.102, $p < 0.05$), the findings leave H12 unproven. In line with that, H9, H15 and H21 hypotheses were not supported due to the p-value being greater than 0.05 (see Figure 6.13). The EE dependent variable was predicted by the independent variables of SL (β = 0.673), SN (β = 0.157) and IA (β = 0.129), supporting H16, H10, H22.

Overall, the students' usage behaviour was predicted by SI, BI and FC while their intention to use was predicted by PE, EE, ESI and SI. In the same vein, the PE was predicted by IQ, EE and ESI whereas EE was predicted by SL, SN, and IA.

6.3.4 Coefficient of Determination (R squared)

The coefficient of determination R^2 is a common measure to assess the structural model. R^2 is the proportion of the variance in the outcome variable that is predictable from the predictor's variable (Hair et al., 2014, 2019; Hair, Hult, et al., 2017). Calculated as the squared correlation between the actual and predicted values of the dependent variables, it represents the combined effects of independent variables on the dependent variables. The coefficient can vary between 0 and 1; the higher the value is, the higher levels of predictive accuracy. While R^2 value of .20 is considered high in some disciplines, Hair et al. (2017) proposed that R^2 values of 0.75, 0.50, or 0.25 for dependent variables can be respectively described as substantial, moderate and weak. Another researcher, however, recommended that R^2 value of 0.67, 0.33 and 0.19 are described respectively high, moderate, and weak effects (Chin, 1998). Chin also proposed that any R^2 value less than 0.19 is unacceptable (Chin, 1998) but others acknowledged the R^2 value as low as 0.10 is considered satisfactory (Hair et al., 2019). In this research, the adjusted coefficient of determination is used to avoid the bias toward a complex model as recommended by Hair et al. (2017) and Hair et al. (2014). The adjusted R^2 deals with a number of independent variables relative to the sample size, compensating the inclusion of several independent variables that were not significant in the regression equation to merely increase the R^2 (Hair et al., 2014). Following Hair et al.'s (2017) recommendation, the adjusted R^2 values of AU (0.48), EE (0.58), PE (0.51) and BI (0.65), can be considered moderate (Table 6.19 and Figure 6.13).

Overall, 48% of the variance in actual use is predictable from BI, FC and SI. Likewise, 65% of the variance in BI is explained by its predictors (mainly from EE, PE, ESI and SI). Thus, the students' intention to use is demonstrated to be well predicted by its independent variables which account for 65% of the variance in student BI to use e-learning system in Saudi higher education (refer to Figure 6.13).

Table 6.19 Adj.R^2 for the Dependent Variable

Constructs	R Square Adjusted
AU	0.48
BI	0.65
EE	0.58
PE	0.51

6.3.5 Blindfolding and Predictive Relevance Q^2

As the purpose of using PLS is to produce a predictive model, researchers have also introduced Stone Geisser's Q^2 measure, to evaluate the model predictive capability (also called Cross-validated Redundancy) (Geisser, 1974; Stone, 1974). In other words, this criterion examines the capability of the independent variables to predict the dependent variables. The Q^2 criterion assesses the predictive relevance, the model's out-of-sample predictive power (Hair, Hult, et al., 2017). Out of sample prediction assesses the extent to how accurately a model will perform in practice using a generated test data. It evaluates whether the prediction of observables is of much greater relevance than the estimation. Q^2 values greater than zero for a particular outcome variable denote the predictive relevance of that variable (Hair, Hult, et al., 2017). In SmartPLS3, the Q^2 can be obtained using the blindfolding procedure applied to the dependent variables. Simply, the procedure removes data points from the data matrix based on a pre-determined omission distance value, usually between 5 and 10, replaces the removed points with the mean and estimates the models with remaining data (Hair et al., 2019; Hair, Hult, et al., 2017). The resulting estimations then predict the data points that were removed for all variables (Hair et al., 2019). The difference between the prediction of omitted data and the original values is the input for Q^2 (Hair et al., 2019; Hair, Hult, et al., 2017). As a guideline, Q^2 values should be larger than zero for a specific outcome construct to indicate predictive accuracy of the structural model for that construct (Hair et al., 2019; Hair, Hult, et al., 2017). As a rule of thumb, Q^2 values higher than 0.10, 0.25 and 0.50 indicate small, medium and large predictive accuracy of the PLS-path model (Hair et al., 2019). Table 6.20 illustrates the blindfolding results. The omission distance D is 7, SSE is the sum of squares of prediction errors, and SSO the sum of squares' error totals using the mean for prediction. As it can be seen in Table 6.20, the *Q^2* values of all the four outcome variables are above zero. More precisely, BI exhibited the highest *Q^2* value (0.494, strong predictive power), followed by the moderate effect of EE (0.421, moderate predictive power) and PE (0.319, moderate predictive power) and finally, AU (0.254, moderate predictive power). Hence, the model's predictive relevance regarding the outcome construct can be established.

Table 6.20 Results of Cross-Validated Redundancy Q^2

	SSO	**SSE**	**Construct Cross validated Redundancy Q^2 (=1-SSE/SSO)**
AU	2,420.00	1,805.27	0.254
BI	2,420.00	1,225.46	0.494
EE	2,420.00	1,402.02	0.421
PE	2,420.00	1,647.25	0.319

In summary, this part focused on the assessment of structural model (the hypotheses; the relationship between the variables). The assessment of the structural model results helps to determine the model's capability to predict the outcomes (Hair, Hult, et al., 2017). To that end, assessment was performed following the four steps: assessment of collinearity issues, hypothesis testing, assessment of coefficient of determination (R^2), predictive relevance Q^2. Collinearity occurs when there are high correlations between the variables. This means the variables can be used to predict the other one resulting in redundant information. By examining the VIF values of all predictor constructs in the structural model, the collinearity is not a problem in the dataset (refer to Table 6.17).

In the hypothesis testing, looking at the relative importance of the driver constructs for the performance expectancy (PE), one finds that the IQ variable is the most important driver followed by EE and ESI, supporting H18, H3 and H24 respectively (see Table 6.18). In contrast, the effort expectancy (EE) was influenced largely by the SL followed by SN and IA, supporting H16, H10, H22 respectively. The SL driver is, however, of increased importance for establishing the students' perception of the LMS effort expectancy. Moving on in the model, that PE is the primary driver for the students behavioural intention followed by EE, ESI and SI (supporting, H1, H2, H26 and H4). Lastly, the usage behaviour is influenced noticeably by SI followed by BI and FC. These results provide support for hypotheses H5, H7 and H8 (see Table 6.18).

As the proposed model was developed primarily for prediction purposes, the coefficient of determination R^2 represents the amount of the explained variance in the outcome. In this research, the adjusted R^2 values of AU (0.48), EE (0.58), PE (0.51) and BI (0.65), can be considered moderate to substantial (Table 6.19). This means that a substantial percentage of 65% of the students behavioural intention was explained by four constructs: EE, PE, ESI and SI. For the AU outcome, three variables were the main determinants namely: BI, FC and SI. These three constructs together explained 48% of the variance in the student usage behaviour which is considered moderate to substantial. Three predictors (SL, SN, and IA) explained 58% of the variance in the effort expectancy outcome variable. It should be noted that SL-> EE is the strongest path coefficient in the model, signifying the importance of system learnability in the students' perception of effort expectancy. Finally, the IQ, EE, and ESI collectively explained 51% of the variance in performance expectancy, which is considered moderate to substantial (see Table 6.19).

The last step was to assess the predictive relevance of the path model with regard to each outcome construct (Q^2 value). The Q^2 measures how well observed values are reproduced by the model. The results showed that BI had the highest Q^2 value (0.494, strong predictive power), followed by the moderate effect of EE (0.421), PE (0.319) and AU (0.254). This means that the model's predictive power ranges from substantial to moderate (see Table 6.20).

Having estimated the measurement and structural models, the analytical procedures of multi-group analysis of the moderating effects and the results obtained from them are described in the next section.

6.4 Moderating Effect

A moderator is the construct directly affecting the relationship between the independent and dependent latent variable (Hair, Hult, et al., 2017). The effect of a moderator (e.g. age and gender) can change the strength or even the direction of the relationship (Baron & Kenny, 1986). This means the relationships between variables might differ depending on the moderator's effect. In the literature, many studies have failed to address whether there are significant differences across two or more groups of data (Henseler & Fassott, 2010; Matthews, 2017). The resulting interpretation from a single population sample can be misleading (Matthews, 2017). Thus, researchers have emphasised the importance of using the Multi-Group Analysis (MGA) using PLS-SEM technique, to analyse the effects of moderation across multiple relationships, rather than standard moderation (Hair et al., 2018; Henseler et al., 2016; Henseler & Fassott, 2010; Matthews, 2017; Sarstedt et al., 2017).

Multigroup analysis allows the researcher to investigate whether the differences between population groups are statistically significant, and the significant difference in the specific group moderator estimates (Hair et al., 2018; Matthews, 2017). The method also uncovers differences of subsamples that is not evident under the total pooled sample (Hair et al., 2018; Matthews, 2017). By applying MGA, a more accurate assessment of each group difference is achieved and based on that, strategy implementation based on the results can be applied to accommodate the heterogeneous groups in the sample (Matthews, 2017). Hence, MGA was used for examining the moderating effect on the proposed model's relationships.

The analysis of MGA can be accomplished using either a bootstrapping or permutation result for each group (Matthews, 2017). The permutation test has been developed to compare parameters across groups (Chin & Dibbern, 2010). It is recommended to use permutation when the goal is to determine if the moderators have a significant influence on the relationship (Hair, Hult, et al., 2017; Henseler & Chin, 2010; Matthews, 2017). This technique yields high statistical power and suggested by many researchers to use over other methods (Hair, Hult, et al., 2017; Henseler & Chin, 2010), hence it was utilised in this research.

In this research, moderators represent observable traits such as age, gender, e-learning system experience and the training on the use of the e-learning system. Based on these categorical moderators, the researcher divides the data set into multiple sets of two groups and estimates the model separately for each group of data. Once the moderator variable is categorical, it can be used as a grouping factor without further refinement (Henseler & Fassott, 2010).

There is a prerequisite for assessing the moderating effects using MGA. Once the group is generated and before multigroup comparisons, the next step is to ensure the validity of the variables. Thus, construct and indicator reliability, convergent, and discriminant validity assessments have to be established for each group (Hair, Hult, et al., 2017; Henseler et al., 2016) as it was established for the entire sample (refer to Section 6.2). The next procedure is to check the measurement model for each group as was conducted in the previous chapter for the whole sample (Matthews, 2017).

After establishing the measurement model, it is important to ensure measurement model invariance (also referred to as measurement equivalence). The process involves a three-step procedure, namely measurement invariance of composite models (MICOM) for each group (Henseler et al., 2016). This procedure is essential to address in MGA as it increases the rigour of data analysis and enhances the validity of the outcomes (Hair et al., 2018; Hair, Hult, et al., 2017; Henseler et al., 2016; Matthews, 2017). In short, measurement invariance refers to whether measurement operations yield measures of the same attribute, measurement equivalence (Henseler et al., 2016). That is, the group differences do not result from the distinctive content of the latent variables across groups. The absence of the measurement equivalence can distort statistical tests of hypotheses, reduce the precision of estimators and ultimately, produce biased results (Hair, Hult, et al., 2017).

MICOM comprises a three-step approach: configural invariance, compositional invariance and equality of mean values and variances that are required for the validity of the results (Hair et al., 2018; Henseler et al., 2016; Matthews, 2017). The first stage is to address the configural invariance to ensure that all groups have equal composites. To this end, composite specifications ensure the use of identical indicators for all groups, identical data treatment, and identical algorithm settings. In order to realize the configural invariance requirement, three criteria must be satisfied (Henseler et al., 2016). These include the following.

- Identical indicators. For this research, the same setup for the measurement model and structural model were used across groups. Hence identical indicators have been established.
- Identical data treatment. This is concerned with coding, reverse coding, missing data handling and outliers. The step has been established already in the first phase of the analysis, the preliminary data analysis with a full set of data (section 5.2), hence, the identical data treatment is established.
- Identical algorithm settings. The algorithm settings for all model estimations are the same for the entire sample. Thus, the identical algorithm criterion is confirmed.

Overall, the researcher ensured the same basic factor structure for all moderators' groups (e.g., number of construct and their indicators are the same). Furthermore, running MICOM in SmartPLS3 usually automatically establishes configural invariance (Step 1) (Hair, Hult, et al., 2017). As a result of MICOM's Step 1, the researcher concluded that configural invariance had been established for all groups.

However, configural invariance is a necessary but not sufficient step for drawing conclusions. The second requirement of MICOM is compositional invariance, which ensures equal indicator weights across groups. MICOM compares group parameters and identifies if there is no measurement invariance, partial measurement invariance, or full measurement invariance (Henseler et al., 2016). Once configural invariance and compositional invariance are established, partial measurement invariance is confirmed (Hair et al., 2018). If partial measurement invariance is confirmed for all constructs, the researcher is able to compare the path coefficients across groups, the moderating effects (Hair et al., 2018; Henseler et al., 2016; Matthews, 2017). However, if measurement problems are detected in the configural or compositional steps, multigroup analysis cannot be computed and the researcher has to delete the construct that causes the problem and rerun the analysis (Hair et al., 2018; Henseler et al., 2016; Matthews, 2017). In the case of the MICOM three step confirmation, full measurement invariance is confirmed which support the analysis of the model using the pooled data (Hair et al., 2018). Therefore, the researcher starts with the measurement of invariance for all four moderators to ensure the validity of the results before undertaking multigroup analysis in PLS-SEM.

After the measurement model and the measurement invariance are met, the multigroup analysis is assessed. The permutation approach in SmartPLS was selected to compare the path coefficients of the different groups. The test randomly exchanges the values between the data groups and re-estimates the model for each permutation (Hair et al., 2018). Computing the differences between each group path coefficients per permutation enables testing whether these also differ in the entire pooled sample (Hair et al., 2018). The permutation test is the most recommended approach to use in MGA as it is based on non-parametric, more conservative than parametric, test and control for Type 1 error (Hair et al., 2018; Hair, Hult, et al., 2017; Matthews, 2017). Hence, this research employed the permutation approach to compare the difference of parameters across two groups.

Overall, to run an MGA for a moderator, it is important to run the PLS path modelling algorithm separately for each group and ensure the data meet the suggested criteria of the measurement model assessment (Hair et al., 2018; Hair, Hult, et al., 2017; Sarstedt et al., 2011). Then, the researcher can run the permutation test and ensure that MICOM has been established. Once established, the standardized path coefficient differences across the two groups can be computed with confidence using a multigroup analysis (Hair et al., 2018; Henseler et al., 2016). That is to investigate whether the moderators influence the relationships between the independent and dependent variables. Thus, the researcher begins by analysing the categorical variable of gender followed by age, experience, and finally the training groups.

6.4.1 Gender

The gender moderator was examined based on a nominal scale therefore, the refinement strategies were not required (Hair et al., 2014). The first step is to assess the measurement model for male and female groups. In this study, males are 279 participants (46.1%) and females are 326 participants (53.9%). The researcher began with the measurement model and structural model analyses.

Table 6.21 provides the summary statistics of the measurement model for male and female subpopulations. The analysis of male and female groups show that all constructs achieved composite reliability values of 0.70 and higher. Moreover, all AVE values exceeded the recommended value of 0.50. In terms of factors loadings, all indicators exhibit loading above 0.70 except the AU2 for both male (0.554) and female (0.602) subsamples. However, Hair et al. (2017) recommended that items with factor loadings between 0.4 and 0.7 should be removed only when removal leads to an increase the composite reliability or the AVE is above the cut-off value (Hair, Hult, et al., 2017). Also, it is suggested to retain item loadings above 0.50 in exploratory research (Hair et al., 2014). Hence, these items were retained for further multigroup analysis.

Table 6.21 The Measurement Model Assessment for Male and Female

	Female Group				**Male Group**			
Construct and Indicators	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
Actual Use								
AU1	0.766	0.758	0.848	0.587	0.737	0.728	0.829	0.554
AU2	0.602				0.554			
AU3	0.895				0.856			
AU4	0.773				0.795			
E-learning System Interactivity								
ESI1	0.864	0.897	0.949	0.822	0.816	0.855	0.898	0.689
ESI2	0.892				0.853			
ESI3	0.866				0.822			
ESI4	0.868				0.829			

Behavioural Intention								
BI1	0.906	0.928	0.949	0.822	0.885	0.918	0.942	0.803
BI2	0.924				0.906			
BI3	0.884				0.882			
BI4	0.913				0.911			
Effort Expectancy								
EE1	0.868	0.913	0.939	0.793	0.827	0.878	0.916	0.732
EE2	0.911				0.890			
EE3	0.909				0.816			
EE4	0.872				0.886			
Facilitating Conditions								
FC1	0.704	0.813	0.868	0.570	0.729	0.771	0.833	0.502
FC2	0.761				0.774			
FC3	0.697				0.612			
FC4	0.784				0.664			
FC5	0.820				0.752			
Instructional Assessment								
IA1	0.826	0.917	0.935	0.707	0.760	0.897	0.921	0.662
IA2	0.856				0.846			
IA3	0.885				0.870			
IA4	0.854				0.867			
IA5	0.812				0.759			
IA6	0.810				0.772			
Information Quality								
IQ1	0.877	0.940	0.954	0.807	0.851	0.909	0.932	0.732
IQ2	0.923				0.864			
IQ3	0.915				0.864			
IQ4	0.893				0.873			
IQ5	0.884				0.825			
System Learnability								
SL1	0.842	0.870	0.906	0.659	0.856	0.882	0.914	0.681
SL2	0.802				0.815			
SL3	0.867				0.867			
SL4	0.820				0.808			
SL5	0.722				0.775			
System Navigation								
SN1	0.846	0.861	0.899	0.642	0.847	0.846	0.891	0.621
SN2	0.748				0.796			
SN3	0.828				0.846			
SN4	0.780				0.709			
SN5	0.800				0.731			
Performance Expectancy								
PE1	0.812	0.850	0.899	0.692	0.847	0.821	0.882	0.654

PE2	0.849				0.86			
PE3	0.893				0.852			
PE4	0.768				0.658			
Social Influence								
SI1	0.739	0.776	0.855	0.597	0.745	0.772	0.854	0.595
SI2	0.793				0.855			
SI3	0.815				0.739			
SI4	0.741				0.741			
Visual Design								
VD1	0.766	0.921	0.939	0.72	0.716	0.905	0.928	0.682
VD2	0.773				0.761			
VD3	0.896				0.859			
VD4	0.905				0.896			
VD5	0.867				0.843			
VD6	0.874				0.866			

CA: Cronbach's alpha, CR: composite reliability, AVE: average variance extracted

Regarding the convergent validity for each group, the AVE values for each construct, presented in Table 6.21, exceeded the cut-off of 0.50 as recommended by Fornell and Larcker (1981). The results confirm that all loadings of the measurement model are highly significant as required for convergent validity (see Table 6.21). Hence, adequate evidence of convergent validity is established.

In recent years, there has been an increasing amount of literature on IS which has used only the criterion of Fornell-Larcker for reporting the discriminant validity (Hair, Hollingsworth, et al., 2017). Thus, the constructs discriminant validity for both male and female groups was assessed using the Fornell-Larcker criterion (Fornell & Larcker, 1981). The elements in the matrix diagonals, presented in Table 6.22, indicate that all the constructs AVE is greater than its squared correlation with other constructs. Hence, discriminant validity is established. Overall, these results provide clear support for the measures' reliability, discriminant and convergent validity of the constructs.

Table 6.22 The Fornell-Larcker Criterion for Male and Female

Male Students												
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**	**VD**
AU	**0.744**											
BI	0.573	**0.896**										
EE	0.404	0.541	**0.855**									
FC	0.494	0.532	0.593	**0.709**								
IQ	0.452	0.546	0.543	0.554	**0.856**							
IA	0.429	0.549	0.531	0.575	0.623	**0.814**						
ESI	0.380	0.590	0.423	0.485	0.572	0.695	**0.830**					
SL	0.511	0.574	0.733	0.666	0.703	0.643	0.550	**0.825**				
SN	0.449	0.548	0.620	0.599	0.617	0.637	0.607	0.762	**0.788**			

PE	0.528	0.756	0.507	0.510	0.599	0.560	0.559	0.570	0.541	**0.809**		
SI	0.560	0.486	0.359	0.502	0.444	0.424	0.418	0.466	0.466	0.536	**0.772**	
VD	0.428	0.463	0.500	0.505	0.671	0.638	0.549	0.655	0.698	0.473	0.459	**0.826**
Female Students												
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**	**VD**
AU	**0.766**											
BI	0.568	**0.907**										
EE	0.551	0.619	**0.890**									
FC	0.610	0.594	0.647	**0.755**								
IQ	0.479	0.533	0.518	0.595	**0.899**							
IA	0.561	0.506	0.557	0.656	0.697	**0.841**						
ESI	0.416	0.491	0.409	0.547	0.58	0.671	**0.873**					
SL	0.594	0.605	0.779	0.718	0.684	0.678	0.59	**0.812**				
SN	0.561	0.535	0.645	0.711	0.618	0.647	0.585	0.763	**0.801**			
PE	0.568	0.792	0.609	0.611	0.640	0.578	0.564	0.631	0.551	**0.832**		
SI	0.628	0.536	0.447	0.527	0.540	0.531	0.395	0.520	0.421	0.553	**0.772**	
VD	0.464	0.401	0.468	0.576	0.607	0.609	0.558	0.680	0.701	0.442	0.386	**0.849**

The next step in the process is to examine the measurement invariance using the MICOM procedure in PLS-SEM. Since the criteria for the configural invariance are established for the gender moderator, the following analysis is the execution of the MICOM procedure, namely the compositional invariance. This assesses whether a composite is formed equally across the groups (Hair et al., 2018; Henseler et al., 2016; Matthews, 2017). For that, the non-parametric permutation tests were conducted to evaluate statistically whether compositional invariance is evident. For each permutation run, the correlations between the composite scores using the weights of the two groups are compared to determine if the correlation is significant (Henseler et al., 2016). As it can be seen in Table 6.23, the MICOM permutation results were generated using SmartPLS3. In order to satisfy the compositional invariance, the original correlations should be equal to or higher than the 5% quantile correlation of the empirical distribution (Hair et al., 2018; Hair, Hult, et al., 2017; Henseler et al., 2016; Matthews, 2017). The first column the Table 6.23 confirms that the first correlation is equal or greater than the 5% column and the p-values are considerably larger than 0.05, hence, the compositional invariance has been demonstrated for all the multi-item constructs.

Table 6.23 MICOM Compositional Invariance Results for Gender

	Original Correlation	**Correlation Permutation Mean**	**5.00%**	**Permutation p-Values**
AU	0.999	0.998	0.995	0.519
BI	1	1	1	0.279

EE	1	1	1	0.095
FC	0.994	0.998	0.994	0.075
IQ	1	1	1	0.442
IA	1	1	0.999	0.370
ESI	0.999	1	0.999	0.183
SL	1	1	0.999	0.480
SN	0.999	0.999	0.998	0.268
PE	1	1	0.999	0.177
SI	0.998	0.998	0.995	0.187
VD	1	0.999	0.999	0.831

Once invariance is established, the focus is to determine whether the path coefficients of the theoretical models for the two groups are significantly different. Thus, using a bootstrapping procedure, the researcher begins with analysing the groups separately prior to determining if there are groups specific differences. Table 6.24 illustrates the path coefficient, *t* statistic and p value for each group. As shown below, the relationships between BI and AU, EE and BI, FC and AU, IQ and PE, ESI and PE, SL and EE, PE and BI as well as SI and AU, are all significant in both male and female subsamples. The only single relationship that is significant in male but not in female groups is the path of ESI and BI ($\beta = 0.192$ and $p < 0.05$). Regarding the unique significant relationships linked with the female group only, it is evident that the effects of EE on PE ($\beta = 0.329$), IA on EE ($\beta = 0.137$), ESI on EE ($\beta = -0.116$), SI on BI ($\beta = 0.113$), VD on EE ($\beta = -0.154$), are all significant in the female subsample but not in the male group.

Table 6.24 Bootstrapping Results for Male and Female Groups

	Male			**Female**		
Paths	**β**	**T**	**P**	**β**	**T**	**P**
BI -> AU	0.336	5.173	0.001	0.191	3.669	0.001
EE -> BI	0.134	2.092	0.036	0.168	2.716	0.007
EE -> PE	0.143	1.890	0.059	0.329	5.308	0.001
FC -> AU	0.154	2.770	0.006	0.302	6.016	0.001
FC -> BI	0.069	1.362	0.173	0.080	1.562	0.118
IQ -> BI	-0.014	0.202	0.840	-0.044	0.795	0.427
IQ -> EE	0.038	0.552	0.581	-0.030	0.459	0.647
IQ -> PE	0.287	4.033	0.001	0.335	4.336	0.001
IA-> BI	-0.010	0.155	0.877	-0.069	1.194	0.233
IA-> EE	0.108	1.460	0.144	0.137	2.173	0.030
IA-> PE	0.113	1.589	0.112	0.021	0.263	0.793
ESI -> BI	0.192	2.603	0.009	0.053	0.869	0.385
ESI -> EE	-0.061	0.947	0.344	-0.116	2.054	0.040
ESI -> PE	0.217	3.158	0.002	0.243	4.425	0.001
SL -> BI	0.024	0.293	0.770	-0.001	0.018	0.986

SL -> EE	0.589	8.268	0.001	0.770	11.045	0.001
SL -> PE	0.064	0.694	0.488	0.055	0.660	0.509
SN -> BI	0.015	0.191	0.849	0.050	0.885	0.376
SN -> EE	0.154	2.135	0.033	0.139	1.967	0.049
SN -> PE	0.078	0.885	0.376	0.012	0.163	0.871
PE -> BI	0.528	8.292	0.001	0.605	11.276	0.001
SI -> AU	0.320	5.001	0.001	0.368	7.143	0.001
SI -> BI	0.044	0.835	0.404	0.113	2.806	0.005
VD -> BI	-0.024	0.378	0.705	-0.030	0.577	0.564
VD -> EE	-0.056	0.733	0.464	-0.154	2.457	0.014
VD -> PE	-0.078	1.094	0.274	-0.110	1.734	0.083

*** $p<.001$, ** $p<.01$, * $p<.05$, β: path coefficient, T: T Statistics, P: p.value

In Table 6.25, the adj.R^2 values are communicated. For the males group, the adj.R^2 values of AU, BI, EE and PE were 0.442 (44%), 0.626 (62%), 0.542 (54%) and 0.457 (46%) respectively. For the females group, the adj.R^2 values for AU, BI, EE and PE were 0.519 (52%), 0.662 (62%), 0.624 (62%) and 0.545 (55%) respectively. There is a clear indication that the female statistics explain more variance compared their male counterpart.

Table 6.25 Adj.R^2 for Male, Female

	Male Adj.R^2	**Female Adj.R^2**
AU	0.442	0.519
BI	0.626	0.662
EE	0.542	0.624
PE	0.457	0.545

Adj.R^2: adjusted coefficient of determination

Since the results support partial measurement invariance, the standardized path coefficient differences across both groups can be computed with confidence using a multigroup analysis (Hair et al., 2018; Henseler et al., 2016). Since the permutation test is non-parametric, two-tailed, more conservative, and recommended by researchers (Hair et al., 2018; Matthews, 2017), the researcher employed them in the analysis. The results obtained from the permutation test, summarised in Table 6.26, show the path coefficients for male and female, followed by the permutation mean differences and the final column represents the permutation p-values. It can be seen from the data in Table 6.26 that most structural model relationships do not differ between male and female subsamples. The only exception is the correlation between the FC and AU which showed a statistical difference between the two groups at 0.05

significant level. This is evident by the permutation p-value of 0.04. Females showed higher perceptions ($\beta = 0.302$) of FC to use the e-learning system than did their male counterparts ($\beta = 0.154$).

Using the information from the group-specific bootstrapping as well as the above permutation test, it can be concluded that the relationship between FC and AU is significantly different between male and female students in Saudi higher education and the moderating effect of gender has an impact on the FC -> AU path in the model.

Table 6.26 Path Coefficients for Male and Female

Paths	β (Female)	β (Male)	Difference (Female - Male)	Permutation p-Values
BI -> AU	0.191	0.336	-0.145	0.083
EE -> BI	0.168	0.134	0.034	0.693
EE -> PE	0.329	0.143	0.186	0.057
FC -> AU	0.302	0.154	0.148	0.044
FC -> BI	0.080	0.069	0.011	0.872
IQ -> BI	-0.044	-0.014	-0.030	0.745
IQ -> EE	-0.030	0.038	-0.068	0.488
IQ -> PE	0.335	0.287	0.047	0.678
IA-> BI	-0.069	-0.010	-0.059	0.501
IA-> EE	0.137	0.108	0.028	0.762
IA-> PE	0.021	0.113	-0.092	0.390
ESI -> BI	0.053	0.192	-0.139	0.159
ESI -> EE	-0.116	-0.061	-0.055	0.535
ESI -> PE	0.243	0.217	0.026	0.768
SL -> BI	-0.001	0.024	-0.025	0.835
SL -> EE	0.770	0.589	0.180	0.076
SL -> PE	0.055	0.064	-0.009	0.940
SN -> BI	0.050	0.015	0.036	0.705
SN -> EE	0.139	0.154	-0.015	0.890
SN -> PE	0.012	0.078	-0.066	0.580
PE -> BI	0.605	0.528	0.077	0.380
SI -> AU	0.368	0.320	0.048	0.565
SI -> BI	0.113	0.044	0.069	0.309
VD -> BI	-0.030	-0.024	-0.006	0.938
VD -> EE	-0.154	-0.056	-0.097	0.326
VD-> PE	-0.110	-0.078	-0.032	0.745

*** p<.001, ** p<.01, * p<.05, β: path coefficient

6.4.2 Age

The next moderator to assess based on groups is age. In this research, age was coded as a continuous variable, in compliance with previous studies (Venkatesh et al., 2003; Venkatesh & Morris, 2000). It has been suggested that when a metrically scaled variable is used, it should be transformed into a categorical variable ("high" and "low") (Henseler & Fassott, 2010). The transfer can be created using median splits based on simulation studies suggested by Iacobucci et al. (2015). Other researchers also recommended using median splits on a variable measured on a continuous scale to create groups for comparison of the moderators' effects (Frazier et al., 2004; Henseler & Fassott, 2010). Hence, using the median-split procedures (median = 21), the data were divided into two age groups: younger age (281) and senior age (324) groups. The younger age group is formed of undergraduates aged between 17 and 21 years. The senior age group consists of the students whose ages are 22 and beyond.

It has been discussed earlier that the validity of variables, including construct reliability and validity, factor loadings and construct convergent and discriminant validity, remain a requirement for all groups estimation (Henseler et al., 2016). In this study, the researcher ran the PLS algorithm for both younger and senior age groups and found all the items ranges were acceptable except one item (AU2 = 0.35) in the younger group, which did not conform to the standard factor reliability cut-off of 0.70 and above. That also affected AU's Cronbach's α and the researcher had to delete the indicator for all groups and re-estimate the model. Similarly, the assessment of compositional invariance was conducted using the permutation test. Results of MICOM represented a problem in the analysis that the VD score was significantly different from the one which did not support the partial measurement invariance. Since VD composites differ regarding their composition across the groups, the researcher eliminated the construct that did not achieve compositional invariance from both groups as suggested by Hair et al. (2018) and Henseler et al. (2016).

The PLS algorithm and permutation test were re-conducted for both age groups. Table 6.27 illustrated the measurement model results for senior and younger age groups. As can be seen from the table below, the results showed that all factor loadings, Cronbach's α , composite reliability and average variance extracted for the models of both groups were satisfactory.

Table 6.27 The Measurement Model Assessment for Age Groups

	Senior Age Group	Young Age Group

Construct and Indicators	Loadings > 0.7	CA > 0.7	CR > 0.7	AVE > 0.5	Loadings > 0.7	CA > 0.7	CR > 0.7	AVE > 0.5
Actual Use								
AU1	0.800	0.777	0.871	0.693	0.760	0.744	0.854	0.662
AU3	0.883				0.856			
AU4	0.811				0.822			
E-learning System Interactivity								
ESI1	0.833	0.893	0.924	0.753	0.858	0.863	0.904	0.703
ESI2	0.886				0.864			
ESI3	0.894				0.792			
ESI4	0.857				0.838			
Behavioural Intention								
BI1	0.890	0.925	0.947	0.817	0.898	0.920	0.944	0.807
BI2	0.905				0.919			
BI3	0.900				0.868			
BI4	0.919				0.907			
Effort Expectancy								
EE1	0.831	0.880	0.918	0.736	0.860	0.907	0.935	0.783
EE2	0.899				0.902			
EE3	0.839				0.889			
EE4	0.860				0.888			
Facilitating Conditions								
FC1	0.745	0.813	0.867	0.566	0.667	0.776	0.843	0.520
FC2	0.739				0.772			
FC3	0.708				0.638			
FC4	0.755				0.733			
FC5	0.810				0.784			
Instructional Assessment								
IA1	0.775	0.918	0.936	0.710	0.814	0.897	0.921	0.661
IA2	0.868				0.833			
IA3	0.902				0.851			
IA4	0.881				0.838			
IA5	0.823				0.753			
IA6	0.799				0.785			
Information Quality								
IQ1	0.854	0.926	0.944	0.773	0.878	0.928	0.945	0.776
IQ2	0.897				0.899			
IQ3	0.900				0.885			
IQ4	0.885				0.883			
IQ5	0.857				0.86			
System Learnability								
SL1	0.843	0.889	0.919	0.693	0.853	0.864	0.902	0.650

SL2	0.820				0.801			
SL3	0.888				0.846			
SL4	0.812				0.820			
SL5	0.797				0.701			
System Navigation								
SN1	0.827	0.862	0.895	0.630	0.862	0.853	0.895	0.631
SN2	0.763				0.769			
SN3	0.852				0.821			
SN4	0.747				0.749			
SN5	0.774				0.765			
Performance Expectancy								
PE1	0.808	0.820	0.881	0.651	0.842	0.852	0.900	0.693
PE2	0.832				0.866			
PE3	0.873				0.871			
PE4	0.705				0.744			
Social Influence								
SI1	0.752	0.757	0.846	0.580	0.723	0.788	0.862	0.609
SI2	0.825				0.815			
SI3	0.753				0.811			
SI4	0.711				0.770			

CA: Cronbach’s alpha, CR: composite reliability, AVE: average variance extracted

In terms of convergent validity, the AVE constructs of both age groups are above the recommended value of 0.5 and factor loading all above the cut-off value of 0.70 except two FC1 and FC3 were greater than 0.60, which also acceptable in the case of exploratory research (Hair et al., 2014; Hair, Hult, et al., 2017), hence convergent validity is established. For the assessment of discriminant validity, the Fornell-Lacker testing system was employed (Fornell & Larcker, 1981). Table 6.28 showed that the levels of the square root of the AVE for each construct are greater than the correlation involving the constructs for young and senior age groups (Hair, Hult, et al., 2017). Hence discriminant validity has been established for both groups. Based on these results, the construct validity, evidenced by convergent and discriminant validity, has been established.

Table 6.28 The Fornell-Larcker Criterion for Age

Young Age											
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**
AU	**0.814**										
BI	0.558	**0.898**									
EE	0.503	0.590	**0.885**								
FC	0.610	0.618	0.611	**0.721**							

IQ	0.410	0.570	0.532	0.541	**0.881**						
IA	0.504	0.570	0.555	0.635	0.641	**0.813**					
ESI	0.370	0.568	0.408	0.523	0.573	0.667	**0.839**				
SL	0.516	0.626	0.775	0.624	0.661	0.659	0.563	**0.806**			
SN	0.470	0.585	0.636	0.676	0.593	0.641	0.592	0.772	**0.794**		
PE	0.567	0.815	0.594	0.625	0.644	0.604	0.590	0.629	0.576	**0.833**	
SI	0.617	0.529	0.404	0.515	0.469	0.479	0.387	0.472	0.378	0.564	**0.781**
Senior Age											
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**
AU	**0.830**										
BI	0.580	**0.900**									
EE	0.460	0.560	**0.860**								
FC	0.500	0.520	0.640	**0.750**							
IQ	0.520	0.510	0.530	0.620	**0.880**						
IA	0.490	0.490	0.540	0.610	0.690	**0.840**					
ESI	0.420	0.500	0.420	0.520	0.580	0.700	**0.870**				
SL	0.560	0.550	0.740	0.690	0.720	0.660	0.570	**0.830**			
SN	0.520	0.480	0.630	0.650	0.640	0.650	0.590	0.680	**0.790**		
PE	0.550	0.710	0.520	0.510	0.600	0.540	0.530	0.570	0.510	**0.810**	
SI	0.620	0.530	0.420	0.530	0.530	0.480	0.430	0.520	0.520	0.550	**0.760**

MICOM was also examined. As we have detailed earlier, the configural invariance was identical for the two groups of data. As a result of MICOM's Step 1, configural invariance has been established. Step 2 concerned with compositional invariance. We have rerun the permutation test with the models without visual design construct as it violated the method criteria. The test substantiated that none of the original correlation values is significantly different from one. As can be seen in Table 6.29, the proportion of composite scores the first and second groups were larger than or equal to the 5% quantile of the empirical distribution. Hence, compositional invariance has been established for all composites in the model.

Table 6.29 MICOM Compositional Invariance Results for Age Groups

	Original Correlation	**Correlation Permutation Mean**	**5.00%**	**Permutation p-Values**
AU	0.999	0.999	0.997	0.529
BI	1	1	1	0.551
EE	1	1	1	0.384
FC	0.999	0.998	0.994	0.586
IQ	1	1	1	0.194
IA	0.999	1	0.999	0.142
ESI	1	1	0.999	0.467
SL	1	1	0.999	0.572
SN	1	0.999	0.998	0.987
PE	1	1	0.999	0.776
SI	0.998	0.999	0.996	0.221

Once we have confirmed that the construct measures are reliable and valid, the next step addresses the assessment of the structural model results for each group. Table 6.30 presents the bootstrapping results for younger and senior age groups. The significant relationships in both young and senior groups are *BI -> AU, EE -> PE, IQ -> PE, ESI -> PE, SL -> EE, PE -> BI and SI -> AU*. However, there some relationships which appear significant only in the senior group such as *EE -> BI* (β = 0.231), *IA -> EE* (β =0.14) and *SI -> BI* (β =0.149).

Table 6.30 Bootstrapping Results for Young and Senior Age Groups

	Young Group			**Senior Group**		
Paths	**β**	**T**	**P**	**β**	**T**	**P**
BI -> AU	0.167	2.847	0.004	0.308	5.307	0.001
EE -> BI	0.082	1.339	0.181	0.231	3.634	0.001
EE -> PE	0.257	3.900	0.001	0.210	2.782	0.005
FC -> AU	0.319	5.972	0.001	0.139	2.792	0.005
FC -> BI	0.067	1.462	0.144	0.054	0.987	0.324
IQ -> BI	-0.038	0.736	0.462	-0.026	0.354	0.723
IQ -> EE	0.023	0.350	0.726	-0.061	0.841	0.400
IQ -> PE	0.278	3.699	0.001	0.308	4.181	0.001
IA-> BI	-0.024	0.429	0.668	-0.038	0.604	0.546
IA-> EE	0.106	1.624	0.105	0.140	2.030	0.042
IA-> PE	0.088	1.167	0.243	0.039	0.556	0.579
ESI -> BI	0.086	1.421	0.155	0.135	1.929	0.054
ESI -> EE	-0.117	1.892	0.058	-0.084	1.516	0.130
ESI -> PE	0.231	3.828	0.001	0.211	3.108	0.002
SL -> BI	0.028	0.363	0.717	0.013	0.152	0.879
SL -> EE	0.681	10.850	0.001	0.642	8.417	0.001
SL -> PE	0.041	0.462	0.644	0.060	0.653	0.514
SN -> BI	0.066	1.079	0.281	-0.067	1.030	0.303
SN -> EE	0.097	1.611	0.107	0.123	1.653	0.098
SN -> PE	0.023	0.295	0.768	-0.020	0.267	0.789
PE -> BI	0.632	11.231	0.001	0.474	7.826	0.001
SI -> AU	0.365	6.738	0.001	0.379	6.301	0.001
SI -> BI	0.062	1.430	0.153	0.149	2.923	0.003

β: path coefficient, T: T Statistics, P: p.value

In Table 6.31, the adj.R^2 values were presented. For the young group, the adj.R^2 values of AU, BI, EE, PE were 0.508 (51%), 0.704 (70%), 0.606 (61%) and 0.550 (55%) respectively. For the senior group, the adj.R^2 values for AU, BI, EE, PE were 0.477 (48%), 0.572 (57%), 0.553 (55%) and 0.437 (44%) respectively. As can be seen, the young students explained variances for the outcome variables are higher than the senior so the explanatory power for the young student's model appeared to range between medium and high.

Table 6.31 Adj.R^2 for Young and Senior

	Young Group Adj.R^2	**Senior Group Adj.R^2**
AU	0.508	0.477
BI	0.704	0.572
EE	0.606	0.553
PE	0.550	0.437

Having established configural and compositional invariance, it is important to compare the path coefficients of young and senior groups using a permutation technique. In Table 6.32, the results of path coefficients of both groups are presented. As can be seen, most structural model relationships were insignificant, as most the p-values are considerably larger than 0.05 with a single exception. The relationship between FC and AU of the e-learning system, differs significantly with $p < 0.05$. The relationship between facilitating conditions and the actual use is significantly different among young students ($\beta^{(1)} = 0.319$) versus those who are senior ($\beta^{(2)} = 0.139$).

The relationship between facilitating conditions and actual use is significant for both young ($\beta^{(1)} = 0.319$ and $p < 0.05$) and senior students ($\beta^{(2)} = 0.139$ and $p < 0.05$) (see Table 6.32). It can be concluded that the first-year and second-year students have a greater tendency to use the e-learning system if the university provides proper support to use the system, compared to the senior students.

Table 6.32 Path Coefficients for Young and Senior Age Groups

Paths	**β (Young Age)**	**β (Senior Age)**	**Difference (Young - Senior)**	**Permutation p-Values**
BI -> AU	0.167	0.308	-0.141	0.097
EE -> BI	0.082	0.231	-0.149	0.094
EE -> PE	0.257	0.210	0.047	0.653
FC -> AU	0.319	0.139	0.179	0.016
FC -> BI	0.067	0.054	0.013	0.870
IQ -> BI	-0.038	-0.026	-0.012	0.901
IQ -> EE	0.023	-0.061	0.084	0.405
IQ -> PE	0.278	0.308	-0.030	0.790
IA-> BI	-0.024	-0.038	0.015	0.865
IA-> EE	0.106	0.140	-0.034	0.718
IA-> PE	0.088	0.039	0.049	0.635
ESI -> BI	0.086	0.135	-0.049	0.609
ESI -> EE	-0.117	-0.084	-0.033	0.711

ESI -> PE	0.231	0.211	0.020	0.827
SL -> BI	0.028	0.013	0.015	0.904
SL -> EE	0.681	0.642	0.040	0.696
SL -> PE	0.041	0.060	-0.019	0.889
SN -> BI	0.066	-0.067	0.133	0.144
SN -> EE	0.097	0.123	-0.026	0.799
SN -> PE	0.023	-0.020	0.042	0.693
PE -> BI	0.632	0.474	0.158	0.068
SI -> AU	0.365	0.379	-0.014	0.871
SI -> BI	0.062	0.149	-0.087	0.187

6.4.3 Experience

The third moderator is the students' LMS experience. The experience moderator was examined based on a ratio scale therefore, the refinement strategies were not required (Hair et al., 2014). The data were divided into low (< 2 years of LMS experience) and high experienced (> 2 years of LMS experience) users. The first step is to ensure the construct reliability and validity, including factor loadings and construct convergent and discriminant validity (Henseler et al., 2016). In this research, the researcher ran the PLS algorithm for both groups and found all the item ranges were acceptable except for one item (AU2 = 0.50) in the advanced users' category, which did not conform to the standard factor reliability cut-off of 0.70 and above. The researcher has decided to remove the AU2 indicator for both groups and re-estimate the model. Another reason for the elimination was that removing AU2 leads to an increase in the composite reliability and the average variance extracted above the cut-off value as suggested by Hair et al. (2017). The results of the PLS algorithm for students' e-learning experiences is presented in Table 6.33. As it can be observed from the data, criteria of indicators loadings, internal consistency reliability, composite reliability and AVE, were satisfactory.

Table 6.33 The Measurement Model Assessment for Experience

	Advanced Users Group				**Beginners Users Group**			
Construct and Indicators	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
Actual Use								
AU1	0.869	0.798	0.881	0.714	0.735	0.774	0.871	0.693
AU3	0.908				0.876			

AU4	0.749				0.879			
E-learning System Interactivity								
ESI1	0.804	0.859	0.902	0.697	0.901	0.905	0.933	0.777
ESI2	0.838				0.928			
ESI3	0.865				0.813			
ESI4	0.833				0.879			
Behavioural Intention								
BI1	0.890	0.903	0.945	0.812	0.875	0.919	0.949	0.824
BI2	0.918				0.949			
BI3	0.873				0.904			
BI4	0.923				0.903			
Effort Expectancy								
EE1	0.830	0.877	0.916	0.731	0.827	0.912	0.938	0.792
EE2	0.891				0.944			
EE3	0.869				0.907			
EE4	0.828				0.879			
Facilitating Conditions								
FC1	0.715	0.792	0.847	0.525	0.675	0.804	0.863	0.559
FC2	0.777				0.738			
FC3	0.704				0.804			
FC4	0.658				0.762			
FC5	0.765				0.754			
Instructional Assessment								
IA1	0.725	0.873	0.904	0.612	0.878	0.914	0.941	0.725
IA2	0.795				0.871			
IA3	0.828				0.86			
IA4	0.824				0.833			
IA5	0.764				0.8			
IA6	0.754				0.864			
Information Quality								
IQ1	0.839	0.917	0.945	0.773	0.887	0.918	0.945	0.776
IQ2	0.884				0.880			
IQ3	0.892				0.910			
IQ4	0.909				0.893			
IQ5	0.871				0.832			
System Learnability								
SL1	0.818	0.846	0.890	0.619	0.899	0.898	0.925	0.712
SL2	0.775				0.825			
SL3	0.850				0.904			
SL4	0.767				0.820			
SL5	0.718				0.764			
System Navigation								

SN1	0.839	0.842	0.888	0.613	0.880	0.848	0.892	0.626
SN2	0.768				0.816			
SN3	0.841				0.841			
SN4	0.723				0.722			
SN5	0.736				0.678			
Performance Expectancy								
PE1	0.836	0.809	0.874	0.638	0.842	0.881	0.918	0.736
PE2	0.846				0.882			
PE3	0.844				0.889			
PE4	0.652				0.818			
Social Influence								
SI1	0.678	0.784	0.86	0.607	0.795	0.810	0.875	0.637
SI2	0.776				0.806			
SI3	0.872				0.782			
SI4	0.779				0.810			
Visual Design								
VD1	0.756	0.912	0.932	0.695	0.817	0.913	0.939	0.720
VD2	0.773				0.779			
VD3	0.890				0.892			
VD4	0.893				0.916			
VD5	0.823				0.853			
VD6	0.859				0.826			

CA: Cronbach's alpha, CR: composite reliability, AVE: average variance extracted

For the assessment of validity, all constructs in both groups have their AVE greater than 0.5 (see Table 6.33) and hence, convergent validity has been established. Using the Fornell–Larcker criterion (Fornell & Larcker, 1981), the constructs presented in Table 6.34 share more variance with their assigned indicators than with any other construct, hence discriminant validity has been established for both beginners and advanced users.

Table 6.34 The Fornell-Larcker Criterion

Beginners												
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**	**VD**
AU	**0.833**											
BI	0.409	**0.908**										
EE	0.379	0.633	**0.890**									
FC	0.581	0.528	0.632	**0.748**								
IQ	0.455	0.665	0.599	0.600	**0.881**							
IA	0.522	0.525	0.495	0.645	0.807	**0.852**						
ESI	0.377	0.574	0.463	0.520	0.757	0.765	**0.881**					
SL	0.479	0.653	0.724	0.676	0.737	0.701	0.587	**0.844**				
SN	0.412	0.649	0.612	0.647	0.656	0.716	0.668	0.709	**0.791**			
PE	0.420	0.776	0.604	0.533	0.669	0.553	0.652	0.631	0.622	**0.858**		
SI	0.720	0.394	0.329	0.520	0.578	0.492	0.468	0.478	0.381	0.448	**0.798**	
VD	0.407	0.319	0.327	0.590	0.611	0.659	0.616	0.653	0.670	0.371	0.536	**0.848**

Advanced Users												
	AU	BI	EE	FC	IQ	IA	ESI	SL	SN	PE	SI	VD
AU	**0.845**											
BI	0.608	**0.901**										
EE	0.474	0.484	**0.855**									
FC	0.527	0.559	0.582	**0.725**								
IQ	0.434	0.404	0.442	0.547	**0.879**							
IA	0.456	0.464	0.440	0.573	0.674	**0.783**						
ESI	0.364	0.525	0.346	0.465	0.528	0.611	**0.835**					
SL	0.537	0.500	0.672	0.679	0.658	0.553	0.522	**0.787**				
SN	0.478	0.481	0.563	0.618	0.530	0.541	0.538	0.720	**0.783**			
PE	0.567	0.700	0.457	0.516	0.532	0.511	0.465	0.504	0.447	**0.799**		
SI	0.539	0.532	0.424	0.563	0.474	0.466	0.385	0.486	0.453	0.545	**0.779**	
VD	0.414	0.379	0.496	0.535	0.571	0.574	0.524	0.686	0.677	0.337	0.365	**0.834**

Since the model set-up is unchanged throughout the analysis, configural invariance is established (see section 6.4). Step 2 is concerned with compositional invariance. The permutation procedure was conducted to evaluate MICOM. A permutation test compares the composite scores of the beginners and the advanced groups to determine if the original correlation is significantly different from the 5.00% quantile (Henseler et al., 2016). The results in Table 6.35 indicate that the original correlations are equal to or higher than the 5% quantile correlation of the empirical distribution and hence, compositional invariance is established.

Table 6.35 MICOM Compositional Invariance Results for Experience

	Original Correlation	**Correlation Permutation Mean**	**5.00%**	**Permutation p-Values**
AU	0.995	0.998	0.994	0.077
BI	1	1	1	0.821
EE	1	1	0.999	0.982
FC	0.993	0.993	0.978	0.282
IQ	1	1	0.999	0.569
IA	0.998	0.998	0.995	0.217
ESI	0.999	0.998	0.995	0.448
SL	1	0.999	0.998	1
SN	0.998	0.998	0.995	0.477
PE	0.999	0.999	0.997	0.366
SI	0.996	0.995	0.985	0.331
VD	0.997	0.997	0.991	0.261

Once the variance is established, the focus is to analyse the groups separately prior to determining if there are specific differences between groups. Table 6.36 illustrated the hypothesized relationship among variables for each group. The significant relationships for both groups are *ESI -> PE, FC -> AU, IQ -> PE, PE -> BI, SI -> AU,* and *SL -> EE*. The strongest path in both groups was *SL -> EE* with the beginners' path coefficient of 0.666 and the advanced category of 0.579. In terms of specific significant relationship associated with each group, the advanced group evidenced the *BI -> AU, EE -> PE, ESI -> BI, FC -> BI, IQ -> BI and VD -> PE* paths as being significant. The only path significant in the beginner subsample is *VD -> EE*.

Table 6.36 Bootstrapping Results for Advanced and Beginner Groups

	Advanced			**Beginner**		
Paths	**β**	**T**	**P**	**β**	**T**	**P**
BI -> AU	0.383	5.842	0.001	0.046	0.443	0.658
EE -> BI	0.108	1.491	0.136	0.039	0.275	0.783
EE -> PE	0.205	2.393	0.017	0.143	1.050	0.294
ESI -> BI	0.227	2.405	0.016	0.040	0.281	0.779
ESI -> EE	-0.083	0.976	0.329	0.073	0.500	0.617
ESI -> PE	0.176	2.359	0.018	0.403	3.211	0.001
FC -> AU	0.181	2.292	0.022	0.258	2.538	0.011
FC -> BI	0.158	2.432	0.015	0.067	0.554	0.579
IA -> BI	-0.021	0.279	0.780	-0.164	1.140	0.254
IA -> EE	0.135	1.713	0.087	-0.141	0.804	0.422
IA -> PE	0.174	1.905	0.057	-0.202	1.435	0.151
IQ -> BI	-0.166	2.203	0.028	0.296	1.723	0.085
IQ -> EE	-0.060	0.639	0.523	0.248	1.105	0.269
IQ -> PE	0.244	2.931	0.003	0.310	1.988	0.047
PE -> BI	0.489	6.435	0.001	0.415	3.730	0.001
SI -> AU	0.234	3.333	0.001	0.570	7.029	0.001
SI -> BI	0.120	1.931	0.054	0.032	0.321	0.748
SL -> BI	-0.011	0.104	0.917	0.113	0.558	0.577
SL -> EE	0.579	5.616	0.001	0.666	3.470	0.001
SL -> PE	0.114	0.963	0.335	0.190	0.964	0.335
SN -> BI	0.029	0.321	0.748	0.300	1.714	0.087
SN -> EE	0.102	0.990	0.322	0.181	1.078	0.281
SN -> PE	0.088	0.895	0.371	0.228	1.262	0.207
VD -> BI	0.008	0.109	0.913	-0.276	1.812	0.070
VD -> EE	0.034	0.359	0.720	-0.329	2.151	0.032
VD -> PE	-0.238	2.641	0.008	-0.260	1.807	0.071

β: path coefficient, T: T Statistics, P: p.value

In Table 6.37, the adj.R^2 values were presented. For the advanced group, the adj.R^2 values of AU, BI, EE, PE were 0.447 (45%), 0.582 (58%), 0.452 (45%) and 0.392 (39%) respectively. For the beginners, the adj.R^2 values for AU, BI, EE, PE were 0.559 (56%), 0.660 (66%), 0.558 (56%) and 0.568 (57%) respectively. As can be seen, the beginners Adj.R^2 values are higher than the advanced so the model of the less experienced students seems to be more influenced by the predictors than their counterparts.

Table 6.37 Adj.R^2 for Advanced and Beginner

	Advanced Users	**Beginner Users**
	Adj.R^2	**Adj.R^2**
AU	0.447	0.559
BI	0.582	0.660
EE	0.452	0.558
PE	0.392	0.568

As demonstrated above, the configural and compositional invariances have been established. Thus, the next procedure is to compare the original path coefficients for the beginner and the advanced users' groups using the information from the group-specific bootstrapping and the permutation test. Table 6.38 presents path coefficients for each group, their differences as well as their permutation significant values. As shown in Table 6.38, some relationships indicate a significant difference between the advanced users and beginners, evidenced by the permutation p-value below the 0.05 significance level. To start with, the relationship between BI and AU is significantly different among advanced users ($\beta^{(1)} = 0.383$) compared to those who are beginners ($\beta^{(2)} = 0.046$) with the path being significant in the advanced group but not in the beginners. Similarly, the effect of IQ on BI is significantly different between advanced students ($\beta^{(1)} = -0.166$) and beginner students ($\beta^{(2)} = 0.299$), with the path being significant in the advanced group but not in the beginner's category. Finally, the relationship between SI and AU is significantly different for experienced students ($\beta^{(1)} = 0.234$) versus inexperienced users ($\beta^{(2)} = 0.570$). However, the relationship between SI and AU is significant for both advanced and novices' groups (see Table 6.36). The other relationships of the model do not indicate a major difference between advanced and beginner groups.

Based on the results of bootstrapping and permutation procedures, it can be concluded that SI has a significant impact on AU for both experienced and inexperienced users. However, the impact on the beginner users of the e-learning system is far more significant (β=0.570, $p<0.001$). Thus, the beginner students seem to be more susceptible to other peers, family members and instructors' opinions in their use of the e-learning system than the experienced users.

Table 6.38 Path Coefficients for E-learning System Experience Groups

Paths	β (Advanced Users)	β (Beginner-Users)	Difference (Advanced Users - Beginners)	Permutation p-Values
BI -> AU	0.383	0.046	0.338	0.018
EE -> BI	0.108	0.039	0.070	0.686
EE -> PE	0.205	0.143	0.062	0.731
ESI -> BI	0.227	0.040	0.187	0.330
ESI -> EE	-0.083	0.073	-0.156	0.330
ESI -> PE	0.176	0.403	-0.227	0.098
FC -> AU	0.181	0.258	-0.077	0.610
FC -> BI	0.158	0.067	0.091	0.502
IA -> BI	-0.021	-0.164	0.144	0.377
IA -> EE	0.135	-0.141	0.276	0.114
IA -> PE	0.174	-0.202	0.376	0.050
IQ -> BI	-0.166	0.296	-0.462	0.003
IQ -> EE	-0.060	0.248	-0.308	0.114
IQ -> PE	0.244	0.310	-0.066	0.687
PE -> BI	0.489	0.415	0.074	0.628
SI -> AU	0.234	0.570	-0.336	0.018
SI -> BI	0.120	0.032	0.088	0.438
SL -> BI	-0.011	0.113	-0.124	0.613
SL -> EE	0.579	0.666	-0.087	0.697
SL -> PE	0.114	0.190	-0.076	0.778
SN -> BI	0.029	0.300	-0.270	0.183
SN -> EE	0.102	0.181	-0.079	0.698
SN -> PE	0.088	0.228	-0.140	0.550
VD -> BI	0.008	-0.276	0.285	0.080
VD -> EE	0.034	-0.329	0.364	0.046
VD -> PE	-0.238	-0.260	0.022	0.901

6.4.4 Training

The last moderator to assess is the students' training. The population sample was divided into trained and untrained users. Trained users are those who received LMS training and untrained students are those who had no previous training in the use of LMS. The trained students formed 316 (52.2%) and untrained formed 289 (47.8%) of the sample.

In order to compare the groups, it is essential to assess the reliability and validity of both, students with and without training, groups (Henseler et al., 2016). The results of the PLS algorithm for LMS training groups are illustrated in Table 6.39. As it can be observed from the data, criteria of indicators loadings, internal consistency reliability, composite reliability and AVE, were satisfactory. Similarly, the assessment of compositional invariance was conducted using the permutation test. The results of MICOM represented a problem in the analysis that SI and FC scores were significantly different from the one which did not support the partial measurement invariance. Since these two variables (SI, FC) composites differ regarding their composition across the groups, the researcher eliminated the constructs that did not achieve compositional invariance from both groups as suggested by Hair et al. (2018) and Henseler et al. (2016).

Table 6.39 The Measurement Model Assessment for Training Groups

	Trained Group				Untrained Group			
Construct and Indicators	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
Actual Use								
AU1	0.718	0.750	0.844	0.578	0.753	0.745	0.840	0.572
AU2	0.643				0.600			
AU3	0.884				0.879			
AU4	0.777				0.767			
E-learning System Interactivity								
ESI1	0.866	0.886	0.920	0.741	0.808	0.864	0.904	0.703
ESI2	0.889				0.852			
ESI3	0.832				0.855			
ESI4	0.857				0.839			
Behavioural Intention								
BI1	0.900	0.922	0.945	0.810	0.893	0.925	0.947	0.817
BI2	0.914				0.917			
BI3	0.875				0.895			
BI4	0.911				0.911			
Effort Expectancy								
EE1	0.871	0.913	0.939	0.794	0.825	0.874	0.914	0.726
EE2	0.904				0.898			
EE3	0.904				0.816			
EE4	0.885				0.868			
Instructional Assessment								
IA1	0.829	0.923	0.940	0.723	0.746	0.887	0.914	0.641
IA2	0.883				0.812			
IA3	0.889				0.864			
IA4	0.878				0.840			
IA5	0.810				0.761			
IA6	0.810				0.773			
Information Quality								
IQ1	0.908	0.945	0.958	0.819	0.810	0.901	0.927	0.718
IQ2	0.922				0.866			
IQ3	0.907				0.876			

IQ4	0.890				0.878			
IQ5	0.899				0.803			
System Learnability								
SL1	0.859	0.897	0.924	0.710	0.836	0.849	0.892	0.625
SL2	0.842				0.770			
SL3	0.886				0.844			
SL4	0.836				0.791			
SL5	0.785				0.704			
System Navigation								
SN1	0.843	0.866	0.903	0.651	0.851	0.839	0.885	0.608
SN2	0.787				0.744			
SN3	0.843				0.821			
SN4	0.756				0.743			
SN5	0.801				0.733			
Performance Expectancy								
PE1	0.835	0.837	0.891	0.673	0.825	0.839	0.893	0.677
PE2	0.849				0.856			
PE3	0.866				0.882			
PE4	0.724				0.718			
Visual Design								
VD1	0.778	0.918	0.936	0.711	0.695	0.909	0.931	0.693
VD2	0.772				0.763			
VD3	0.877				0.885			
VD4	0.901				0.903			
VD5	0.863				0.845			
VD6	0.860				0.883			

CA: Cronbach's alpha, CR: composite reliability, AVE: average variance extracted

For the assessment of validity, all constructs in both groups have their AVE greater than 0.5 (see Table 6.39) and hence, convergent validity has been established.

The discriminant validity was assessed using the Fornell–Larcker criterion (Fornell & Larcker, 1981). The results in Table 6.40 show that the square root of each construct's AVE, presented on the diagonal line, is larger than the construct's correlation with other constructs, hence discriminant validity has been established.

Table 6.40 The Fornell-Larcker Criterion for Training Groups

Trained										
	AU	BI	EE	ESI	IA	IQ	PE	SL	SN	VD
AU	**0.760**									
BI	0.565	**0.900**								
EE	0.523	0.656	**0.891**							
ESI	0.453	0.588	0.481	**0.861**						
IA	0.549	0.570	0.594	0.727	**0.850**					
IQ	0.496	0.628	0.538	0.650	0.736	**0.905**				
PE	0.599	0.792	0.620	0.630	0.648	0.713	**0.821**			
SL	0.592	0.647	0.792	0.640	0.731	0.701	0.657	**0.842**		

SN	0.549	0.606	0.706	0.639	0.688	0.653	0.633	0.750	**0.807**	
VD	0.455	0.479	0.522	0.566	0.694	0.653	0.516	0.702	0.704	**0.843**
Untrained										
	AU	BI	EE	ESI	IA	IQ	PE	SL	SN	VD
AU	**0.757**									
BI	0.577	**0.904**								
EE	0.453	0.493	**0.852**							
ESI	0.323	0.479	0.340	**0.839**						
IA	0.442	0.472	0.487	0.620	**0.800**					
IQ	0.436	0.429	0.520	0.477	0.568	**0.847**				
PE	0.501	0.757	0.494	0.481	0.477	0.509	**0.823**			
SL	0.506	0.511	0.705	0.486	0.569	0.678	0.529	**0.791**		
SN	0.469	0.467	0.545	0.545	0.591	0.575	0.450	0.717	**0.780**	
VD	0.429	0.370	0.437	0.532	0.531	0.604	0.383	0.631	0.695	**0.832**

The following analysis is the execution of the MICOM procedure which involves evaluating the compositional invariance (Hair et al., 2018; Henseler et al., 2016; Matthews, 2017). As it can be seen in Table 6.41, the MICOM permutation results were generated. The first column in the Table 6.41 confirms that the first correlation in is equal or greater than the 5% column and the p-values are considerably larger than 0.05, hence, the compositional invariance has been demonstrated for all the multi-items constructs.

Table 6.41 MICOM Compositional Invariance Results for Training

Constructs	Original Correlation	Correlation Permutation Mean	5.00%	Permutation p-Values
AU	0.998	0.998	0.993	0.540
BI	1	1	1	0.945
EE	1	1	1	0.295
ESI	0.999	1	0.999	0.201
IA	1	1	0.999	0.344
IQ	1	1	1	0.117
PE	1	1	0.999	0.768
SL	1	1	0.999	0.517
SN	0.999	0.999	0.998	0.216
VD	0.999	0.999	0.999	0.309

However, it is also important to analyse the group separately to determine whether the path coefficient is significant. Therefore, the researcher run the bootstrapping for trained and untrained users separately. Table 6.42 presents the path analysis of the two sub-samples. The BI->AU, EE->PE, ESI->PE, IQ->PE, PE->BI, SL->EE showed statistically significant in both categories, trained and untrained of the LMS use altogether. However, the paths EE->BI, ESI->BI, ESI->EE, SN -> EE and VD -> EE are signified in the trained students uniquely whereas the path IA -> EE is the only significant path coefficient in the untrained users. The strongest significant path in the students who received training is SL -> EE (β = 0.697), compared with PE -> BI (β = 0.629) in the other category. There are more significant relationships in the learners who trained in the use of LMS in Saudi higher education, indicating the model fits well with this classification.

Table 6.42 Results of Path Analysis for Training Groups

	Trained			Untrained		
Paths	**β**	**T**	**P**	**β**	**T**	**P**
BI -> AU	0.566	12.894	0.001	0.578	12.308	0.001
EE -> BI	0.250	4.062	0.001	0.105	1.696	0.090
EE -> PE	0.281	4.289	0.001	0.207	2.879	0.004
ESI -> BI	0.134	1.990	0.047	0.100	1.550	0.121
ESI -> EE	-0.101	1.635	0.102	-0.082	1.394	0.163
ESI -> PE	0.199	3.446	0.001	0.248	4.065	0.001
IA -> BI	-0.104	1.679	0.093	0.048	0.854	0.393
IA -> EE	0.115	1.761	0.078	0.149	2.220	0.026
IA -> PE	0.057	0.780	0.436	0.074	1.055	0.292
IQ -> BI	0.072	1.137	0.256	-0.076	1.355	0.176
IQ -> EE	-0.038	0.663	0.507	0.060	0.761	0.447
IQ -> PE	0.416	6.279	0.001	0.196	2.399	0.016
PE -> BI	0.557	8.129	0.001	0.629	12.500	0.001
SL -> BI	0.030	0.390	0.697	0.045	0.554	0.579
SL -> EE	0.697	9.599	0.001	0.610	8.258	0.001
SL -> PE	-0.033	0.376	0.707	0.137	1.587	0.112
SN -> BI	-0.004	0.068	0.946	0.078	1.167	0.243
SN -> EE	0.236	3.082	0.002	0.081	1.246	0.213
SN -> PE	0.094	1.238	0.216	0.012	0.148	0.882
VD -> BI	-0.008	0.156	0.876	-0.031	0.505	0.614
VD -> EE	-0.131	2.154	0.031	-0.080	1.037	0.300
VD -> PE	-0.100	1.769	0.077	-0.092	1.180	0.238

β: path coefficient, T: T Statistics, P: p.value

The explained variance (Adj.R^2 values) is presented in Table 6.43. For the trained group, the adj.R^2 values of AU, BI, EE and PE were 0.318 (32%), 0.674 (67%), 0.643 (64%) and 0.611 (61%) respectively. For the untrained category, the adj.R^2 values for AU, BI, EE, PE were 0.331 (33%), 0.601 (60%), 0.506 (51%) and 0.385 (39%) respectively. The explanatory power for the trained students model ranges between moderate and high, indicating a relatively higher adj.R^2 than the untrained model achieved.

Table 6.43 Adj.R^2 for Trained and Untrained Groups

	Adj.R^2 for Trained Users	**Adj.R^2 for**

		Untrained Users
AU	0.318	0.331
BI	0.674	0.601
EE	0.643	0.506
PE	0.611	0.385

Having established configural and compositional invariance, the next step is to run the moderating effects of both groups using multigroup analysis. In Table 6.44, the results of path coefficients of both groups were presented. It can be seen from the data in Table 6.44 that the only moderating effect of training is the correlation between the IQ and PE which showed a statistical difference between the two groups at 0.05 significant level. These relationships were significant. Nonetheless, trained students showed higher perceptions (β = 0.416) of the LMS IQ and its effect on the system usefulness than did the untrained counterpart (β = 0.196).

Table 6.44 Moderating Effects for Training Groups

Paths	β Trained	β Untrained	β Difference (Trained - Untrained)	Permutation p-Values
BI -> AU	0.565	0.577	-0.012	0.843
EE -> BI	0.255	0.104	0.151	0.089
EE -> PE	0.275	0.211	0.064	0.514
ESI -> BI	0.134	0.102	0.032	0.746
ESI -> EE	-0.101	-0.081	-0.019	0.814
ESI -> PE	0.200	0.246	-0.046	0.606
IA -> BI	-0.103	0.047	0.150	0.076
IA -> EE	0.115	0.149	-0.034	0.728
IA -> PE	0.058	0.076	-0.018	0.863
IQ -> BI	0.075	-0.076	0.150	0.088
IQ -> EE	-0.038	0.061	-0.099	0.315
IQ -> PE	0.417	0.196	0.221	0.043
PE -> BI	0.550	0.625	-0.075	0.376
SL -> BI	0.029	0.047	-0.018	0.879
SL -> EE	0.698	0.605	0.092	0.368
SL -> PE	-0.030	0.134	-0.164	0.209
SN -> BI	-0.002	0.078	-0.080	0.407
SN -> EE	0.236	0.087	0.149	0.150
SN -> PE	0.092	0.010	0.082	0.477
VD -> BI	-0.010	-0.033	0.023	0.785
VD -> EE	-0.131	-0.077	-0.054	0.601
VD -> PE	-0.098	-0.090	-0.007	0.940

In summary, the research analyses the effect of a moderator (e.g. age, gender, experience, and training) on the model relationships. The model is estimated for each of the distinct subsamples (e.g., females vs. males). This means the relationships between variables might differ depending on the moderator's effect. Multi-Group Analysis (MGA) was used to analyse the effects of moderation across multiple relationships. To begin with, gender and age variables moderated the FC->AU path and is significant for male and female sub-groups as well as for young and senior students. However, the female group exhibited a stronger effect ($\beta = 0.302$) than did their male counterparts ($\beta = 0.154$) whereas young students showed a stronger influence ($\beta = 0.319$) compared with seniors ($\beta = 0.139$). This means that the strength of the relationship between FC->AU depends on the values of age and gender.

In contrast, experience moderates three relationships namely: BI -> AU, IQ -> BI and SI->BI. For BI -> AU and IQ -> BI. The relationship is more pronounced in the advanced students than in the beginners so the more experience students acquire in the use of LMS, the more the affirmation of the usage behaviour. Conversely, the SI->BI is more significant for less experienced users. This means that the less experienced users tend to be more susceptible to others' opinions, which is expected in Saudi higher education as students tend to comply with other expectations.

Finally, the LMS training moderates the IQ -> PE relationship. The trained students exhibited higher perceptions of the LMS IQ and its effect on the PE than did their untrained counterparts. Therefore, the relationship (IQ -> PE) is not the same for all students but instead differs depending on their training level. These results help universities to direct the required resources to the desired groups to improve the acceptance and use of LMS in Saudi higher education.

6.5 Summary

This chapter has described the results of the analysis conducted in this investigation in three phases. The first part of this analysis examined the measurement model – the reliability and validity of the proposed scale. The internal consistency reliability, including composite reliability and Cronbach's α, demonstrate that the UTAUT and usability variables are robust in terms of their internal consistency, and that the proposed scale is well-constructed. Furthermore, the validity of construct measures, including indicator reliability and AVE confirm the convergent validity. Also, cross-loadings, the Fornell-Larcker criterion and HTMT criterion established the discriminant validity. The satisfactory outcomes of the measurement model are prerequisites for structural model assessment.

The next section, therefore, moves on to analyse the structural model in terms of model fit, collinearity, path coefficients, coefficient of determination (R^2) and cross-validated redundancy (Q^2). The multicollinearity phenomenon was absent in the dataset. Importantly, out of the 26 proposed hypotheses, half were supported. Besides, the model's outcomes were well predicted by the independent variables (48% in AU behaviour, 65% in BI, 58% in EE and 51% of the PE was predicated by the input variables).

The last segment dealt with the moderating effect. Although the study shows some variations in the demographic differences concerning path significance and intensity, the four demographic moderators were shown to have little impact on the students' use of LMS in Saudi higher education.

The next chapter will interpret these findings, discuss their relationship to the prior literature and explain any insights that emerged from the analysis.

CHAPTER 7: DISCUSSION

7.1 Introduction

The previous chapter discussed the preliminary data analysis, along with a rigorous analysis of the empirical research findings. Following the study findings in the previous chapter, this chapter aims to interpret and describe the significance of the posed hypotheses, discuss their relationship to the prior literature and explain any insights that emerged from the analysis. Therefore, the effects of usability, and social and organisational variables, on the student's intention and use of an e-learning system will be discussed. To begin with, the results of the analysis of the UTAUT model relationships, predictors, and outcomes will be discussed, in order to answer the question of how psychological, social and organisational variables influence a students' intention to use the e-learning system in Saudi higher education. The next section presents a discussion of the findings of the usability effects on a student's intention to use the LMS in Saudi higher education. This is followed by the effect of the demographic characteristics on the model relationships. This explains the (extent of the) moderators' influence of the demographic characterises (age, gender, e-learning system experience, training) on the model relationships. The last section provides a comprehensive summary of the research findings.

7.2 UTAUT variables

In this section, a detailed discussion of the base model (UTAUT) variables is presented:

7.2.1 Performance Expectancy (PE)

The theoretical model hypothesised that PE will have a direct effect on students' behavioural intention to use the e-learning system (**H1**). The findings demonstrated that PE displayed a robust effect on the students' intention to use an LMS, thus, **H1 was supported**. The construct has the highest path coefficient ($\beta = 0.571$, $p < 0.05$, Table 6.18) explaining more than half of the variance in the student's behavioural intention to use the LMS in the Saudi universities. It was highly expected that this hypothesis would be supported. In tandem with our findings, Chiu and Wang (2008), Raman et al. (2014), Decman (2015) and Thongsri et al. (2019), in studying LMS acceptance, revealed that PE exhibited the maximum weight on the students' intention to use the system. Furthermore, in a number of meta-analysis research outcomes, the PE was the only construct in the complete list of analysed cases that showed a substantial influence on BI among all relationships of the UTAUT model (Dwivedi et al., 2011; Khechine et al., 2016; Taiwo & Downe, 2013). Similarly, a seminal study of Venkatesh et al. (2003) noted that performance expectancy appears to be a determinant of intention in most experiments. Venkatesh & Bala (2008) and Davis (1989) in their seminal studies found the same. In a study conducted across the UK and Turkey, Efiloğlu Kurt and Tingöy (2017) demonstrated that PE had a greater effect on BI in both samples. In the Gulf region, it has been observed that PE has a significant positive effect on the students' BI to use an e-learning system (Salloum & Shaalan, 2019). These results are also in accord with a recent study that revealed that half of the study sample regarded PE as the most influential factor that affects students' acceptance of the Blackboard system in the Saudi context (Alotaibi, 2017). However, there are some contrasting studies, for example, insufficient evidence was found regarding the effect of PE on BI to use Moodle in the context of Slovenia (Šumak et al., 2010). This finding suggests that the students are driven to accept the e-learning system primarily on the basis of its usefulness. In other words, once the benefits of the e-learning system are realized among students, the willingness and use of the system would be more likely to increase.

7.2.2 Effort Expectancy (EE)

The second and third hypothesised relationships were the paths of EE with BI **H2** and PE **H3** respectively. The current study found the link between EE and BI was significant ($\beta = 0.159$, $p<0.05$). As such, **H2 was supported** (refer to Table 6.18).

Many studies support the direct impact of EE on BI (Alenezi et al., 2011; Alrawashdeh et al., 2012; Bellaaj et al., 2015; Usoro et al., 2013). Likewise, the study of Efiloğlu

Kurt and Tingöy (2017) found that EE positively affected students' intentions to use the e-learning system among the British and the Turkish samples. The meta-analysis such as that conducted by Khechine et al. (2016) has shown that EE is a significant determinant of BI to use an LMS. In Saudi higher education, Bellaaj et al. (2015) reported a substantial positive impact of EE on the intention to use an e-learning system in the University of Tabuk. Even though many studies support the direct impact of EE on BI, the literature has shown that the influence of EE on BI and usage of technologies to be inconsistent (Taiwo & Downe, 2013). Chen (2011) in the study of e-learning system acceptance using the UTAUT model, found that EE had no significant effect on user intention. This corresponds with the studies conducted by Sumak et al. (2010), and Salloum and Shaalan (2019) who found no statistical evidence of a link between EE and BI. El-Masri and Tarhini (2017) found that the EE->BI was statistically significant in the Qatari sample, but not in the American sample. An insignificant weight of EE is also consistent with the findings of Ahmed et al. (2019a). In Ahmed et al. (2019a) study, the level of significance of the proposed relationship between EE and intention to use was larger than the threshold of 0.05 but at the margin of statistical significance. As the EE variable is expected to be more salient in the early stage of the system experience, EE becomes less significant with sustained use (Venkatesh et al., 2003). Therefore, in this context i.e. where the university students have had some experience of using the e-learning system, this familiarity with the system also might be a plausible explanation for the insignificant relationship in the Ahmed et al. (2019a) study. Nonetheless, in the current research, the wide exploration of the EE -> BI link in the Saudi universities showed that the link is statistically significant. Prior research has indicated that EE is more salient for females (Venkatesh et al., 2003; Wang, 2016). Since more than half of the participants were female, this phenomenon might explain why EE revealed a more salient effect on the students' BI. To further substantiate this finding, the EE->BI path coefficient in the female group is higher than in the male counterpart, as well as the pooled sample (refer to Table 6.26).

The present study was designed to determine the effect of EE on PE (**H3**). The results indicate that the relationship EE->PE is statistically significant. Thus, **H3 was supported**. In this respect, the predictive strength of EE -> PE ($\beta = 0.245$, $P<0.001$) is stronger compared with the EE-> BI but weaker compared to that of PE in the previous discussion. Thus, if the students found that the system requires minimum effort to use, their perceptions about usefulness would be strengthened. This finding is in line with IS adoption studies (Islam, 2013; Venkatesh & Davis, 2000)

Several studies have demonstrated the positive effect of EE on PE. These results reflect those of Chiu and Wang (2008) who also found that EE had a direct effect on PE. Similarly, Al-Gahtani (2016), whose EE was called PEOU (EE pertains to Perceived Ease of Use in TAM), found that the PEOU has a significant positive influence on students' perceived usefulness of an e-learning system in Saudi higher education. This is consistent with many studies in the prior literature (Ameen et al., 2019; Binyamin et al., 2019a; Davis, 1989; Davis et al., 1989; Moreno et al., 2017; Teo, 2009). This finding was expected, and suggests that a platform that is easy to use would save students time and effort, thereby allowing them to learn more effectively, accomplish tasks quickly and as a result, increase their academic productivity.

Overall, if the e-learning system is relatively easy to use (e.g. it provides a clear, understandable and user-friendly interface), students will be more likely to regard it as useful, and be willing to learn about the e-learning system features and use them in their studies. This leads them to form a positive intention to use it which influences their actual usage behaviour (Saadé & Bahli, 2005).

7.2.3 Social Influence (SI)

This research hypothesised that SI will have an influence on the BI to use **(H4)** and on the AU behaviour with an e-learning system **(H5)**. Regarding the path of SI->BI, the findings illustrated that the SI factor had a small but significant impact on BI ($\beta = 0.081$, $P<0.05$). **Hence H4 was supported**. Given the small effect, it can be inferred that SI association with BI is not relevant in the model. In a recent study, the SI was found to be insignificant in explaining the students' BI to use e-learning in a Saudi university (M. Almaiah & Alyoussef, 2019). This finding is not usually observed in the Saudi context.

Nonetheless, and similar to the study findings, the effects of SI were classified as small on the intention to use the system (Chen, 2011; Taiwo & Downe, 2013). In a meta-analysis study conducted by Williams et al. (2015), 75% of the studies reported a significant relation between SI and BI. These results match those observed in earlier studies, whereby social factors significantly affect the students' intention to adopt LMSs (Alrawashdeh et al., 2012; Chu & Chen, 2016; Khechine et al., 2014; Raman et al., 2014; Salloum & Shaalan, 2019; Šumak et al., 2010; Thongsri et al., 2019). Efiloğlu Kurt and Tingöy (2017) in their comparative study of students in the UK and Turkey found that the SI variable had the strongest effect on BI among the Turkish sample of students rather than the UK subpopulation.

In this research, the SI association with the LMS AU behaviour was examined (**H5**). Remarkably, the construct had a significant positive effect on students' AU behaviour ($\beta = 0.340$, $P<0.01$). **Hence H5 was supported**. The examination of the strength of the association between SI and the AU behaviour appeared to be the strongest among all other associations. The relationship appeared to significantly influence the variance in the students' usage of the e-learning system (due to the direct relationship (0.34)). The findings also showed that the explanatory power of the theoretical model improved significantly when SI was explicitly theorized (i.e., from 40% without SI to 48% of the variance in usage behaviour explained with the construct in the model).

However, very little was found in the literature that examined the association between SI and usage behaviour (Eckhardt et al., 2009). Jong and Wang (2009) found that SI had a significant impact on the students' usage of the e-learning system. Van Raaij and Schepers (2008) performed a similar series of experiments to show that SI impacts system usage only indirectly via perceived usefulness. Detailed examination of SI reported that the relationship has a larger impact on BI in the Western context than non-Western. However, the effect of SI on AU is smaller in Western than non-Western cultures due to the cultural norms and characteristics (Schepers & Wetzels, 2007). In accordance with the present results, El-Masri and Tarhini (2017), in their comparative studies between Qatar and the US, showed that SI's association with e-learning system usage behaviour tended to be more influential in the non-western context, the Qatari sample, more than the US sample. This result is consistent with the finding of Im et al. (2011) in which SI is more salient in the Korean context compared with the States. The findings also corroborate the ideas of Al-Gahtani et al. (2007), who suggested that a low individualism culture such as Saudi Arabia might exhibit a significant relationship between social construct and the use of web-based technology.

One plausible explanation could be that those living in a high collectivistic culture structure (e.g. Saudi Arabia) tend to regard SI as a significant element in the usage behaviour of technology (Al-Gahtani et al., 2007; Ameen et al., 2019; Oshlyansky, 2007). Thus, students may be influenced by the opinion of others such as peer pressure, instructors and thus involved in certain behaviour even if they do not want to, so the members tend to act in the way that conforms to a specific person or group.

7.2.4 Facilitating Condition (FC)

In order to achieve the objective of observing how the perceived organisational support influences students' intentions and usage behaviour, two hypotheses were proposed: **H6:** FC -> BI and **H7:** FC -> AU.

In the FC -> BI path, the current study did not find a significant link between FC and BI ($\beta = 0.065$, $P>0.05$), **leaving H6 unproven**. Whereas Venkatesh et al. (2012) proposed that facilitating condition was a direct determinant of BI, the current study did not support that claim. This matches with the study conducted by Hsu (2013), Ain et al. (2015) and Ahmed et al. (2019a). These results reported the absence of a significant relationship between FC and students' BI to use the e-learning system. However, Venkatesh et al. (2003) anticipated that when performance expectancy and effort expectancy factors are present, the FC construct becomes non-significant in predicting an intention to use technologies. In this research, the relationship between

FC and the students' BI to use an LMS was not supported. The presence of PE and EE in our proposed model might explain the reason for this hypothesis to be unsupported, as established by Venkatesh et al. (2003).

The study reported that FC was found to be a strong predictor of LMS actual use (β = 0.229, $p < 0.05$), **indicating a support for H7**. FC has in the past been found to be the most significant factor for predicting the students' use of an LMS (Buchanan et al., 2013; Deng et al., 2011). Substantial empirical evidence has supported the impact of the perceived resources on the individuals' AU of the e-learning system (Buchanan et al., 2013; Deng et al., 2011; Efiloğlu Kurt & Tingöy, 2017; Khechine et al., 2014; North-Samardzic & Jiang, 2015; Šumak et al., 2010). Even though Šumak et al. (2010) found that FC is a direct determinant of usage behaviour for MOODLE, our findings indicated a greater magnitude of the relationship on the usage of the system. The FC construct is the third-highest path coefficient on student usage behaviour, explaining more than a fifth of the variance in the LMS usage behaviour in the Saudi university. Based on this, recognition of the presence of favourable facilitating conditions is demonstrated to have an impact on the student's AU. A plausible explanation for this could be that students are now able to access resources, such as well-equipped e-learning centres with a cooperative learning approach around some universities' campuses to engage all learners in active learning practices. Another interpretation could be that when students have experienced the e-learning system, they might become more familiar with the available organisational resources and they are more willing to find support to facilitate the actual use of the system.

7.2.5 Behavioural Intention (BI)

As the theoretical foundation of TAM, TRA and UTAUT postulated that the BI is a direct determinant of AU behaviour (Davis, 1989; Fishbein & Ajzen, 1975; Venkatesh et al., 2003), the study also hypothesised the direct influence of BI on AU (**H8**). The research findings indicate that BI demonstrated a positive effect on the e-learning usage of students (β = 0.266, $P<0.05$) (see Table 6.18). **Hence H8 was supported**. The vast majority of studies on technology acceptance have proved that BI has a significant positive influence on LMS use (Ain et al., 2015; Alshehri et al., 2019a; Ameen et al., 2019; C. C. Lewis et al., 2013; Mohammadi, 2015; North-Samardzic & Jiang, 2015; Salloum & Shaalan, 2019; Šumak et al., 2010). Weight analysis of BI and AU relationship was found to be positively correlated in 82% of studies, qualifying for the best predictor category of usage behaviour (Williams et al., 2015). Also, the use of LMS is mandatory for students in Saudi higher education, so it is rational to consider the connection between the two dependent variables.

7.3 Usability variables

The following discusses the impact of usability parameters on the PE, EE and BI.

7.3.1 System Navigation (SN)

In this study, it was hypothesized that SN has a direct positive influence on students' PE and EE and BI of the LMS use, representing **H9**, **H10** and **H11** respectively.

Regarding the path of SN->PE, the analysis revealed that the SN factor had an insignificant effect on performance expectancy ($\beta = 0.05$, $P > 0.05$). **Hence, H9 was not supported**. This result was unexpected and is contrary to prior research findings e.g. Khan and Qutab (2016) and Scholtz et al. (2016) in which SN significantly predicted the users' perception of the system usefulness. Nonetheless, in an e-library system, the navigation association with the system's usefulness was found to have insignificant influence on the perceived usefulness (Jeong, 2011). Similarly, Cheng (2015) and Binyamin et al. (2019a) demonstrated that SN is not a significant predictor for the students' perceived usefulness in the context of the e-learning environment. This result might be attributed to the lack of awareness of e-learning system features such as navigational structure. Another interpretation might be related to the scarcity of training in the use of LMSs in Saudi higher education (Al-Alwani, 2010; Alenezi, 2018; Asiri et al., 2012; Mulhim, 2014). Together with the limited use of LMS, this might be explained by the inadequate exploitation of e-learning system tools in Saudi higher education, as outlined by Alotaibi (2019).

In this study, it was also hypothesized that SN has a direct positive influence on students' effort expectancy of LMS. The results confirmed that SN had a significant positive effect on the students' perceived effort expectancy ($\beta = 0.157$, $P<0.05$) thus, **H10 was supported**. The findings are in accordance with previous investigations of Cheng (2015), Binyamin et al. (2019a) and Theng and Sin (2012) who established a significant influence between e-learning interface navigation and the students' perceived ease of use. A possible explanation for this might be that the ease of navigational structure between the module content along with the operating links might encourage students to consider the LMS as easy to use, and ultimately use it. Ahmed et al. (2019) demonstrated that SN emerged as the students' second most important category in the evaluation of an e-learning system in Saudi tertiary education. In general, therefore, it seems that the ease of finding the information, correctness of navigation buttons, menu, site map, and links are significant elements for the students' ease of use of an e-learning system.

The last hypothesised relationship in the construct is SN->BI. The findings indicated that navigation had no effect on a student's BI ($\beta = 0.037$, $P=0.428$) to use an LMS, leaving **H11 unproven**. Although Wu et al. (2009) reported that navigation is a significant influence on BI to use an e-commerce system, there is a dearth of research considering the causal impacts between the usability factors and the intention and usage behaviour, especially in e-learning settings. Although limited studies have examined such associations, usability variables seem to directly affect a system's ease of use and usefulness more than they influence the intention and AU behaviour of the system.

7.3.2 Visual Design (VD)

The SEM results in Table 6.18 provided empirical evidence that the path VD->PE was insignificant ($\beta = -0.102$, $p < 0.05$), and accordingly **H12 was rejected**. Even if it is a weak correlation, this indicates an inverse relationship; the direction was opposite to that anticipated. Contrary to the conceptualized path model, the students' perception of the system's VD is negatively associated with the students' perception of the system usefulness. This might be merely due to statistical noise – data that are rendered meaningless or too small to be useful. Another interpretation might be that students might become more accustomed to the LMS screen design as they gained additional knowledge and experience in using LMS so the perception dwindles regarding the usefulness. This observation is similar to those findings of Binyamin et al, (2019a) and Al-Aulamie (2013) in the Saudi educational context. Other researchers found otherwise (M. Almaiah & Alyoussef, 2019; Cho et al., 2009; Khedr et al., 2011; Mouakket & Bettayeb, 2015). The observed effects deserve further analysis.

Contrary to the previous research, the effect of VD on EE was found to be insignificant ($\beta = -0.111$, $p < 0.05$), **failing to support H13**. These results corroborate the findings of a Binyamin et al. (2019a) in a Saudi context. However, this result has not previously been described as Al-Aulamie (2013) Khedr et al. (2011), Cheng (2012), Theng and Sin (2012) Liu et al. (2010) and Cho et al. (2009) in which the e-learning system interface design was confirmed to be an important determinant that affects perceived ease of use. A plausible reason for this discrepancy might be related merely to the statistical noise. Another possible explanation for the unsupported relations of VD on EE might be attributed to the fact that the majority of the respondents acknowledged moderate and advanced levels of e-learning system experience. Thus, the students' familiarity with the system and their high exposure to it might minimize the effect of the interface's visual appearance.

Regarding VD -> BI, it was hypothesised that BI is directly affected by the VD of LMS. The results in Table 6.18 showed empirical evidence that hypothesis **H14 was not proven** ($\beta = -0.033$, $p = 0.406$). This accords with the study of Shaouf et al. (2016), which did not find a direct effect between VD and users' BI to use an e-commerce system. Even though this was not in an educational context, the overall pattern of the findings failed to demonstrate the support of the visual aesthetics in e-learning system acceptance and use. The descriptive statistics in Table 5.8 illustrate that the mean and central tendency of VD ranges were between 3.45 (1.015) and 3.88 (1.201), endorsing the students' perceptions of interface design of the e-learning system were less attractive and appealing. These results seem to be consistent with other research which found that an e-learning system's visual appearance was considered a less important design category in the e-learning system evaluation from Saudi students' perspective (Ahmed et al., 2019). These results are likely to be related to the fact that the design of an LMS interface might lack the balance elements of design: line, shape, white space, volume, value, colour and texture (Hashimoto & Clayton, 2009; Interaction Design Foundation, 2019). The placement and balance of each element in a webpage is crucial for the system designer (Hashimoto & Clayton, 2009; Interaction Design Foundation, 2019). Therefore, in Saudi tertiary education, the aesthetic aspects of the system stimuli such as colours, images, shapes, font style and graphical information, as well as screen design consistency across pages, appeared to be less attention-grabbing and are not congruent with the student's beliefs of PE and EE as well as their willingness to use the system.

7.3.3 System Learnability (SL)

In the proposed model, it was hypothesised that the SL construct would have a significant positive influence on PE (**H15**), EE (**H16**), and the students' BI to use the system (**H17**).

Regarding SL -> PE, it was assumed that PE is directly influenced by the SL of the LMS. However, the observed p value of the relationship between SL and PE in this study was not significant ($\beta = 0.056$, $p > 0.05$) and thus **H15 was rejected**. The results concur with the result published by Binyamin et al. (2019a) in which the system ease of learning, in terms of time or effort, was found not to play a significant role in the students' decisions about the LMS usefulness in Saudi higher education. In contrast to earlier findings, however, evidence of a positive and significant relationship between SL and system usefulness has been detected (Aziz & Kamaludin, 2014; Gul, 2017; Scholtz et al., 2016). It is worth mentioning that the later studies were conducted in different contexts with different systems, e.g., ERP system.

The results of the model testing in Table 6.18 supported the positive and significant relationship between SL -> EE ($\beta = 0.673$, $p < 0.05$), indicating **acceptance for H16**. The findings demonstrated that SL showed the strongest effect in the conceptual model. The construct also has the highest predictor on the students' perception of the LMS ease of use in Saudi tertiary education; judged by the largest effect of SL on EE. This result is aligned with the result found by Binyamin et al. (2019a), and Scholtz et al. (2016). Furthermore, Ahmed et al. (2019a) revealed that the learnability of the e-learning system was the third most important category among students in Saudi tertiary education. The rationale behind the significant association between Sl and EE could be that the EE of the system can be explained by learnability. So, the ease of learning, the sufficiency of the user manual and the clarity of wording characteristics not only improve the learnability of the e-learning system but also influence the students' perception of EE.

The last hypothesized relationship between SL and BI was not supported ($\beta = 0.009$, P =877), leaving **H17 unproven**. The result is consistent with a previous study in which a lack of ease of learning did not correlate with the usage behaviour (Mendoza et al., 2010). Therefore, and like most usability variables in this study, it can be concluded that the study findings reject the direct influence of SL on students' intention to use an LMS in Saudi higher education.

7.3.4 Information Quality (IQ)

In this study, it was hypothesized that IQ has a direct positive influence on students' PE and EE and BI of the LMS use, representing **H18**, **H19** and **H20** respectively.

The results revealed that IQ has a significant influence on PE ($\beta = 0.309$, $p < 0.05$), indicating **a support for H18**. Across the significant factors, IQ->PE exhibited one of the strongest effects in the proposed framework. Comparison of the findings with those of other studies confirms that the path IQ ->PE has been demonstrated in an e-learning context (Alkandari, 2015; Ameen et al., 2019; Binyamin et al., 2019a; Cheng, 2012; Lee et al., 2014; Salloum, 2018; Shah et al., 2013) and IQ was found to be an important predictor of the system usefulness in an e-commerce context (Green & Pearson, 2011). Likewise, in empirical research within the authors' UK educational institution, the LMS information quality was confirmed to be a determinant for the perceived usefulness (Al-Fraihat et al., 2019). Thus, the quality of information as understandable, useful, clear, relevant, sufficient, and up to date, are important for students' decisions to acknowledge the system usefulness. A plausible explanation for this is that students might find multiple learning resources and materials in different forms such as books, lecture slides, online quizzes, and discussion, that enhance their education. These resources appeared to be useful, sufficient, and appropriate for the students' learning in which they can access materials anytime and from everywhere. Accordingly, it is rational for this relationship to be significant and salient.

The results of the structural model assessment unexpectedly disclosed a lack of a direct positive influence of information quality on effort expectancy ($\beta = 0.003$, $p > 0.05$), leaving **H19 unconfirmed**. This outcome is contrary to the findings of Shah et al. (2013), Lee et al. (2014), Alkandari (2015) and Binyamin et al. (2019a) who found that the quality of e-learning information directly affected students' perceived ease of use. This rather contradictory result may be due to the fact that students consider the e-learning system to be more convenient and less complex nowadays, especially with recent technological advances and the greater sophistication of information technology products. Nowadays, many modern and user-friendly learning technologies consider web usability attributes in their design, so this might also be the reason why many students tend to see a decline in the dominance of information quality.

The SEM results showed no statistical influence between the IQ and the BI path ($\beta = -0.029$, $p > 0.05$), leaving **H20** unproven. The insignificant findings between the IQ and the students' intention to use the e-learning system are in accordance with those studies of Al-Aulamie (2013), Ameen et al. (2019) and Terzis & Economides (2011). In a similar finding within the UK higher educational institution, Al-Fraihat et al. (2019) showed that high-quality information does not influence the students' use of the LMS. It might be the case that some students (e.g., those have who laboratory tasks) have limited access to educational materials in Blackboard so they use the system for their assignments and quizzes submission, thus, the information quality aspects of LMS might be of less concern. That said, the effect between IQ and intention and use behaviour is lacking, so more research is needed to investigate the association between IQ and BI in an e-learning system context (Terzis & Economides, 2011). Overall, as the construct of IQ seemed to be a significant determinant of performance expectancy, it can be concluded that if an e-learning system offers effective content, understandable, complete, up-to-date, and sufficient learning materials, students will perceive the e-learning system as useful. This, in turn, would lead to an increase in the intention and use of e-learning systems.

7.3.5 Instructional Assessment (IA)

It is assumed in this research that, IA would have a significant positive influence on performance expectancy **H21**, effort expectancy **H22** and the BI **H23** to use the LMS. The parameter estimates for these hypothesised relationships are: ($\beta = 0.068$, $p > 0.05$), ($\beta = 0.129$, $p < 0.05$), and ($\beta = -0.034$, $p > 0.05$), respectively. These results indicate that **hypotheses H21 and H23 were rejected**, whereas only **hypothesis H22 with this construct was supported**.

The current study found that the LMS assessment tools seem to influence the ease of use, whereas no influence was found regarding the usefulness and the willingness to use. This does not necessarily detract from the worth of assessment tools. Once students are provided with effective assessment tools, they are more likely to perceive the LMS as being easy to use. However, it is worth mentioning that the literature seems to be limited in investigating such associations. For instance, in Saudi higher education, supporting the IA->EE path accords with that of Binyamin et al. (2019a) whereas the IA->PE relationship contradicts the finding of Binyamin et al. (2019a) and Almaiah and Alyoussef (2019). Similar results were obtained by Al-Fraihat et al. (2019) in which the analysis showed that educational system quality, which includes LMS assessment feature measurements, was found to have non-significant influence in the LMS usefulness and usage behaviour. Ahmed et al. (2019) found that IA was the fifth most important design category in the e-learning system usability evaluation in Saudi higher education. The most likely explanation for this surprising result is that the students may differ in their awareness and utilization of assessment tools. There might be a lack of maturity among students regarding the use of the wide diversity of assessment features that are offered by the LMS (e.g., tests, quizzes, and survey feedback facilities). Hence, students might be unaware of the complete assessment and feedback functionalities in the LMS. The system is used mainly for assignment submission and other e-learning system features such as tests, quizzes, and surveys, are practically unutilised in the students learning process. This claim was supported by Alruwais et al.'s (2018) study, in which the students' lack of familiarity with assessment features was categorised as the main challenge in higher education. Similarly, it was found that instructors had no previous experience with the e-learning system, and did not receive proper training on the use of the system hence unfamiliarity with the system assessment tools might be evident in Saudi higher education (Tawalbeh, 2017). Thus, this might be a plausible explanation for the discrepancy. This finding is unexpected, and suggests that the matter should be explored further in future research

7.3.6 E-learning System Interactivity (ESI)

The theoretical model hypothesised that perceived ESI would have a significant positive effect on PE (**H24**), EE (**H25**) and student's BI (**H26**) to use the LMS.

The hypothesis testing results showed that ESI->PE ($\beta = 0.228$, $P < 0.05$) path was significant, hence **H24 was supported**. The results are in parallel with previous studies which have demonstrated that ESI has a significant positive influence on the students' PE (Al-Harbi, 2011b; Alkandari, 2015; Alrawashdeh et al., 2012; Baleghi-Zadeh et al., 2017; Binyamin et al., 2019a; Cheng, 2012; Moreno et al., 2017; Pituch & Lee, 2006). Some researchers even demonstrated that for the perceived usefulness, the interactivity had the most significant direct effect in the e-learning context (Pituch & Lee, 2006). Thus, the higher the student's perception of ESI is, the stronger they believe the LMS to be useful as a means to assist them achieving their educational objectives. It can be interpreted that if the students have experience in using a wide spectrum of features in the LMS (email, discussion board, chat room), they then perceive those features increase their performance.

Among all antecedents examined in this study, ESI exhibited a small negative direct impact on EE ($\beta = -0.092$, $p < 0.05$) and thus, **H25 is rejected**. This study supports evidence from previous observations, e.g., Pituch and Lee (2006), Abbad, Morris, and de Nahlik (2009), Baleghi-Zadeh et al. (2017) and Uğur and Turan (2018). Nonetheless, other scholars, e.g., Binyamin et al. (2019a) and Cheng (2012), demonstrated a positive significant relationship between SI and perceived ease of use. Thus, and contrary to expectation, Saudi students tend not to perceive that the LMS communication tools' effectiveness has an impact on their effort to use the system. This discrepancy may be attributed to the fact that some students are enrolled in blended learning modules in which the traditional mode of face-to-face communication is dominant (e.g., laboratory sessions). Therefore, some students may take advantage of being more involved in active participation with lecturers in face-to-face classrooms rather than being anonymous in online communication. Another possible explanation for these results may be the lack of awareness regarding the e-learning system communication functionalities among university teachers and students. This may be caused in part by the lack of training and support for academics and students to support teaching practices using an e-learning system. In our study, nearly 50% students have not received any training in the use of an e-learning system. This concurs with the research conducted by Alenezi (2018) that inadequate training was among the main challenges of LMS adoption in Saudi Arabian universities.

As expected, the significant and positive influence of ESI on a students' BI ($\beta = 0.112$, $P < 0.05$) **H26 was supported**. The only usability variable that directly affected the students' intention to use LMS in Saudi Arabia was LMS interactivity. Even if the previous literature is limited in terms of interactivity (Sun & Hsu, 2013), some have demonstrated such an effect, e.g., Uğur and Turan (2018), Agudo-Peregrina et al, (2014) and Wrycza and Kuciapski (2018) while others revealed indirect influence in an e-learning context, e.g., Alrawashdeh et al. (2012). Nonetheless, Alrawashdeh et al. (2012) investigation was conducted in enterprise settings. In the same vein, it was confirmed that the existence of communication tools and interactivity features had a strong influence on students utilization of the LMS. Thus, students are more likely to use it (Al-Fraihat et al., 2019). This result indicated that a student's willingness to use the LMS is affected by their perception of the interaction between students, the interaction between lecturers and students, as well as the effectiveness of the system's communication tools. A possible explanation for this is that previous and current research has demonstrated that the SI construct appeared to be important in the students' use of an e-learning system (Alshehri et al., 2019a) (using a different dataset). Hence, the social communication between the learners themselves and their teachers tended to be more effective and more engaging for their knowledge exchange, contributing to efficiency in learning.

7.4 Moderating Effect:

As outlined in the Mutli-Group Analysis (MGA) in the analysis chapter, a permutation algorithm was used to test the moderating effects of the categorical variables: gender, age, experience and the training provided to students. The permutation technique (5000 permutation runs; two-tailed 0.05 significance level) is non-parametric, two-tailed, more conservative, and recommended by many researchers (Hair et al., 2018; Hair, Hult, et al., 2017; Henseler & Fassott, 2010; Matthews, 2017). This method allows a comparison within the study to assess theoretical differences between sub-samples of the same population (Calvo-Mora et al., 2016). In this study, the responses were divided into two groups for each selected nominal category (e.g., male vs. female, young vs. senior group, experienced vs. less experienced, trained, and untrained students). The researcher then estimated the measurement model along with the structural model for each subsample (Sarstedt et al., 2011). In this communication, therefore, the differences between the path coefficients were analysed using the permutation technique. The focus is on the variabilities between the subsamples. If the p value is significant, the results can be interpreted as having a moderating effect for the analysed variable (Calvo-Mora et al., 2016). Also, a discussion of the group differences in terms of the path coefficients and the explained variance (R^2) will be offered.

7.4.1 Gender

The permutation test, expressed by MICOM results, confirmed that the indicators associated with each construct are invariant between males and females (see Table 6.23). In this study, the theoretical model hypothesised that gender moderates the relationships in the proposed model, **H27.** Since the invariance was established, the standardized path coefficient differences between males and females show that most structural model relationships do not differ between male and female subsamples with one exception: the effect of FC on AU (refer to Table 6.26). Thus, **H27 was not supported.** It is somewhat surprising that in this research no other significant relationships were noted in the Saudi higher education as females are separate in terms of education and location. The results overlap with several e-learning studies in which male and female students are equally motivated to the use of an LMS in different contexts (Ameen et al., 2019; Arenas-Gaitán et al., 2010; Decman, 2015; Khechine et al., 2014; Marchewka et al., 2007; Raman et al., 2014; Ramírez-Correa et al., 2015).

The results indicate, however, that gender moderated the FC->AU path and is significant for male and female sub-groups. The female group exhibited a stronger effect (β = 0.302) than did their male counterparts (β = 0.154). In line with this, Alshehri et al. (2019a) study (using a different data set) found that FC was the highest path coefficient that affected LMS use in Saudi higher education (β = 0.511). In tandem with this result, the gender differences were found to have an impact on technology acceptance where women place more emphasis on FC, which was more pronounced with increasing age (Venkatesh et al., 2012). Furthermore, Kibelloh and Bao (2014) focused on the female perceptions of e-learning and revealed key concerns regarding the poor and costly internet connectivity in developing countries. This outcome is compatible with that of Ameen (2017) who found that gender was insignificant in moderating the effect of FC on AU to use a mobile phone in three

Arabian countries, Iraq, Jordan and United Arab Emirates (UAE). This can be interpreted by the cultural influence of gender segregation, where females' segregated colleges are more demanding of organisational resources (e.g., technological support and technical ICT infrastructure) to support the use of LMS in Saudi higher education. Females have dispersed campuses and the availability of support might be limited. In the context of the study, some universities might not have the appropriate ICT infrastructure, especially those who were recently established, so female students might find limited avenues for help and support at university campuses.

Regarding group differences, there are 14 significant relationships in the female versus 10 in the male category (refer to Table 6.24). To start with, the relationships between BI and AU, EE and BI, FC and AU, IQ and PE, ESI and PE, SL and EE, PE and BI, as well as SI and AU, are all significant in both male and female subsamples. The only single relationship that is significant in males but not in females is the path of ESI and BI. Regarding the unique significant relationships linked with the female group only, it is evident that the effects of EE on PE, IA on EE, ESI on EE, SI on BI, VD on EE, are all significant in the female subsample but not in the male group. In particular, the SI effect on intention and usage behaviour tended to be higher for the female group. This is in line with the results obtained by Bellaaj et al. (2015) in a Saudi university. Thus, Saudi female students are more influenced by other peoples' expectations. This is also in accordance with Gefen and Straub's (1997) conclusion, in which the importance of SI for women has been demonstrated. Overall, a clear indication that the predictors have more effect on the female sample than they did for males.

Regarding the gender difference, the female group model accounted for 52% of the variance in AU behaviour, and 62% for BI compared with 44% for usage behaviour and 62% for the BI to use in the male group (refer to Table 6.25). Similarly, in the female sub-sample, 62% of variability in the EE variable was explained the predictors, and 55% of the variability in the PE construct was explained by the predictors. There is a clear indication that females had more explained variances compared to their male counterpart. Thus, females exhibited more variance in the dependent variables than male. In fact, the variance explained by the quality factors in the female model's outcome variables tends be higher than the pooled sample R^2 values. This is in line with the study of Ramírez-Correa et al. (2015) and Wang et al. (2009) in which the female group explained more variance than males in the acceptance of mobile learning.

In this regard, universities should create strategies for ongoing enhancement of the LMS organizational and technical infrastructure to support the learners' use of the system, particularly, for female colleges. Services such as online support, the timeframe of assistance, training provided and resource availability have been suggested as fundamental to successful e-learning implementation (Buchanan et al., 2013; S. Lin et al., 2013; Sánchez & Hueros, 2010).

7.4.2 Age

As can be seen in Table 6.32, the age moderating variable did not affect the young and senior population except for one path: FC on AU. Since the research did not prove the moderating effect of age with other relationships in the model, **H28 was rejected**. Consistent with our results, the moderating factor of age did not moderate most of the relationships in the model as of the Ameen et al. (2019) study in the Iraqi context. Similarly, the age moderating effect did not play an important role in the relationships between the psychological constructs of the UTAUT model and the intention to use technology in Saudi Arabia higher education (Bellaaj et al., 2015). Similar findings were concluded by Binyamin et al. (2019a).

FC->AU is the only path coefficient where the p value is less than 0.05. The influence of FC on AU is significant for both groups. However, the relationship is significantly different among young students ($\beta^{(1)} = 0.319$) versus those who are senior ($\beta^{(2)} = 0.139$). Considering the system usage behaviour, it was found that the age attribute was more significant for older workers with more experience (Venkatesh et al., 2003; Venkatesh & Morris, 2000). Nonetheless, and unlike our results, age moderated all of the key relationships in the Venkatesh UTAUT model (Venkatesh et al., 2003). Age was shown to explain the willingness of students to use an LMS (Khechine et al., 2014). In this research and similar to the gender moderator, it is evident that young students are more focused on the available IT support and infrastructure (FC) than older students. A possible explanation for these results may be the lack of adequate support and poor Internet access, especially in the newly established universities, as confirmed in the previous studies in Saudi education (Alenezi, 2018; Alturki et al., 2016; Basri et al., 2018). As most of the respondents are undergraduates, young students may require more IT support and available Internet access to help in the use of LMS, especially in the recently established universities. Furthermore, it seems possible that these results are due to the lack of training on LMS platforms. The descriptive statistics showed that the majority of students had no previous training in the use of LMS (47.8%). Thus young students might be more in need of LMS training at the university's campuses.

In terms of path coefficients differences, the senior group sample has 11 significant relationships as opposed to 8 in the young category. Furthermore, and unlike the younger student model, the mature group model showed some significant relationships, e.g., *EE -> BI* ($\beta = 0.231$), *IA -> EE* ($\beta =0.14$) and *SI -> BI* ($\beta =0.149$). In particular, in accordance with the UTAUT research, the effect of EE on intention is more significant with seniors (Venkatesh et al., 2003). Likewise, the impact of SI on intention was significant for older people which is consistent with previous research (Venkatesh et al., 2003; Venkatesh & Morris, 2000). This implies that senior Saudi students place more importance on the opinion of others in the use of LMS, in which social influences change over time. This indicates its important role in driving behaviour in Saudi education. Overall, the senior model has more statistically significant relationships, indicating that the LMS implementation might have more significance for mature students (refer to Table 6.32).

Regarding the explained variances differences, the adj.R^2 values of the young group AU, BI, EE and PE were (51%), (70%), (61%) and (55%) respectively (refer to Table 6.31). The percentages of 48%, 57%, 55% and 44% accounted for AU, BI, EE and PE in the senior group respectively. Thus, the young students' explained variances are higher than the senior group's, meaning a better model fit for younger students in the dependent variables AU, BI, EE and PE. A similar conclusion was reached by Chawla and Joshi (2012).

7.4.3 Experience

The permutation test in Table 6.38 reveals that LMS experience moderated three out of 26 relationships: BI -> AU, IQ -> BI and SI->BI. Since the student's experience of LMS did not moderate the interaction of the model variables, **H29 was not supported.** This is similar to the Ameen et al.'s (2019) conclusion in which not much difference was found between students with low or high levels of experience. To start with, the relationship between BI and AU is significantly different among advanced users ($\beta^{(1)} = 0.383$) compared to those who are beginners ($\beta^{(2)} = 0.046$) with the path being significant in the advanced group but not in the beginners. This means that LMS experience has moderated the effect of BI on student's usage behaviour of the LMS in Saudi Arabia. This is consistent with results obtained by Taylor and Todd (1995b) where the path from intention to usage behaviour was stronger for experienced users than for less experienced users. The results are also in line with the findings of Sun and Zhang (2006). In contrast with UTAUT findings, the students with prior experience seem to be more motivated to use LMS than less experienced users (Venkatesh et al., 2003). Even though the latest UTAUT2 model hypothesised that the effect of behavioural intention on use is moderated by experience Venkatesh et al. (2012), the results contradict the study in which the BI effect on technology use was stronger with less experienced users. It may be that these participants benefited more from the LMS, as PE->BI was stronger for experienced users than for the beginners, supporting previous findings of Tarhini, Hone, and Liu (2014c). Furthermore, EE->PE was significant in the advanced group only, indicating a greater inclination to system ease of use and this might add further insight to the students affirmed the intention to use LMS. This finding is in agreement with Venkatesh and Balas' (2008) conclusion in which the influence of perceived ease of use on usefulness will be stronger with advanced users. Thus, with increasing experience, Saudi use of LMS appears to be more for pragmatic purposes, such as gains in efficiency and effectiveness. This will eventually reinforce actual behaviour. Therefore, LMS experienced users utilize their prior experience when forming their intentions, so the more experience students acquire in the use of LMS, the more the affirmation of the usage behaviour.

The experience also moderated the IQ -> BI relationship. The effect of IQ on BI differs significantly between advanced students ($\beta^{(1)} = -0.166$) and beginner students ($\beta^{(2)} = 0.299$), with the path being significant in the advanced group but not in the beginners' category. This means that the quality of the content of the LMS, its relevancy, completeness and up-to-date contents negatively impact the students' willingness to use the LMS. It is rather an unanticipated finding and it merits further exploration. The negative interaction of experience on the effect of IQ on BI could be interpreted, such that more experienced individuals possess stable perceptions about the LMS usefulness and ease of use irrespective of the LMS content. This then translated into affirmed intention to use the LMS. Another plausible explanation might be related to the fact that highly experienced students might find the information about LMS overwhelming, thereby discouraging them from using the system.

Finally, the relationship between SI and AU is significantly different for experienced students ($\beta^{(1)} = 0.234$) versus less experienced users ($\beta^{(2)} = 0.570$) where both paths were significant. The less experienced users of LMS tend to be more susceptible to referents' opinions and the effect did not attenuate with increased experience. The findings in this investigation were consistent with those of other studies (Venkatesh et al., 2003; Venkatesh & Morris, 2000) in which in the mandatory settings, SI appears to be important only in the early stages of individual experience with the technology. A similar finding was demonstrated by Calisir, Altin Gumussoy, and Bayram (2009) who asserted that less experienced respondents showed high social influence toward the individuals' intention to use the ERP system in Turkey. Moreover, it was demonstrated that the SI effect on perceived usefulness and BI was weaker with increased hands-on experience on the system (Venkatesh & Bala, 2008). However, this is contrary to the findings of Al-Gahtani (2016) in his application of TAM3 in an e-learning context. Nonetheless, the results are also in tandem with the Sun and Zhang (2006) findings in which SI is stronger for individuals in high power distance cultures. Therefore, our result is expected in Saudi higher education as students comply with other expectations, especially in the early stages of experience where students' opinions are relatively ill-informed.

The results demonstrate that the shared variance in advanced group for AU, BI, EE and PE is 0.447 (45%), 0.582 (58%), 0.452 (45%) and 0.392 (39%) respectively. In the less experienced student sample, the explained variance for AU, BI, EE and PE is 0.559 (56%), 0.660 (66%), 0.558 (56%) and 0.568 (57%) respectively (refer to Table 6.37). Thus, the proposed model explains more variance in the less experienced category. This is in agreement with a recent study in the Saudi context, where lower-level experienced usage behaviours were well predicted by the independent variables (Binyamin et al., 2019b). However, our model exceeded the level of explained variance in the usage behaviour (56%) to a much greater degree than was the case in the Binyamin et al. (2019b) research (37%). The results are in parallel with previous studies of Taylor and Todd (1995b) which demonstrated that the inexperienced users' intentions were better predicted by the antecedent variables in the model than were the intentions of experienced users. This indicates a better model fit for younger students in the dependent variables AU, BI, EE and PE. A plausible explanation for this difference might be the fact that our study sample comprises students from newly established universities where LMS has recently been introduced, so the students might have been more encouraged to use the system. Changes of perception are anticipated as the individuals gained more experience and knowledge about the system (Hu et al., 2003).

The significant relationships were higher in the high experience group compared with less experienced students. There were 12 significant relationships in the advanced group compared with 7 in the beginners. This was evidenced by the significant paths in the higher experience category, the *BI -> AU, EE -> PE, ESI -> BI, FC -> BI, IQ -> BI and VD -> PE* compared with VD->EE in the beginners group. These results are consistent with Taylor and Todd (1995b), in which they found more significant paths in the experienced users' category. This is consistent with the notion that experienced users employ the knowledge gained from their prior experience to form more favourable perceptions about usability variables. It may be inferred that the proposed model might be more important for highly experienced students. This may suggest alternative ways to effectively manage the implementation and operation of the LMS in Saudi universities.

7.4.4 Training

The results of the permutation algorithm, presented in Table 6.44, established that LMS training moderates a single hypothesis out of 22 – the IQ influence on PE – leaving **H30 unsupported**. This result means that the proposed model is appropriate irrespective of the students' training. The lack of support in other relationships might be explained by the fact that around half of the participants in the study sample did not receive any training in the use of LMS (refer to Table 5.6). This was supported in the previous studies in which a number of researchers acknowledged the lack of training in the use of LMS in Saudi universities (Al-Alwani, 2010; Asiri et al., 2012; Mulhim, 2014). However, significant differences in the group-specific path coefficients were noted. The trained students exhibited higher perceptions (β = 0.416) of the LMS IQ and its effect on the system usefulness than did their untrained counterparts (β = 0.196). These relationships were significant in both groups. This means that trained students found the information in the LMS platform to be accurate, relevant, up-to-date, sufficient, and complete. These attributes subsequently contribute to the system usefulness more than the effect on the untrained students. Such findings are unsurprising, as the training given about the use of LMS seems not only to improve the students' technical skills but also the related pedagogical knowledge (i.e. LMS content). This is consistent with previous research (Hu et al., 2003), in which some relationships were intensified over the course of the training.

Regarding the group path coefficient differences, it seems that in the trained group, the path coefficients may become more prominent and significant as students acquire training (refer to Table 6.42). There is a total of 11 significant paths in the trained students compared with 7 significant paths in the untrained group. Judged by the respective statistical significance levels and path coefficients, the paths EE->BI, ESI->BI, ESI->EE, SN -> EE and VD -> EE are significant in the trained students uniquely whereas the only significant path coefficient in the untrained users is IA -> EE. Considering the strength of the path coefficients, most significant relationships had intensified in the trained students, indicating that students tend to accept the LMS as they gain additional knowledge and experience.

Regarding the model's explanatory power, the model was able to account for a substantial portion of the variances in students' acceptance decisions: 67% with training and 60% without training. In a comparison of the R^2 values of performance expectancy and effort expectancy, the trained model explained 61% of the variances for perceived usefulness and 64% for perceived ease of use. Conversely, there was 39% for the variance of usefulness and 51% for the variance for perceived ease of use in the untrained model. This is in line with Hu et al.'s (2003) finding in which the model's explanatory power appeared to increase over the course of the training. Clearly, the model's explained variances appeared to increase with training, indicating the important moderation effect of training in the students' acceptance and use of LMS in Saudi higher education.

7.5 Summary

This chapter has discussed the results and explained any insights that emerged from the analysis. The first section delineated the impact of psychological, social and organisational variables on the student's use of LMS in Saudi tertiary education, which answered the first research question in section 1.5. In total, 13 of the proposed hypotheses were supported out of 26, which assists our understanding of the influence of the main determinants on the students' use of LMS in Saudi higher education.

The next section presented a discussion of the findings of the usability effects on a student's intention to use the e-learning system in Saudi higher education, which answered the second research question posed in section 1.5. The UTAUT theory was extended with six usability dimensions: SN, VD, SL, IQ, IA, and ESI. PE was affected by IQ and ESI, whereas EE was influenced by SN, SL and IA. Among the proposed usability qualities, the interactivity was found to be a key determinant of students' intention to use the LMS. It can be observed here that some usability variables affect the student's use of an LMS in Saudi tertiary education.

The last section discussed how various individual characteristics, namely gender, age, LMS experience and LMS training moderate the effect on conceptual model relationships. This is concerned with the answer to the third research question in section 1.5. The moderating effect is important, because understanding the use of LMS among male and female, younger and senior, more-experienced and less-experienced, as well as the trained and untrained students, in Saudi higher education help direct appropriate resources toward improving educational experiences. It can be concluded that few of the structural model relationships did differ between subsamples.

The next chapter draws conclusion from this study. This includes the key findings, the implications of these findings, the theoretical and methodological contributions, research limitations and directions for future research.

CHAPTER 8: CONCLUSION

8.1 Introduction

In recent years, the use of LMSs has become important in education to provide recipients with informational content and instructive resources. The incorporation of technology into the learning and teaching environment is no longer an option, but a necessity. Even though the Saudi government is keen to incorporate e-learning services into the teaching and learning environment and is investing considerable resources, it seems that it does not fully benefit from LMSs and they often remain underutilized. Thus the assessment of learners' perceptions of LMSs is becoming an essential element in improving educational inputs and outcomes. Nonetheless, the challenge concerns the disagreements that persist about the factors that may influence the use of LMSs, especially in developing countries such as Saudi Arabia. In order to address the gap, this research has attempted to amalgamate the unified acceptance model, UTAUT, with six usability factors to investigate empirically the influence on students' intentions and usage behaviour in Saudi tertiary education. In conjunction with this, the study investigated the effect of different demographic characteristics on the students' use of LMSs in Saudi universities. To this end, a new theoretical framework was formulated to investigate the use of LMS, from the students' perspective. This chapter deals with the overall conclusion of the research, reiterating the research overview and key findings, research questions and the methods used to address them. This is followed by the research implications and recommendations that are important for different stakeholders (e.g. educational decision-makers). The next section presents the contribution from three different perspectives: theoretical, practical and methodological. The chapter ends by considering the study's limitations along with the future research direction.

8.2 Summary Overview and Key Findings

The main goal of the current study was to investigate the effects of usability, social and organisational variables on the students' behavioural intention and usage behaviour in Saudi tertiary education. The research also measures the impact of demographic characteristics (e.g., gender, age, LMS experience and training) on the proposed model relationships. It has been well established that LMS implementation at universities is an ideal investment for students' learning and teaching (Dahlstrom et al., 2014). This is evident in Saudi higher education, where one of the primary objectives of the promising Vision 2030 is to build life-long learning and improve the students' learning outcomes (higher and vocational), accentuating the importance of e-learning services to achieve these objectives (KSA Vision 2030, 2016). The LMS implementation at universities requires considerable management support, i.e., planning, IT infrastructure availability, personnel, LMS deployment, and licencing, training and operation. In spite of this effort and investment, prior studies have disclosed that Saudi education is still under the traditional pedagogy and the new proposed innovations such as LMSs lack acceptance and utilization (Al-Asmari & Rabb Khan, 2014; Alenezi, 2012b; Alshammari et al., 2016; Alshehri et al., 2019a; Binyamin et al., 2019a). Consequently, the focus of students' perceptions of LMSs has come into prominence. This research attempts to address the gap by developing a theoretical framework that examines the usability, social and organisational factors' impact on the use of LMS in a Saudi university from the students' standpoints.

Drawing on extensive studies of technology acceptance, the UTAUT model was designated as a base model because 1) it is a relatively new model, 2) it has a robust predictive explanatory power, and 3) it includes demographic variables (Venkatesh et al., 2003). It was thus viewed as a powerful stimulus to adopt in different Eastern contexts such as Saudi Arabia (see Section 2.3.4). As well as this, the comprehensive review of the e-learning system usability evaluation literature assists in identifying the most appropriate usability attributes. These were posited to affect the use of the e-learning system in Saudi higher education (refer to section 3.4). The incorporation of relevant usability principles into the acceptance model to be explored in Saudi Arabia education is seen as an important step forward for effective LMS utilization. The proposed research model comprises 10 predictors and 4 outcome variables, specifically, SN, IQ, SL, VD, ESL, IA, PE, EE, SI, FC, BI and AU as well as four moderating variables, namely gender, age, experience, and the received training. The developed conceptual model is depicted in Figure 8.14.

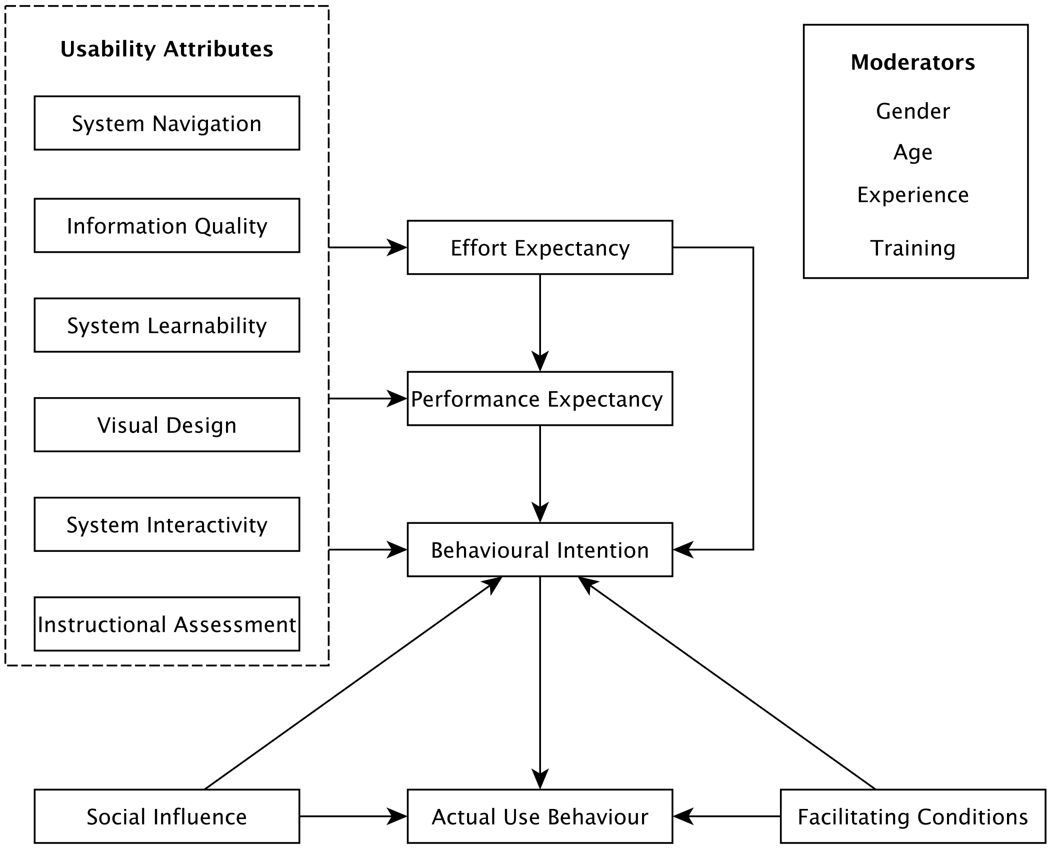

Figure 8.14 Proposed research model

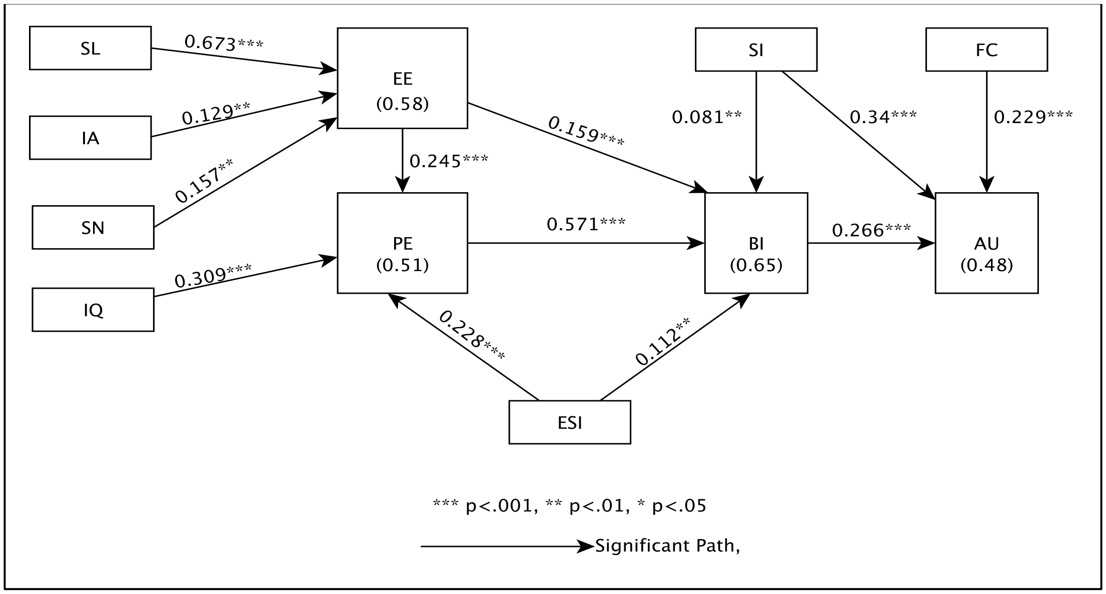

Figure 8.15 Final model

The summary of the main results of this investigation is presented in Figure 8.15. This study aimed to answer three essential questions, as follows.

The first research question was:

1. *To what extent do psychological, social and organisational variables influence a student's acceptance and use of learning management systems in Saudi state universities?*

This inquiry was addressed in three stages of work. To start with, a comprehensive literature review about the UTAUT model and its utilization in an educational context was conducted (refer to section 2.4). The selection of the UTAUT model as a theoretical foundation was based on theoretical grounds and supported by empirical studies. A self-administered, online questionnaire was developed to collect data from students in five public universities, representing five Saudi regions. Subsequently, a number of hypotheses were formulated and examined against the collected data using PLS path analysis. The results of the measurement model confirm that all psychological, social and organisational variables of the UTAUT model are valid and reliable to measure students acceptance in Saudi Arabian context.

The key findings obtained from the UTAUT analysis are summarised as follows:

1. Three factors were revealed to have a direct, significant, and positive influence on the BI to use LMS in Saudi universities. The attributes are, in order of significance, as follows: PE, EE and SI.
2. Three factors were revealed to have a direct, significant and positive influence on the students' usage behaviour. The attributes are, in order of significance, as follows: SI, BI and FC.
3. The study revealed the significant positive effect of EE on PE.

The experiments confirmed that all data elements and parameter values of UTAUT theory are valid and robust in a Saudi context.

The second research question was:

2. *To what extent do usability attributes influence the students' acceptance and use of learning management systems in Saudi state universities?*

Similar to the previous question, the researcher conducted a comprehensive literature review to identify the most important usability principles that affect students' use of LMSs in Saudi higher education (refer to section 3.4). Accordingly, six usability variables – SN, VD, SL, IQ, ESI and IA, – were selected to evaluate their effects. The effects were measured on students' perceptions of PE and EE as well as on their intention to use in Saudi tertiary education. The establishment of the relationships between constructs was achieved by formulating hypotheses, based on theoretical support. The researcher investigated the model using the composite-based SEM-PLS. All the constructs' indicators were valid and reliable, substantiated by various criteria, factor loadings, Cronbach's α , composite reliability, AVE, convergent validity and discriminant validity (refer to section 6.2). Based on the quantitative analysis, the summary of the main key findings of this investigation is as follows (see Figure 8.15).

1. Two usability factors were revealed to have a direct, significant and positive influence on PE (similar to perceived usefulness in TAM). The relationship between IQ and PE is the most significant relationship, followed by the relationship between ESI and PE.

2. Three usability factors were revealed to have a direct, significant, and positive influence on effort expectancy (similar to perceived ease of use in TAM). The attributes are, in order of significance, as follows: SL, SN and IA.
3. From the usability factors, only the LMS ESI dimension was found to have a direct, significant, and positive influence on students' BI.

The third research question was:

3. *To what extent do the demographic variables of gender, age, experience and training moderate the relationships of the model?*

In the literature, the scarcity of research that addresses whether there are significant differences across two or more groups of data has been highlighted (Henseler & Fassott, 2010; Matthews, 2017; Sun & Zhang, 2006). Thus, the research examined the effect of the four demographic variables in the model relationships. To this end, the researcher utilised multi-group analysis using the PLS-SEM technique, to analyse the effects of moderation across several relationships rather than standard moderation. The data set was divided into multiple sets of two groups (gender: male and female; age: younger and senior; experience: more and less experienced groups; training: trained and untrained students). A new set of model coefficients was then estimated separately for each group of data. The permutation technique was used to examine the moderating effects. Here are a few brief observations regarding the effect of moderation on the model relationships.

1. The gender moderated the FC->AU path and is significant for the male and female sub-groups. The female group exhibited a stronger effect than did their male counterpart.
2. Similar to gender, the age moderated the FC->AU path where the relationship is significantly different between young students and those who are senior.
3. LMS experience moderated three relationships: BI -> AU, IQ -> BI and SI->BI. The BI -> AU and IQ -> BI relationships are significantly different among advanced users versus those who are beginners. The SI->BI relationship

indicates that the less experienced users of LMS tend to be more susceptible to referents' opinions.

4. The training variable moderated the information quality influence on performance expectancy (IQ -> PE). The trained students exhibited higher opinions of the LMS information quality and its effect on performance expectancy than did the untrained counterparts.

Given that the research overview and key findings have been presented, these findings have significant implications for the understanding of the factors that influence the students' use of LMS in Saudi tertiary education. The next section provides the practical and theoretical implications, along with the recommendations derived from the research results.

8.3 Research Implication

This deductive approach to research has implications for a diverse audience. This section presents guidelines for educational authorities, decisions makers, system developers and educators in higher educational institutions in Saudi Arabia on how to improve the quality and use of LMSs. By drawing inferences and conclusions from the results, implications will be provided for relationships between the models' variables.

8.3.1 Performance Expectancy (PE)

The findings show that PE was found to be a key driver for the students' acceptance and usage of LMS. Overall, the current results validate the assumption that if the university students perceive the usefulness and benefits of the LMS, then they will form the intention of using the system and will be willing to use it as a part of their studies; obtaining a return on their investment of time in the e-learning system. The path of PE->BI was significant in all different demographics' characteristics. Thus, the students' examined groups seemed to acknowledge the importance of LMS usefulness. This implies that university management and academics are inclined to focus on e-learning systems' usefulness. In this respect, lecturers, module designers, system administrators and students should work together to enhance the usefulness of the system; seeking to influence learners' perceptions. As an illustration, more detailed e-learning context and content, including module content, assessments and delivery activity, could be planned and clearly presented in the e-learning system for the target students. To this end, training should be provided for both instructors and students on LMS utilities, educational material, communication channels and the assessment. This would help students to better realize the advantages of the e-learning system and increase the belief that using the system can enhance their learning performance and productivity.

8.3.2 Effort Expectancy (EE)

It is evident from the results that EE has not only influenced the students' willingness to use the LMS but also their perceptions of its usefulness. As the study revealed that EE had a positive effect on both PE and BI, students tended to place more importance on the easy operability of the LMS in order to increase their academic performance and improve their intention to use the system. Regarding the effect of EE in demographic characteristics, the emphasis of significance is observed with students who are females, senior, highly experienced and those who received training on the use of LMS. Thus, the challenges facing developers and system administrators would become clearer: to improve the system's ease of use, clarity and understanding (i.e., 'ease of understanding'), to make the students' learning experience more efficient and effective. As learners are more inclined to feel that the ease of using an LMS tends to boost their performance and intention, module designers should consider content that meets the learners' needs. With this in mind, instructors are also advised to best utilise LMS features that facilitate effective module activities, simultaneously promoting the students' LMS skills, perceptions of usefulness and willingness-to-use.

8.3.3 Social Influence (SI)

One of the more significant findings to emerge from this study is that SI is a key determinant of the students' acceptance and use of LMS in Saudi higher education.

The effect is more salient in the student's AU behaviour. This finding is more relevant for students who are females, seniors and highly experienced users, where the universities' executives and instructors should pay more attention to these groups. Thus, the results further supported the notion that Saudi students are highly sensitive to other people's opinions, and they regard the system as important if their instructors, peers and university authority also place importance on the use of the system. Therefore, these referents, e.g., university officials and teachers, should make it clear to students that the use of the e-learning system is mandatory and promulgate a generally positive word-of-mouth message. More importantly, they should develop initiatives to encourage awareness about the efficiency and the effectiveness of the e-learning system for teaching and learning e.g., through social media such as university official social networking sites, Facebook, Twitter and newspapers that might arouse young peoples' interest. In Saudi, social media such as Twitter and WhatsApp, are increasingly common, mostly due to the significant proportion of the young population. A recent statistic showed that the number of Internet users in Saudi has reached 24 million; 83.83% of individuals aged between 12 and 65 years use the Internet and 92% of the Saudi population use cell phones (General Authority of Statistics, 2018). The use of social media can be expanded to promote educational materials, share practices, exchange knowledge and employ training programs about the use of LMSs in Saudi universities. Ultimately, and since students' action is influenced by others (e.g. lecturers and peers), this might help students to learn more about the advantages of using e-learning services, which further shapes their actual use of the system.

8.3.4 Facilitating Condition (FC)

Evidence from this study suggests that the available organisational support towards the LMS shaped the student usage behaviour in Saudi Arabia. The effect is more noticeable in females, young and less experienced groups, where the administration should take further consideration of these categories. More specifically, it is important to provide proper technical support, guidance and required training on the use of the system, considering the aforementioned groups of students. It is believed that this would signpost students to the relevant information, fix problems that students face with LMS, make the system easier to use and increase students' use of the system. In this regard, universities should create strategies for enhancing the LMS organizational and technical infrastructure to support the learners' use of the system. Services such as online support, the timeframe of assistance, training and resource availability have been suggested as fundamental to the successful implementation of e-learning. Thus, universities should encourage learners to take advantage of e-learning services by providing the necessary resources and support (e.g., enhance the ICT infrastructure, give timely, appropriate technical support, and deliver training by a qualified individual).

8.3.5 System Navigation (SN)

The current data highlights the importance of the navigational structure which encourages students to consider the LMS system easy to use and ultimately use it. The impact is more significant among males and students who attended training sessions. Since LMS is a medium to disseminate information and knowledge, its navigational structure design should make it easy for learners to understand the system and its content. System developers should ensure that the icons and menus are visible, the links are active and lead to the specified destination, and the buttons are familiar, so learners can navigate to the next module easily and quickly. Moreover, designers should create the LMS navigational flow, which not only controls the access of various groups who interact with the system but also customises the navigational structure. Hence, specific navigation flow can be separately designed for students. Based on this, learners can find the information of interest effortlessly, identify their position in the structure of the application, and leave and return easily.

8.3.6 Visual Design (VD)

It is evident that there was an inverse relationship between the effects of the LMS VD and the students' perceptions of ease of use and usefulness. The results are more relevant for females, less experienced users and the trained groups of students. This study has raised important questions about the VD aspects that influence students' acceptance. Considering the high and moderate experience of students using an LMS, it seems that the students regarded aesthetic aspects of the system such as colours, images, shapes, font style and graphical information, to be less attention-grabbing and less appealing to the learner's senses. This issue might also be related to the placement and balance of fundamental design elements, including line, shape, white space, volume, value, colour, and texture, which are crucial for successful website design. In some cases, certain screen design elements are considered desirable, so LMS designers challenges should prioritise and group these elements visually and identify any relationships between various forms of information. In particular, administrators should focus on the arrangement of content in terms of layout, colour, paragraphs, icons, buttons, font sizes, and line spacing.

8.3.7 System Learnability (SL)

The results of this research support the idea that SL was found to be a significant contributor to the students' acceptance and use of LMS. Since usability and learnability are inextricably linked and the latter is considered the most important measure of usability in e-learning, the construct was the highest predictor of the students' perception of the LMS ease of use in the Saudi universities. Understanding the strongest predictor of students' acceptance will be of great usefulness for academics and pedagogical specialists in higher education. The findings are more significant for all moderating groups. Hence, learning technologists should consider the ease of learning with the groups' demographics characteristics. In this respect, the system designers have a significant role in making the LMS easy to learn – the clarity of wording, the familiarity and predictability of commands and buttons, the availability of on-line help manuals, the site maps availability with a reasonable hierarchy. Incorporating these into an LMS design not only facilitates the students' learning but also maximises the speed of the learning process. Furthermore, module instructional designers should consider and plan the requirements for students' learning, including module content, learning objectives, audience, the delivery formats and evaluation strategies. Once the module is engineered to be usable, the learnability is enhanced.

8.3.8 Information Quality (IQ)

The results showed that IQ has a significant role in the students' acceptance use of LMS. Since the quality of information is considered crucial for the success of e-learning systems, the significance of the construct cannot be ignored. In particular, the students acknowledged the effect of the LMS information quality on the system usefulness. The results are more relevant to females, seniors, highly experienced and trained demographic groups. E-learning technology designers are in a unique position to enrich the system with clear, complete, sufficient, accurate and up-to-date content. These are critical characteristics for the successful use of an e-learning system, especially in Saudi Arabian higher education. Furthermore, the organisation of LMS content into logical and understandable components allows learners to accomplish their learning tasks quickly and effectively. In addition to this, university training programmes should provide guidance for students on how to obtain high-quality information through online resources such as journals, articles, and books. Importantly, university authorities should consider the learners' requirements, i.e., content should be well-organised and appropriately presented with adequate, complete, relevant, and free from error information, and not be overwhelming.

8.3.9 Instructional Assessment (IA)

The outcomes of this research emphasise the importance of assessment tools in the use of LMS in Saudi education. The effect of IA was manifest in LMS effort expectancy. In particular, the results were more noticeable in females, seniors, and untrained groups of students, so practitioners should consider IA when dealing with these demographic differences. Students should be advised about the usefulness of assessment functions in the LMS, e.g., the need to upload a modulework assignment. The lack of assessment tool utilization might affect the students' progress and performance. The various LMS self and peer assessment tools not only measure the learning objectives, but also facilitate comprehension skills for students through different forms of feedback. Thus, learning technologists should focus on creating easy to use assessment tools to enable students to understand the module materials and measure their achievement of the learning objectives. A feedback facility should be provided to help learners identify the behaviours and skills sets that need to be improved. This can be achieved by conducting regular assessment strategies and evaluation of learners, providing them with constructive feedback and suggestions with the aim of reducing the gap between current performance and the desired goal.

8.3.10 E-learning System Interactivity (ESI)

The interactivity dimension is a determinant of students' acceptance and use of LMS at Saudi higher educational institutions, evidenced by its influence on students' willingness to use an LMS as well as their perceptions of performance expectancy. The results are more pertinent to males, young students, and highly experienced and trained groups. An implication of this is the possibility of enhancing the system with asynchronous and synchronous interactions, among students, and between students and instructors. System designers should ensure that a system's components are highly interactive and intuitive to use, so students are involved and willing to learn. Instructors should motivate the collaboration between students and facilitate better communication with the help of activity streams. A good relationship between students and lecturers not only provides opportunities for learners to share their thoughts, but also facilitates cooperative learning. Social media can also be used to increase learner engagement with learning materials and improve motivation for learning.

8.4 Research Contribution

This study makes several scientific contributions to the fields of information systems in general and e-learning systems in particular. These contributions may be viewed from different perspectives: theoretical, practical, and methodological.

8.4.1 Theoretical Contribution

1. *A novel model development:* The main contribution of this study lies in its ability to develop a unified model for the assessment of the students' acceptance and use of e-learning in Saudi educational institutions. This project is the first comprehensive investigation that amalgamates the UTAUT model with usability principles, pertaining to the e-learning environment, while considering the moderating effect of demographic characteristics in Saudi tertiary education. The model encompasses different quality perspectives: users' beliefs, organisational factors, social factors, technological dimensions, acceptance, and use of LMS. This finding provides a new theoretical basis with empirical support to further understand individuals' intention and usage behaviour in Saudi universities.
2. *Usability and technology acceptance*: The results of this endeavour contribute to the body of literature on technology acceptance and usability studies of collaborative e-learning environments in developing countries such as Saudi Arabia. According to the prior literature, there is a dearth of research that investigates perceived usability with technology acceptance models in Saudi higher education (refer to section 3.3). This study bridges the gap between technology acceptance and human-computer interaction techniques, such as perceived usability assessment. It expands the body of knowledge about LMS adoption by applying an amended UTAUT model within a developing nation, i.e., Saudi Arabia.
3. *E-learning system usability attributes propositions*: There is a lack of empirical evidence regarding the usability attributes that affect students' use of e-learning systems in Saudi Arabia. This research reveals the usability variables that reinforce and motivate the intention to use and sustained usage of LMS. There are six usability metrics, as antecedents of performance expectancy, effort expectancy and behavioural intention. These are proposed and empirically examined: navigation, learnability, visual design, information

quality, instructional assessment and interactivity. Collectively, these usability dimensions have been particularly suggested as potentially important in an e-learning system, but had not been included in empirical work on UTAUT, nor had they been investigated in relation to e-learning acceptance in an Arab cultural context. They have been shown to be valid and important measures of e-learning system use.

4. *Re-contextualization of UTAUT theory:* A new significant contribution is related to the study context. The project used the UTAUT model as a base model due to its high predictive capability, its inclusion of moderating effects and limited employment in the educational context of Saudi Arabia. The present study is one of the first investigations to employ UTAUT with usability metrics, along with four demographics moderators, to understand the variables that influenced the students' intention and usage behaviour, in an environment where there is still the segregation of men's and women's education. Furthermore, as the Saudi government has established several new universities in the last decade, the study encompassed two newly established universities (Saudi Electronic University and Al-Jouf University). The study results are not only relevant to educational institutions in the large cities with more developed e-learning infrastructure, but also in smaller towns where e-learning resource development is still only emerging.
5. *The model performance:* The fifth contribution revolves around the performance of the developed model, judged by the explained variance of the outcome variables. A fair amount of variance of LMS usage behaviour can be explained by the original UTAUT and perceived usability variables. The explained variance of the pooled sample is as follows: actual use (0.48), effort expectancy (0.58), performance expectancy (0.51) and behavioural intention (0.65) (refer to Table 6.19). Overall, 48% of the variance in actual use is predictable from behavioural intention, facilitating conditions and social influence. This indicates a moderate predictive power, which when compared to previous models, is considered a novelty.

6. *The study of moderating effect:* The effects of moderating variables (gender, age, LMS experience, and training provided) on the model relationships adds theoretical value to the results. The assessment of the demographic characteristics has been emphasised in the seminal literature of technology acceptance (Sun & Zhang, 2006; Venkatesh et al., 2003; Venkatesh & Morris, 2000). The inclusion of the moderating effects of age, gender and experience further enhance the predictive power of the model. In particular, the incorporation of a training moderator is absent from the earlier studies in Saudi Arabian higher education, so its application is another significant contribution to the existing body of knowledge.

8.4.2 Practical Implications

In consideration of the substantial investment in the e-learning system implementation and the significant growth in the use of different LMSs (e.g. Blackboard) to facilitate the teaching and learning process at Saudi universities, this research offers several practical recommendations that should be taken into account to boost the perceptions of performance expectancy, effort expectancy as well as the intention and use of e-learning systems in Saudi higher education.

The Saudi government stands to benefit from this evaluation as to the most effective approach to implement a new e-learning system or improve and address shortfalls in the current e-learning systems in its universities. The Ministry of education may benefit from this research for e-learning system acceptance in an academic setting and eliminate any impediments to its implementation. This study brings awareness to the ministry and higher education institutions of the important role of usability, social and organisational variables in the acceptance and use of the LMS. Since the results indicate that social influence has a significant and positive influence on the students' usage behaviour, this can be expanded to disseminate the advantages and usefulness of using e-learning services at universities to increase their utilization and popularity. This, in turn, will improve their future strategic initiatives of technology implementation so as to consider students' learning challenges and preferences and the usability factors relevant to their use. Thus, a key policy priority could therefore be to enhance the strategic plan for e-learning system implementation at universities.

Furthermore, university students will be able to identify the factors and motivations driving their adoption of the system. In particular, usability attributes, social and organisational factors that affect their use of an e-learning system would be better understood. It might also be useful to be informed about the individuals' demographics differences, so further consideration can be taken of the groups' differences. This would potentially result in an enhancement to the quality of student learning, improvement in academic performance, as well as effective teaching and learning strategies.

From a pedagogical angle, the knowledge gained from this investigation could be of benefit to university academics. By providing extensive training and awareness on the use of an LMS, teachers not only gain an in-depth understanding of the LMS features but also an increase in the sense of efficacy in the use of the system. This might lead to the realization of the benefits of the LMS for providing students with learning materials, announcements, and feedback. In particular, once the recognition of the usability factors that affect e-learning acceptance is realised, educators would be able to identify the usability problems that students encounter and prepare strategies to deal with them.

More broadly, the study should help the research community in technology acceptance and usability studies to determine the students' perceptions and experiences towards e-learning usability, social and organisational factors that influence their acceptance, specifically in a Saudi context where students have unique psychological and social characteristics. The insights gained from this study may be of assistance to a usability practitioner by helping them to better understand the usability attributes that affect the LMS usage behaviour among students. Administrators and designers could also better understand areas of improvement for usability issues and develop design solutions based on the findings of this study. The study highlights focal points in the existing literature such as the fact that usability metrics influence user acceptance and the adoption of technology. In fact, the findings might be beneficial in addressing similar situations in different contexts. Overall, the suggestions made here have been offered in order to accelerate and increase the use of e-learning services in Saudi higher education. System designers and administrators should have a better insight into the user interface design, considering system-independent metrics that could enhance user acceptance of e-learning systems.

8.4.3 Methodological Contribution

This empirical study was conducted in Saudi tertiary education and from the students' standpoint. As a result of this, there are several methodological contributions that stem from conducting this research.

1. *PLS-SEM techniques:* This study contributes to IS research which uses the partial least squares structural equation modelling PLS-SEM approach to test the measurement and structural models. Recently, there has been an increasing interest in the use of PLS-SEM in information system studies (Hair et al., 2017). Indeed, this research is one of the few studies to use PLS-SEM techniques to investigate the key determinants affecting the acceptance of e-learning environments in Saudi higher education. Not only this, the study utilised the multi-group analysis technique (MGA) to test the moderating effects of demographic variables. Multigroup analysis allows the researcher to measure the significant difference in the specific group moderator estimates. In the Arab world, there seems to be a scarcity of studies employing MGA to detect and analyse moderation effects, and this research attempts to fill this gap. By using MGA, the researcher was able to draw conclusions about the effect on the model of the different students' demographic data: age, gender, LMS experience and training received. Thus, researchers and practitioners would benefit from the group comparisons using MGA, not only in IS research, but also in the Saudi context, where research into moderating effects marks the beginning of an upward trend.

2. *Multi-clustering sampling technique*: The second methodological contribution is the employment of the multi-cluster sampling. In this study, a probability sampling method was used, based on geographical clustering. To ensure representativeness, the sample of the study selects randomly five different universities (cluster), from different regions of Saudi Arabia. The sample uses four cardinal directions to cover each part of Saudi provinces and increase accuracy. This yields a more reliable conclusion. This method is ideal for the generalization of the results to the entire population (Babbie, 2014; Bryman & Bell, 2015). Furthermore, the quantitative study is based on a relatively large sample size (n=605) which provides another foundation for producing broad generalizability.
3. *Instrument development:* the third contribution is concerned with the research instrument development. The research adopts the usability constructs and their measurement items from prior studies. In the literature, the empirical testing and validation of these instruments have been conducted in other cultural environments, i.e., North American and European contexts. Hence, the need for further refinement and validation is evident. Therefore, this study develops and validates a novel instrument in a different context: Saudi Arabia. Initially, the instrument validation has gone through different multiple processes including construct validity, face validity, expert assessment, and pilot study. After conducting this check, all survey items were translated into an Arabic version using the Brislin (1986) back-translation method. The researcher verified the items using bilingual professors to ensure linguistic equivalence and also that all translated scales remain accurate. Later, all the rigorous statistical assessments (e.g., construct and indicator reliability, convergent validity, and discriminant validity) were applied to check the reliability and validity of the instrument. The satisfactory outcomes of the testing confirm the robustness of the constructs and their measurement items. Therefore, the developed instrument can be used not only in similar LMS with similar cultural settings, but can also be further confirmed with different systems and users.

8.5 Limitations and Directions for Future Research

Before drawing definitive conclusions from these results, it is important to consider the study's limitations. To begin with, this cross-sectional study analysed data at a specific point of time. Several lines of evidence suggest that longitudinal research is recommended in which the same students are observed over the study period (Roca et al., 2006; Venkatesh et al., 2003). This would serve to include the time and the dynamics of students' usage behaviour. The students' perceptions and preferences about technology may change as they gain more experience in LMS, so continuous improvement of an LMS is advised to address any issues and shortfalls. Secondly, since the study was limited to five regions of Saudi universities, it was not feasible to include another educational institution within the allocated region, considering the study time and resource constraints. In fact, there are 30 public universities distributed throughout the Saudi area where various cultures, nationalities and backgrounds might be evident. Thus, the validity and reliability of the developed model might improve if different universities were surveyed, especially those which were recently founded. Apart from the intra-cultural context limitations, the scope of this study was limited to higher education in Saudi Arabia, so the generalisation at a cross-cultural level is undetermined. Thus, it is desirable to include geographically distributed universities around the Gulf region which might improve the generalizability of our research outcomes. Thirdly, the current research targeted students' experience of the Blackboard system. Thus, an issue that was not addressed in this study was whether other platforms, e.g., Moodle and Desire2Learn, would lead to similar conclusions. Students have different motivation and experience in using different types of platforms, thus, this could be a fruitful area for further work. The fourth limitation lies in the use of a quantitative methodological approach. The study was grounded on the inquiry-based survey to collect data from the target population. Even though the survey method is the most common approach used in technology acceptance and usability research, more information derived from qualitative methods (e.g., interviews and focus groups) would also help to establish a greater degree of accuracy on the investigated model. This might help to have an in-depth understanding of the research problems and the surrounding issues towards students' attitudes and perceptions. Finally, the study focused on the students' perspective; a natural progression of this work is to involve other e-learning stakeholders (teachers and administrators). This could enrich the research by providing a better understanding of undisclosed issues, offering different views about the implementation and use of an e-learning system in Saudi Arabia.

There are three suggested directions for further studies: firstly, to increase the scope and cover data from a larger student population (e.g., private institutions), with different demographic characteristics such as income, cultural aspects and level of education. A second direction might be to consider other technological attributes such as other system functionalities, and service qualities such as privacy, to investigate their effects on the students' use of LMSs. If the debate is to be moved forward, a better understanding of students' use and acceptance to be developed and this might advance the predictive power of the developed model, i.e., the R^2 value. The proposed model has explained 48% of the variance in actual use, 58% in effort expectancy, 51% in performance expectancy and 65% in behavioural intention. Nonetheless, further studies with other quality factors need to be carried out, in order to increase the predictive power of the developed model, and to help explain more variance in the outcome variables. Lastly, an important issue for future research is to conduct a comprehensive test involving various techniques such as usability testing and expert evaluation (e.g., objective usability), to further improve the existing design of LMS and maximise their effective utilization. This is expected to add valuable insights to inform the decision-making processes at the university higher management and administrative level.

8.6 Summary and Closing Remarks

This piece of research has attempted to explore the students' acceptance of an LMS in Saudi higher education. The empirical findings demonstrate the importance of usability, social and organisational factors in the students' use of LMS, through validating a new theoretical framework. The results confirmed that the extended UTAUT model is valid and reliable to measure the students' use of LMS in Saudi universities. What stands out from the analysis is that the system learnability has the highest effect on effort expectancy, indicating that an easy-to-learn LMS leads students to perceive it as hassle-free. In the same vein, information quality is the most significant driver for students' perceptions of performance expectancy, endorsing the importance of the quality of LMS content. Besides, social influence has the greatest effect on the students' actual use of LMS while students' perceptions of performance expectancy are the most significant factor in the behavioural intention to use LMS. Regarding the moderating effects, this research examined the four personal moderators: gender, age, level of experience and the received training. The statistical analysis reveals that six associations were moderated by the four proposed personal characteristics. The most important message here might be that demographic moderators have little influence on a student's use of an LMS in Saudi higher education. Nonetheless, the proposed model can be used as a frame of reference to universities that seek to implement and adopt the LMS.

This chapter aims to provide a comprehensive summary of the findings in relation to the research questions. The implications of each construct used in the model have been presented. Based on the results, recommendations have been suggested regarding, policy, practice and future research. Furthermore, the contribution of the research to the body of knowledge was provided from different perspectives: theoretical, practical and methodological. The evidence presented in this study has important limitations while offering suggestions for future research avenues.

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APPENDIX A: QUESTIONNAIRE (ENGLISH)

I am Ahmed Alshehri, a PhD student in Edinburgh Napier University in the United Kingdom. My research is titled:

The Effects of UTAUT and Usability Qualities on Students' Acceptance and Use of Learning Management Systems in Saudi Tertiary Education

This survey is part of the PhD research about the Blackboard use in Saudi higher education from students' perspective.

The overall objective of this study is to understand the impact of usability, social and organisational factors on the intention and use of Blackboard system in Saudi universities.

Edinburgh Napier University requires that all persons who participate in research studies give their consent to do so. Please read the following and click on NEXT button if you agree with what it says:

1. I freely and voluntarily consent to be a participant in this research project to be conducted by Mr. Ahmed Alshehri, a PhD student in the School of Computing at Edinburgh Napier University.
2. I have understood the broad goal of this research study. I have been told what is expected of me and that the study should take no longer than 15 minutes to complete.
3. My responses will be anonymized. My name will not be linked with the research materials, and I will not be identified or identifiable in any report subsequently produced by the researcher. I have been told that these data may be submitted for publication.
4. I also understand that if at any time during the survey. If I feel unable or unwilling to continue, I am free to leave. That is, my participation in this study is completely voluntary, and I may withdraw from it at any time without negative consequences.

5. In addition, should I not wish to answer any particular question or questions, I am free to decline.

6. I have read and understand the above and consent to participate in this study.

If you have any questions or concerns about the study or the online survey procedures, please contact me a.alshehri@napier.ac.uk or my supervisors m.rutter@napier.ac.uk and s.smith@napier.ac.uk

If you have read and understood the above and consent to participate in this study, please click on NEXT button below.

Without your co-operation, it is not possible to complete my research. Responses are based on your own experience where there are no right or wrong answers.

Thank you very much in advance for your cooperation and support.

Part 1: Demographic Details:

1. Gender: □Male □ Female
2. Age: [ ] Years
3. University: □King Khalid University □ Saudi Electronic University
   □ Al Jouf University □ King Abdelaziz University
   □Imam Abdulrahman Bin Faisal University
4. Education level: □ Undergraduate □ Graduate
5. Blackboard Experience: □ Less than a Year □ 1-2 years □ More than 2 years
6. Blackboard Usage Frequency: □ Daily □ Weekly □Monthly □ Almost never
7. Blackboard Taught Modules: □ 1-3 modules□ 4-5 modules□ More than 6 modules □ I do not use Blackboard in any module.
8. Blackboard Training: □ None □ 1-3 hours □ 4-6 hours □ More than 6 hours

Part 2: Perceptions of UTAUT variables towards Blackboard:

Performance Expectancy (PE)

1. I find Blackboard useful in my modules.
2. Using Blackboard enables me to accomplish tasks more quickly.
3. Using Blackboard increases my academic productivity.
4. If I use Blackboard, I will increase my chances of getting high grades.

Effort Expectancy (EE)

5. I find Blackboard clear and understandable.
6. It would be easy for me to become skilful at using Blackboard.
7. Learning to operate Blackboard is easy for me.
8. Overall, I find Blackboard easy to use.

Social Influence (SI)

9. People who influence my behaviour think that I should use Blackboard.
10. My classmates and friends think that I should use Blackboard.
11. My instructors encourage the use of Blackboard.
12. In general, the university encourages students to use of Blackboard.

Facilitating conditions (FC)

13. I have the resources necessary to use Blackboard.
14. I have the knowledge necessary to use Blackboard.
15. The e-learning support staff are available when I face any problem with Blackboard.
16. Training and manuals for Blackboard is available.
17. The management would provide the necessary help for using Blackboard.

Behavioural Intention (BI)

18. I intend to continue using Blackboard in the future.
19. I would prefer my instructors use Blackboard more frequently.
20. I would like to use Blackboard in all future modules.

21. I would recommend using Blackboard to others.

Actual Use (AU)

22. I have used Blackboard this semester.
23. I have been using Blackboard regularly in the past.
24. I have used Blackboard frequently in my studies.

25. I usually use Blackboard for my learning activities.

<u>Part 3: Perceptions of Usability variables towards Blackboard:</u>

System Navigation (SN)

26. The navigational structure of Blackboard is easy for me.
27. Hyperlinks in Blackboard are working satisfactorily.
28. Navigation options are visible in each page.
29. Learners always know where they are in the module.

30. I can leave Blackboard at any time and easily return.

System Learnability (SL)

31. Learning how to perform tasks using Blackboard is easy.
32. I can predict the general result of clicking on each button or link.
33. The Blackboard system provides clarity of wording for easy learning.
34. I can learn how to use Blackboard without a long introduction.
35. There is sufficient on-line help to support the learning process.

Visual Design (VD)

36. Texts, fonts and colours are easy to read.
37. The most important information on the screen is placed in the areas most likely to attract attention.
38. Blackboard layout follows a good structure.
39. Terminology, symbols, and icons are used consistently throughout Blackboard.
40. Blackboard operates consistently throughout my modules.
41. Blackboard visual design is attractive and appealing to the learner's senses.

Information Quality (IQ)

42. Blackboard provides easy to understand information for my study.
43. Blackboard provides complete information for my study.
44. Blackboard provides sufficient information for my study.
45. Blackboard provides accurate, free form error information for my study.
46. Blackboard provides up-to-date information for my study.

Instructional Assessment (IA)

47. Blackboard contains self-assessment tools (i.e. exams, quizzes, case studies… etc.) that advance my achievement.
48. It is easy for me to use the self-assessment tools in Blackboard.

49. Assessment features in Blackboard are effective to help understanding the material.
50. The self-assessment tools in Blackboard measure my achievements of learning objectives.
51. Blackboard provides learners with opportunities to access extended feedback from instructors, experts, peers, or others.
52. Blackboard provides informative feedback to online assessments.

E-learning System Interactivity (ESI)

53. The communicational tools in Blackboard (email, discussion board, chat room, etc.) are effective.
54. Blackboard enables interactive communication between instructor and student.
55. Blackboard enables interactive communication among students.
56. Blackboard makes my learning process more engaging.

Thank you for your participation.

Researcher: Ahmed Alshehri

a.alshehri@napier.ac.uk

APPENDIX B: QUESTIONNAIRE (ARABIC)

استبانة لدراسة تأثير خواص سهولة الاستخدام على استخدام الطلاب لنظام البلاكبورد في الجامعات السعودية

عزيزي المشارك/ة:

السلام عليكم ورحمة الله وبركاته:

أنا طالب دكتوراه في كلية الحاسبات بجامعة أدنبره نابيير بالمملكة المتحدة. آمل منك المشاركة في تعبئة الاستبيان المرفق شاكرًا ومقدرًا حسن تعاونك واهتمامك سلفًا.

الهدف من الدراسة:

دراسة العوامل المؤثرة على استخدام نظام إدارة التعلم (بلاك بورد) في الجامعات السعودية الحكومية من وجهة نظر الطلاب، علمًا بأن المشاركة في هذه الدراسة تستغرق من 10 إلى 15 دقيقة لإكمالها ومشاركتك معنا موضع تقدير وامتنان.

يتطلب من جميع المشاركين في هذه الدراسة البحثية إعطاء موافقتهم. لذا يرجى قراءة ما يلي في حال الموافقة:

1. المشاركة في هذه الدراسة التي سيجريها الأستاذ/ أحمد الشهري (طالب دكتوراه في كلية الحاسبات بجامعة أدنبره نابيير) تطوعية بشكل كامل.

2. إذا كنت تشعر بأنك غير قادر أو غير راغب في المتابعة في أي وقت أثناء تعبئة الاستبانة فيمكنك المغادرة.

3. المشاركة في هذه الدراسة ستكون سرية، حيث أن المعلومات المتعلقة بهوية المشارك في هذه الدراسة سرية ولن يتم الكشف عنها لأي أطراف أخرى في أي تقرير سيتم عمله لاحقًا من قبل الباحث، وسيتم استخدام هذه البيانات بغرض النشر العلمي فقط.

4. بإمكانك التحفظ عن الإجابة في حالة عدم الرغبة على إجابة أي سؤال.

5. من المتوقع أنك مدرك لهدف هذه الدراسة البحثية.

6. توقيعك لا تعني التنازل عن أي حقوق قانونية.

7. في حال موافقتك على المشاركة في هذه الدراسة، يرجى تعبئة الاستبانة ادناه

معلومات شخصية (ضع علامة √ على اختيار واحد فقط لكل خاصية:

1. الجنس: ☐ذكر ☐أنثى
2. العمر:
3. الجامعة التي تدرس بها: ☐جامعة الملك عبد العزيز ☐جامعة الملك خالد ☐جامعة الجوف
   1. ☐الجامعة السعودية الالكترونية ☐جامعة الامام عبدالرحمن بن فيصل
4. المرحلة الدراسية: ☐دبلوم وبكالوريوس ☐دراسات عليا
5. سنوات استخدام البلاكبورد: ☐اقل من سنة ☐سنة الى سنتين ☐أكثر من سنتين
6. معدل استخدام البلاكبورد: ☐يوميًا ☐اسبوعيًا ☐شهريًا
7. المقررات التي تستخدم فيها البلاكبورد: ☐١-٣ مقررات ☐٤-٥ مقررات ☐أكثر من ٦ مقررات
   ☐لا استخدم النظام في أي مقرر
8. مدة التدريب على استخدام البلاكبورد: ☐لا يوجد ☐١-٣ ساعات ☐٤-٦ ساعات ☐أكثر من ٦ ساعات

ما هو مدى اتفاقك أو مخالفتك للنقاط التالية المتعلقة بالنظرية الموحدة لتقبل التقنية واستخدامها:

الأداء المتوقع

1. أجد من المفيد استخدام البلاكبورد في دراستي.
2. استخدام البلاك بورد يمكنني من إنجاز المهام بسرعة أكبر.
3. استخدام البلاكبورد يزيد من إنتاجيتي الدراسية.
4. استخدام البلاكبورد يزيد فرصتي في الحصول على درجات عالية.

الجهد المتوقع

5. استخدام البلاكبورد واضح ومفهوم بالنسبة لي.
6. من السهل أن أصبح ماهرًا في استخدام البلاكبورد.
7. من السهل علي تعلم استخدام البلاكبورد.
8. بشكل عام أجد البلاكبورد سهل الاستخدام.

التأثير الاجتماعي

9. الأشخاص الذين لهم تأثير على سلوكي يعتقدون أنه ينبغي على استخدام البلاكبورد.
10. زملائي وأصدقائي يعتقدون أنه ينبغي علي استخدام البلاكبورد.
11. اساتذتي يعتقدون أنه ينبغي على استخدام البلاكبورد.
12. بشكل عام، الجامعة تشجع الطلاب على استخدام البلاكبورد

العوامل المساعدة

13. لدي الموارد اللازمة لاستخدام البلاكبورد.
14. لدي المعرفة اللازمة لاستخدام البلاكبورد.
15. موظفو الدعم الفني متاحون للمساعدة في حل مشكلات البلاكبورد.
16. الجامعة توفر التدريب والأدوات المساندة الخاصة بالبلاكبورد.
17. الجامعة توفر الدعم اللازم لاستخدام البلاكبورد.

النية السلوكية لاستخدام النظام

18. أرغب الاستمرار في استخدام البلاكبورد في المستقبل.
19. أود أن أشجع الأساتذة على استخدام البلاكبورد باستمرار.
20. أرغب في استخدام البلاكبورد في جميع المقررات القادمة.
21. أوصي زملائي الطلاب باستخدام البلاكبورد.

استخدام النظام

22. لقد استخدمت البلاكبورد في هذا الفصل الدراسي.
23. استخدمت البلاكبورد بانتظام في الماضي.
24. استخدم البلاكبورد بشكل متكرر.
25. عادة أستخدم البلاكبورد في أنشطتي الدراسية.

قابلية استخدام النظام:

التنقل في النظام

26. التنقل في البلاكبورد سهل بالنسبة لي.
27. تعمل الروابط في النظام بشكل مُرضٍ.
28. تسلسل الصفحات في البلاكبورد سلس وواضح.
29. أعرف دائمًا موقعي (مكان تواجدي) في البلاكبورد.
30. يمكنني الخروج من النظام في أي وقت والعودة إليه بسهولة.

سهولة التعلم

31. من السهل على تعلم كيفية تنفيذ المهام باستخدام البلاكبورد.
32. يمكنني توقع النتيجة العامة بالنقر على كل زر أو رابط.
33. نظام البلاكبورد واضح الوظائف والأوامر ويسهل تعلمي.
34. يمكنني تعلم كيفية استخدام البلاكبورد في وقت قصير.
35. هناك ما يكفي من المساعدة عبر النظام لدعم تعلمي.

تصميم النظام

36. النصوص والخطوط والألوان في البلاكبورد سهلة القراءة.
37. يتم وضع أهم المعلومات على الشاشة في أكثر المناطق عرضة لجذب انتباهي.
38. يتمتع نظام البلاكبورد بتخطيط وتصميم جيد.
39. المصطلحات والأيقونات والرموز متناسقة في جميع صفحات البلاكبورد.
40. بشكل عام، يعمل نظام البلاكبورد بشكل متناسق في جميع المقررات.
41. بشكل عام، التصميم العام للبلاك بورد جذاب بالنسبة لي.

جودة المعلومات

42. يوفر البلاكبورد معلومات سهلة الفهم لدراستي.
43. يوفر البلاكبورد معلومات مكتملة لدراستي.
44. يوفر البلاكبورد معلومات كافية لدراستي.
45. يوفر البلاكبورد معلومات دقيقة وخالية من الأخطاء لدراستي.
46. يوفر البلاكبورد معلومات حديثة لدراستي.

التقييم التعليمي

47. يوفر البلاكبورد أدوات تقييم جيدة مثل الاختبارات والواجبات والاستطلاعات.
48. يعتبر استخدام أدوات التقييم في البلاكبورد سهل بالنسبة لي.
49. تعتبر أدوات التقييم في البلاكبورد فعالة ومساعدة في فهم المواد.
50. تقيس أدوات التقييم في البلاكبورد إنجازاتي المرتبطة بأهداف المقرر.

51. يوفر البلاكبورد فرصًا للوصول إلى التعليقات والملاحظات من المعلمين أو الطلاب.
52. يوفر البلاكبورد ملاحظات وردود مفيدة لاختباراتي وواجباتي.

التفاعل في النظام

53. تعتبر أدوات التواصل في البلاكبورد (البريد الإلكتروني، لوحة المناقشة، غرفة الدردشة) فعالة بالنسبة لي.
54. يتيح البلاكبورد الاتصال التفاعلي بيني وبين أستاذ المادة.
55. يتيح البلاكبورد الاتصال التفاعلي بيني وبين الطلاب.
56. البلاكبورد يجعل العملية التعليمية أكثر جذبًا.

أي اقتراح أو تعليق على الاستبانة:

شكرًا جزيلًا على المشاركة...

بإمكانك مراسلة الباحث والحصول على النتائج النهائية عن طريق البريد الالكتروني المدون بالأسفل أو تزويدي ببريدك الإلكتروني وطلب الحصول على موجز لنتائج الدراسة.
للحصول على المزيد من المعلومات والاستفسارات المتعلقة بهذا الاستبيان يرجى التواصل ب:

الباحث: أحمد الشهري
كلية الحاسبات
جامعة أدنبره نابيير
M: +44 7426949293(UK)
(SA) 966569501440+
a.alshehri@napier.ac.uk

APPENDIX C: ETHICAL APPROVAL

Edinburgh Napier
UNIVERSITY

School of Computing
Edinburgh Napier University
Merchiston Campus
Edinburgh
EH10 5DT

T +44 (0)131 455 2700
F +44 (0)131 455 2727
W www.soc.napier.ac.uk

26 April 2018

Dear Sirs,

Ahmed Ali Alshehri (40225725)

I am writing to confirm that Mr. Ahmed Alshehri will be distributing the research instruments using Novi online survey.

Mr. Alshehri is researching, "**The Impact of Usability, Social and Organisational Factors on Students' intention and Use Of E-Learning System in Saudi Tertiary Education**".

I have discussed the ethical implications of undertaking an on-line survey using Novi Survey and that I am satisfied that the proposed questions to be included in the survey carry no ethical implications.

Yours Sincerely,

[redacted]

Dr. Malcolm Rutter
Lecturer
Academic Supervisor
School of Computing
Edinburgh Napier University
Email: m.rutter@napier.ac.uk

INVESTORS IN PEOPLE | Silver

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2015

APPENDIX D: APPROVAL OF SAUDI UNIVERSITY

KINGDOM OF SAUDI ARABIA
MINISTRY OF EDUCATION
AL- BAHA UNIVERSITY (042)

المملكة العربية السعودية
وزارة التعليم
جامعة الباحة (٠٤٢)

VISION 2030 رؤية
المملكة العربية السعودية
KINGDOM OF SAUDI ARABIA

سعادة / الملحق الثقافي ببريطانيا وفقه الله

السلام عليكم ورحمة الله وبركاته وبعد،

نفيد سعادتكم بموافقتنا المبدئية على طلب المبتعث / أحمد بن علي محمد الشهري، هوية وطنية رقم (١٠٦٠٤٦٦٧٥٠) وبحسب الطلب رقم (١٨٦٨١١٢٧) للقيام برحلة علمية إلى المملكة العربية السعودية وذلك لجمع بيانات متعلقة برسالة الدكتوراه لمدة (٩٠ يوما) اعتبارا من تاريخ ١٤٣٩/١٢/٢٢هـ الموافق ٢٠١٨/٠٩/٠٢م.

هذا وتفضلوا بقبول وافر تحياتنا وتقديرنا . .

وكيل الجامعة
للدراسات العليا والبحث العلمي المكلف

[redacted]

أ.د / غانم بن محمد الغامدي

جامعه الباحه
رقم المعاملة: ٣٩١٨٩٨٦٧
تاريخ التحرير: ١٤٣٩/٠٩/١٢
وقت التحرير: ٢٢:٥١
المرفقات:

1439-44-39189867

الرقم : .... التاريخ : .... المشفوعات : ....

تليفون : ٧٢٧٤١١١ - ١٧ - ٠٠٩٦٦ فاكس : ٧٢٤٧٢٧٢ - ١٧ - ٠٠٩٦٦ الباحة : ص . ب (١٩٨٨)
Tel. : 00966 17 7274111 Fax : 00966 17 7247272 AL- Baha P.O.Box (1988)

APPENDIX E: PILOT STUDY QUESTIONNAIRE

Effects of Usability, Social and Organisational Factors on the Use of Blackboard

I am Ahmed Alshehri, a PhD student in Edinburgh Napier University in the United Kingdom. My research is titled:

The Impact of Usability, Social and Organisational Factors on Students' intention and Use of E-Learning System in Saudi Tertiary Education

This survey is part of the PhD research about Blackboard use in Saudi higher education from students' perspective.

The overall objective of this study is to understand the impact of usability, social and organisational factors on the intention and use of Blackboard system in Saudi universities.

Edinburgh Napier University requires that all persons who participate in research studies give their consent to do so. Please read the following and click on NEXT button if you agree with what it says:

1. I freely and voluntarily consent to be a participant in this research project to be conducted by Mr. Ahmed Alshehri, a PhD student in the School of Computing at Edinburgh Napier University.

2. I have understood the broad goal of this research study. I have been told what is expected of me and that the study should take no longer than 15 minutes to complete.

3. My responses will be anonymized. My name will not be linked with the research materials, and I will not be identified or identifiable in any report subsequently produced by the researcher. I have been told that these data may be submitted for publication.

4. I also understand that if at any time during the survey. If I feel unable or unwilling to continue, I am free to leave. That is, my participation in this study is completely voluntary, and I may withdraw from it at any time without negative consequences.

5. In addition, should I not wish to answer any particular question or questions, I am free to decline.

6. I have read and understand the above and consent to participate in this study.

If you have any questions or concerns about the study or the online survey procedures, please contact me a.alshehri@napier.ac.uk or my supervisors m.rutter@napier.ac.uk and s.smith@napier.ac.uk

If you have read and understood the above and consent to participate in this study, please click on NEXT button below.

Without your co-operation, it is not possible to complete my research. Responses are based on your own experience where there are no right or wrong answers.
Thank you very much in advance for your cooperation and support.

1

Effects of Usability, Social and Organisational Factors on the Use of Blackboard

Part 1: Demographic Details:

1	**Gender**	O Male	O Female	
2	**Age**	O [ ] Years		
3	**University**	O King Khalid University	O King Abdelaziz University	
4	**Education level**	O Undergraduate	O Graduate	
5	**Field of Study**	O Science	O Art	O Engineering
6	**Blackboard Experience**	O Less than a Year	O 1-2 years	O More than 2 years
7	**Blackboard Usage**	O Daily	O Weekly	O Monthly O Almost never
8	**Blackboard Taught Courses**	O 1-3 courses	O 4-5 Courses	O more than 6 Courses O I do not use Blackboard in any course
10	**Blackboard Training**	O None	O 1-3 hours	O 4-6 hours O More than 6 hours

Please answer the following questions:
Your university year -----------------, Your GPA (cumulative rate) -----------------

Part 2: Perceptions towards Blackboard: (Please tick the number that indicates your level of disagreement/agreement with the following statements where 1 means strongly disagree and 5 means strongly agree:)

	Measurements	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
	Performance expectancy (PE)					
1	I find Blackboard useful in my courses.					
2	Using Blackboard enables me to accomplish tasks more quickly.					
3	Using Blackboard increases my academic productivity.					
4	If I use Blackboard, I will increase my chances of getting a high grade.					
	Effort Expectancy (EE)					
5	I find Blackboard clear and understandable.					
6	It would be easy for me to become skillful at using Blackboard.					
7	Learning to operate Blackboard is easy for me.					
8	Overall, I find Blackboard easy to use.					
	Social Influence (SI)					
9	People who influence my behavior think that I should use Blackboard.					
10	My classmates and friends think that I should use Blackboard.					
11	My instructors encourage the use of Blackboard.					
12	In general, the university encourages students to use of Blackboard.					
	Facilitating conditions (FC)					
13	I have the resources necessary to use Blackboard.					
14	I have the knowledge necessary to use Blackboard.					
15	The e-learning support staff are available when I face any problems with Blackbaord.					
16	Training and manuals for Blackboard is available.					
17	The management would provide the necessary help and resources for using Blackboard					

2

Effects of Usability, Social and Organisational Factors on the Use of Blackboard

	Behavioral Intention (BI)					
18	I intend to continue using Blackboard in the future.					
19	I would prefer my instructors use Blackboard more frequently.					
20	I will like to use Blackboard in all future courses.					
21	I would recommend using Blackboard to others.					
	Actual Use (AU)					
22	I have used Blackboard this semester.					
23	I have been using Blackboard regularly in the past.					
24	I have used Blackboard frequently in my studies.					
25	I usually use Blackboard for my learning activities.					

Part 3: Usability questions: (Please tick the number that indicates your level of disagreement/agreement with the following statements where 1 means strongly disagree and 5 means strongly agree:)

	Usability Measurements	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
	System Navigation (SN)					
26	The navigational structure of Blackboard is easy for me.					
27	Hyperlinks in Blackboard are working satisfactorily					
28	Navigation options are visible in each page.					
29	Learners always know where they are in the course					
30	I can leave Blackboard at any time and easily return.					
	System Learnability (SL)					
31	Learning how to perform tasks using Blackboard is easy					
32	I can predict the general result of clicking on each button or link					
33	The Blackboard system provides clarity of wording for easy learning					
34	I can learn how to use Blackboard without a long introduction					
35	There is sufficient on-line help to support the learning process					
	Visual Design (VD)					
36	Texts, fonts and colours are easy to read.					
37	Fonts, colours and sizes are consistent throughout Blackboard.					
38	The activity, icon, button, label, and links actually lead to the content					
39	The most important information on the screen is placed in the areas most					
40	Blackboard layout follows a good structure.					
41	Terminology, symbols, and icons are used consistently throughout					
42	Blackboard operates consistently throughout my courses.					
43	Blackboard visual design is attractive and appealing to the learner’s					
	Information Quality (IQ)					
44	Blackboard provides easy to understand information for my study.					
45	Blackboard provides complete information for my study.					
46	Blackboard provides sufficient information for my study.					
47	Blackboard provides accurate, free form error information for my study.					
48	Blackboard provides up-to-date information for my study.					
	Instructional Assessment (IA)					
49	Blackboard contains self-assessment tools (i.e. exams, quizzes, case					
50	It is easy for me to use the self-assessment tools in Blackboard.					
51	Assessment features in Blackboard are effective to help understanding					
52	The self-assessment tools in Blackboard measure my achievements of learning objectives.					

3

Effects of Usability, Social and Organisational Factors on the Use of Blackboard

53	Blackboard provides learners with opportunities to access extended feedback from instructors, experts, peers, or others.					
54	Blackboard provides informative feedback to online assessments.					
55	I receive regular feedback about my performance in a timely manner					
	E-learning System Interactivity (ESI)					
56	The communicational tools in Blackboard (email, discussion board, chat room, etc.) are effective					
57	Blackboard enables interactive communication between instructor and students					
58	Blackboard enables interactive communication among students					
59	Interacting with other students and the instructor using Blackboard became more natural as the course progressed					
60	Blackboard makes my learning process more engaging					

Any comments:

Thank you for your participation.
Researcher: Ahmed Alshehri
a.alshehri@napier.ac.uk

4

APPENDIX F: PUBLICATIONS

The following papers have been directly published (or under review) from this thesis.

Paper (1): Alshehri, A., Rutter, M., & Smith, S. (2020). The moderating effects of experience and training on students' use of a learning management system. *International Journal of Information and Education Technology. Accepted to be published in Sep 2020.*

The Moderating Effects of Experience and Training on Students' Use of a Learning Management System

Ahmed Alshehri, Malcolm Rutter, and Sally Smith

***Abstract*—E-learning systems have become progressively more vital for universities, schools and other organisations to provide informational content and instructive resources. Incorporation of technology in learning and teaching environment is no longer an option, but a necessity. Still, the challenge for educational institutions is how to attract learners to their e-learning services. The study utilised an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model to investigate empirically the variables that influenced the students use of a Learning Management System (LMS) in Saudi tertiary education. The focus of this study is the impact of demographic characteristics of experience and training on the students' use of the LMS. Based on survey data from 605 respondents, Partial Least Squares Structural Equation Modelling (PLS-SEM) in conjunction with multigroup analysis techniques were employed to assess the model. The results showed that experience moderated the relationship between behavioural intention and actual use, information quality and behavioural intention as well as social influence and actual use. Whereas only the association of information quality on performance expectancy was moderated by the training variable. These findings may contribute to a deeper understanding of e-learning students' adoption behaviour. In light of these findings, the recommendations along with the study's' limitations were communicated.**

***Index Terms*—e-learning systems, PLS-SEM, moderators technology acceptance, UTAUT.**

I. Introduction

Technological advancements have progressed substantially in the past decades. While the progress of technological innovations is continuing, the transfer of these advances into education has become a current issue. The successful experience of e-services around the world has led to the redefinition of the role of educational institutions. That is through the adoption of e-learning services and techniques. The goal is to create a lifelong learning environment with cost-efficient, flexible and accessible education regardless of geographic and time boundaries. Among the diverse educational technologies, the LMS is a common e-delivery medium within academic institutions, possessing robust capabilities for delivering online courses in distance learning as well as augmenting on-campus courses in blended learning [1]. Educational institutions implement LMSs such as the Blackboard system to administer their curricula with various types of functionalities, such as announcements, discussion board, online assessment and document sharing [2], [3].

In Saudi Arabia, most universities are equipped with the Blackboard system as the main application for learning and teaching. A more recent statistic indicated that the Blackboard system is by far the most prevalent LMS in Saudi higher education used by 90% of kingdom public universities [4]. Nonetheless, having access to an LMS does not necessarily mean that effective learning has occurred [5]. Despite the apparent usefulness, the issue of effective use of an LMS is an intriguing one [5]. In fact, the decisions about the integration of LMS into universities are often at a higher management level. Yet, it is the individual adoption patterns that illustrate the successful implementation [6]. Salloum & Shaalan [7] reported that developing countries have failed, fully or partially, to implement LMSs effectively. A lack of utilization of these systems has been observed and the need to explore this challenge is still evident [7]–[9]. Therefore, understanding why students decide to use or reject an e-learning system can create a more favourable environment for greater adoption, as well as helping to design strategies to promote acceptance.

To address this gap, the technology acceptance models and theories examine the individual and the choices that are made to accept or reject a particular system [6]. Venkatesh and colleagues [10] developed a Unified Theory of Acceptance and Use of Technology (UTAUT) model based on a comprehensive review of diverse theories for computer use predication. The model unifies the theoretical models in information system studies and integrates human and social constructs to form a unique extensive model [10]. The model established a unique measure with four essential constructs of user behavioural intention and usage, including Performance Expectancy (PE), Effort Expectancy (EE), Social Expectancy (SE) and necessary Facilitating Condition (FC). All these elements are direct determinants of user intention and behaviour [10].

Demographic characteristics such as age, experience, gender and voluntariness are posited to moderate the influence of the four key constructs on behavioural

Manuscript received Septemper 29, 2019; revised December 20, 2019. This research was financially supported by the Saudi Arabian Ministry of Education.

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M.Rutter and S.Smith are with School of Computing, Edinburgh Napier University, Edinburgh, United Kingdom (e-mail: m.rutter@napier.ac.uk, s.smith@napier.ac.uk).

intentions [10]. The amalgamation of the core constructs and the moderating inputs has improved the predictive efficiency to 70% of the variance in behavioural intention to use technology [10]. Furthermore, the presence of demographics moderators in the UTAUT model has strengthened the model's power to explain technology acceptance and usage [10]. It has been established that users' individual differences, such as age, experience, training, can have an influence on the users' beliefs in using the system [11]. The moderators of gender, experience and training have been critical in using the LMS in Saudi Arabia [12]. It has been established that moderating factors have profound effects on user technology acceptance [13]. This not only contributes to the potential increase in the models' explanatory power but also leads to a better understanding of the dynamics of the user technology acceptance phenomenon [13].

From a methodological perspective, it is evident that the majority of structural equation models have not examined the moderating effects [14]. Many studies have failed to address whether there are significant differences across two or more groups of data [15]. The result interpretation from a single population sample can be misleading and may contribute to an invalid conclusion [15]. Moderator variables are considered important as specific variables are often expected to influence the relationships between the predictors and the outcomes [14], [16], [17].

This study attempts to extend the UTAUT model with six external variables and two demographic moderators. In particular, the proposed model measured the effects of the moderators LMS experience and given training on the students use of LMS in Saudi tertiary education.

II. Theoretical Model

The UTAUT model has been extended with six usability attributes to measure students' behavioural intention and actual use of an LMS in Saudi higher education. The selection of the UTAUT framework was due to its comprehensiveness and powerful explanatory power in the students' use of the e-learning system [7]. It is now well established from a variety of studies that usability attributes and user acceptance variables are essential to the diffusion of a given technology [18]. In this research, the UTAUT model was extended with six usability dimensions namely: system navigation, system learnability, visual design, information quality, instructional assessment and e-learning system interactivity. These six usability variables have been validated extensively in prior studies in the domain of usability, e-learning and educational technologies [19]–[24]. Along with that, the two moderators of students' LMS experience and training were posited to influence all the model relationships. In this endeavour, the focus is on the influence of the moderation effect of LMS experience and training on the model relationships. The proposed model is depicted in Figure 1.

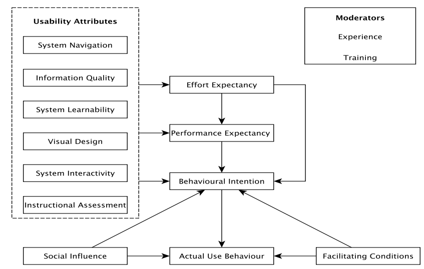

Fig. 1. The proposed model

A. Experience Moderating Effect

The first moderating variable is LMS experience. Experience refers to the individuals' involvement with the system over a period of time [10]. It is measured by a number of years that students have been using an LMS [25]. It is an important moderating variable in IT adoption contexts as individuals' reactions toward an IT may change over time [26], [27]. In a study set out to compare the determinants of IT usage for experienced and inexperienced users, it was discovered that the inexperienced users placed a different emphasis on the determinants of usage and intention [27]. Extensive research has shown that the students' experience in the use of LMS can change the intention usage behaviour [28]. Perceptions of intention differed significantly between students with and without prior experience [28]. Recently, Zhang et al. [29] findings demonstrated the significant difference in the effect of usage experience, as a moderator, in the students' attitude and intention to use LMS. The intention in low-experienced users was influenced by information quality and perceived usefulness whereas for highly experienced users, the intention was influenced positively by information satisfaction, interaction satisfaction and perceived usefulness [29]. Consequently, this stimulus would affect students' intention and actual use of the targeted system. Furthermore, Venkatesh et al. [30] postulated that the experience will moderate the effect between behavioural intention and actual use behaviour and that will be stronger with less experienced users. In the Arab world, the previous student experience came as the most critical factor in the e-learning success model [31]. Drawn up for the earlier discussion, it is assumed that different factors within the model may have different influences on students' perceptions of performance expectancy and effort expectancy as well as on intention and usage, depending on the students' experience with the LMS. Since the experience variable has the potential to modify the model relationships, this study will postulate that the students experience of LMS moderates the interaction of the model variables.

H_1: LMS experience will moderate all relationships in the proposed model.

B. Training Moderating Effect

The success of the e-learning system implementation depends primarily on training and professional development [12], [32], [33]. Individuals can benefit from many forms of training such as workshops, online tutorials, courses, and seminars [34]. Training programmes affect significantly the individuals' computer self-efficacy [35]. In this study, the training variable was measured by a number of training hours given to students. In a study set out to determine the effect of demographic characteristics on the acceptance and use of technology, the training determinant was found to be the most important driver of users perception of technological innovation [36]. The training can also boost the users' confidence with regard to the capability to learn and use of technology [36]. Besides, it was established that training promotes greater understanding, favourable attitudes, more frequent use, and more diverse use of applications [37]. Problems of using technology are likely to arise if users are not provided with adequate training [35]. Data from several sources have concluded that the scarcity of training has been considered among the most significant barriers in the use of e-learning system services in Saudi higher education [12], [33]. The effect of training moderation is lacking in the IS/IT acceptance research especially in the Arab context [38]. In the study conducted by Asiri et al, [12], the individuals' characteristics of training was reported to be a critical factor that influenced the utilization of LMS in Saudi Arabia. Furthermore, the availability of training has a direct effect on individuals' beliefs of perceived usefulness and perceived ease of use, where the latter is affected the most by the training variable [38]. Likewise, in an investigation into LMS acceptance in Saudi tertiary education, Alshehri et al. [9] found that the majority of students had no previous training in the use of LMS (64.3%) whereas a minority (32.2%) reported some training (1-5 hours). The lack of training and the absence of administrative support was a major barrier to the integration of technology in higher education [39]. External variables such as system training can affect the user beliefs in using the system [11], [40]. Hu, Clark, & Ma [41] compared the moderating effect of teachers' training on the Technology Acceptance Model (TAM) relationships. Several noticeable changes in TAM key acceptance drivers and their influence patterns or magnitudes were observed over the course of the training [41]. Therefore, the following hypothesis was proposed to investigate the effect of students' training.

H_2: Training will moderate all relationships in the proposed model.

III. Methodology

The target sample for this study was taken from students in Saudi higher education. The researcher targeted the students in Saudi higher education with geographically dispersed universities. Due to the large sample frame of Saudi students, a sampling technique was necessary. Hence, the study approaches this concern using a multi-stage cluster sampling technique as suggested by [42].

Quantitative research in the form of an online questionnaire-based survey was performed to test the hypotheses. The instrument was divided into three main sections. The first section included information about the respondents' characteristics. In this section, the students select the number of hours of provided training as well as the years of LMS experience. The second section is concerned with UTAUT constructs. This section comprises 25 positive statements divided into six subscales using a five-point Likert scale, based on LMS use in higher education. The last part elicits students' perception of the six usability variables, containing 31 positive statements.

Three thousand emails, providing a hyperlink the Web-based survey, were distributed to students in five public universities. Specifically, the online survey was employed to reach the wider population of the females' colleges as female students study in gender-segregated campuses. A total of 861 (28%) were returned and 256 (30%) questionnaires were incomplete and considered unusable due to the excessive missing data. Those instances had to be discarded before the process of data analysis. Besides, after the preliminary examination for outliers, normality and unengaged responses, 605 responses (20% response rate) were used for data analysis. The results indicated that males represent 46.1% (279 participants) and females 53.9% (326 participants).

IV. Data Analysis

This study employed the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach to test the measurement and structural model using SmartPLS 3 [43]. The multigroup analysis (MGA) technique was used to test the moderating effects. Many researchers emphasised the importance of using multigroup analysis using PLS-SEM technique, to analyse the effects of moderation across multiple relationships rather than standard moderation [14]–[16], [44], [45].

A. Measurement Model Assessment

1) Experience

The experience moderator was examined based on a nominal scale. Therefore the refinement strategies were not required [46]. The data were divided into low and high experienced users. The first step of analysis is to ensure construct reliability and validity, including construct reliability and construct convergent and discriminant validity [44]. Cronbach's Alpha (CA) is the measure for the internal consistency; the degree to which responses are consistent across items within variable [47]. The Composite Reliability (CR) is a more conservative measure of internal consistency reliability where varying factor loadings are taken under consideration [17]. The items in the composite reliability are weighted based on the constructs' indicators loadings so the reliability is higher than Cronbach's alpha [48]. In this research, the researcher ran the PLS algorithm for both groups and found all the items' ranges were acceptable except one item (AU2 "I have been using Blackboard regularly in the past" = 0.50) in the high experienced students' category, which did not conform to the standard factor reliability cut-off of .7 [46]. The researcher has decided to remove the AU2 indicator for both groups and re-estimate the model. The results of the PLS algorithm for students' e-learning experience is presented in Table I. As it can be observed from the data, for each construct, criteria of internal consistency reliability, composite reliability exceeded the threshold of 0.7 as suggested by [46], providing evidence of high reliability of the constructs. For the assessment of validity, all constructs in both groups have their Average Variance Extracted (AVE) greater than 0.5 as recommended by [46] and hence, convergent validity has been established.

TABLE I. THE MEASUREMENT MODEL ASSESSMENT FOR EXPERIENCE

Construct	High Experience			Low Experience		
	CA > 0.7	CR > 0.7	AVE > 0.5	CA > 0.7	CR > 0.7	AVE > 0.5
Actual Use (AU)	0.79	0.88	0.71	0.77	0.87	0.69
Behavioural Intention (BI)	0.90	0.95	0.81	0.91	0.95	0.82
Performance Expectancy (PE)	0.81	0.87	0.64	0.88	0.92	0.74
Social Influence (SI)	0.78	0.86	0.61	0.81	0.88	0.64
Effort Expectancy (EE)	0.88	0.92	0.73	0.91	0.94	0.79
Facilitating Conditions (FC)	0.79	0.85	0.53	0.80	0.86	0.56
Instructional Assessment (IA)	0.87	0.90	0.61	0.91	0.94	0.73
Information Quality (IQ)	0.91	0.95	0.77	0.91	0.95	0.78
System Learnability (SL)	0.85	0.89	0.62	0.88	0.93	0.71
System Navigation (SN)	0.84	0.89	0.61	0.85	0.89	0.63
Visual Design (VD)	0.91	0.93	0.70	0.91	0.94	0.72
E-learning System Interactivity (ESI)	0.86	0.90	0.70	0.91	0.93	0.78

CA: Cronbach's alpha, CR: composite reliability, AVE: average variance extracted

The values of the Fornell-Larcker discriminant validity for lower and higher experienced students are shown in Table III. Using the Fornell–Larcker criterion [49], the constructs share more variance with its assigned indicators than with any other construct, hence discriminant validity has been established for both sub-samples. Therefore, the measurement model assessment was successful for both high and low-experienced groups.

2) Training

The population sample was divided into trained and untrained users. Trained users are those who received LMS training and untrained students are those who had no previous training in the use of LMS. The trained students constituted 316 (52.2%) and untrained comprised 289 (47.8%). The investigation, therefore, proceeded with the other prerequisites of the MGA.

The results of the PLS algorithm for LMS training groups are illustrated in Table II. As can be observed from the data, criteria of internal consistency reliability, composite reliability and AVE, were satisfactory. Similarly, the assessment of compositional invariance (MICOM) was conducted using a permutation test. Results of MICOM represented a problem in the analysis that Social Influence (SI) and Facilitating Condition (FC) scores were significantly different from one which did not support the partial measurement invariance. Since these two variables (SI, FC) composites differ regarding their composition across the groups, the researcher eliminated the construct that did not achieve compositional invariance from both groups as suggested by Hair et al. [16] and Henseler et al. [44].

TABLE II. THE MEASUREMENT MODEL ASSESSMENT FOR TRAINING

Construct	Training Group			Untrained Group		
	CA > 0.7	CR > 0.7	AVE > 0.5	CA > 0.7	CR > 0.7	AVE > 0.5
Actual Use (AU)	0.750	0.844	0.578	0.745	0.840	0.572
Behavioural Intention (BI)	0.902	0.945	0.810	0.915	0.947	0.817
Performance Expectancy (PE)	0.837	0.891	0.673	0.839	0.893	0.677
Effort Expectancy (EE)	0.913	0.939	0.794	0.874	0.914	0.726
Instructional Assessment (IA)	0.903	0.940	0.723	0.887	0.914	0.641
Information Quality (IQ)	0.915	0.958	0.819	0.901	0.927	0.718
System Learnability (SL)	0.897	0.924	0.710	0.849	0.892	0.625
System Navigation (SN)	0.866	0.903	0.651	0.839	0.885	0.608
Visual Design (VD)	0.918	0.936	0.711	0.909	0.931	0.693
E-learning System Interactivity (ESI)	0.886	0.920	0.741	0.864	0.904	0.703

CA: Cronbach's alpha, CR: composite reliability, AVE: average variance extracted

The elements in the matrix diagonals, presented in Table IV, indicate the square roots of the average variance extracted. The diagonal bold values confirmed that all the AVEs are higher than any other correlation. Therefore, the discriminant validity of the constructs is established for both trained and untrained sub-samples.

TABLE III. FORNELL–LARCKER DISCRIMINANT VALIDITY FOR EXPERIENCE

Lower Experience Students												
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**	**VD**
AU	**0.833**											
BI	0.409	**0.908**										
EE	0.379	0.633	**0.890**									
FC	0.581	0.528	0.632	**0.748**								
IQ	0.455	0.665	0.599	0.600	**0.881**							
IA	0.522	0.525	0.495	0.645	0.807	**0.852**						
ESI	0.377	0.574	0.463	0.520	0.757	0.765	**0.881**					
SL	0.479	0.653	0.724	0.676	0.737	0.701	0.587	**0.844**				
SN	0.412	0.649	0.612	0.647	0.656	0.716	0.668	0.709	**0.791**			
PE	0.420	0.776	0.604	0.533	0.669	0.553	0.652	0.631	0.622	**0.858**		
SI	0.720	0.394	0.329	0.520	0.578	0.492	0.468	0.478	0.381	0.448	**0.798**	
VD	0.407	0.319	0.327	0.590	0.611	0.659	0.616	0.653	0.670	0.371	0.536	**0.848**
Higher Experience Students												
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**	**VD**
AU	**0.845**											
BI	0.608	**0.901**										
EE	0.474	0.484	**0.855**									
FC	0.527	0.559	0.582	**0.725**								
IQ	0.434	0.404	0.442	0.547	**0.879**							
IA	0.456	0.464	0.440	0.573	0.674	**0.783**						
ESI	0.364	0.525	0.346	0.465	0.528	0.611	**0.835**					
SL	0.537	0.500	0.672	0.679	0.658	0.553	0.522	**0.787**				
SN	0.478	0.481	0.563	0.618	0.530	0.541	0.538	0.720	**0.783**			
PE	0.567	0.700	0.457	0.516	0.532	0.511	0.465	0.504	0.447	**0.799**		
SI	0.539	0.532	0.424	0.563	0.474	0.466	0.385	0.486	0.453	0.545	**0.779**	
VD	0.414	0.379	0.496	0.535	0.571	0.574	0.524	0.686	0.677	0.337	0.365	**0.834**

TABLE IV. THE FORNELL-LARCKER DISCRIMINANT VALIDITY FOR TRAINING

Trained Students										
	AU	BI	EE	ESI	IA	IQ	PE	SL	SN	VD
AU	**0.760**									
BI	0.565	**0.900**								
EE	0.523	0.656	**0.891**							
ESI	0.453	0.588	0.481	**0.861**						
IA	0.549	0.570	0.594	0.727	**0.850**					
IQ	0.496	0.628	0.538	0.650	0.736	**0.905**				
PE	0.599	0.792	0.620	0.630	0.648	0.713	**0.821**			
SL	0.592	0.647	0.792	0.640	0.731	0.701	0.657	**0.842**		
SN	0.549	0.606	0.706	0.639	0.688	0.653	0.633	0.750	**0.807**	
VD	0.455	0.479	0.522	0.566	0.694	0.653	0.516	0.702	0.704	**0.843**
Untrained Students										
	AU	BI	EE	ESI	IA	IQ	PE	SL	SN	VD
AU	**0.757**									
BI	0.577	**0.904**								
EE	0.453	0.493	**0.852**							
ESI	0.323	0.479	0.340	**0.839**						
IA	0.442	0.472	0.487	0.620	**0.800**					
IQ	0.436	0.429	0.520	0.477	0.568	**0.847**				
PE	0.501	0.757	0.494	0.481	0.477	0.509	**0.823**			
SL	0.506	0.511	0.705	0.486	0.569	0.678	0.529	**0.791**		
SN	0.469	0.467	0.545	0.545	0.591	0.575	0.450	0.717	**0.780**	

VD	0.429	0.370	0.437	0.532	0.531	0.604	0.383	0.631	0.695	**0.832**

B. Structural Model Assessment

Table V presented path coefficients for each group, the explained variance (R^2) along with the test of differences between the sub-samples. Since the permutation test is non-parametric, two-tailed, more conservative, and recommended by researchers [15], [16], the researcher employed it in the analysis. Some relationships indicate a significant difference between the higher and lower users, evidenced by the p-value below 0.05 significant level. To start with, the relationship between behavioural intention and actual use is significantly different among higher experienced users ($\beta^{(1)} = 0.383$) versus those who are beginners ($\beta^{(2)} = 0.046$) with the path being significant in the higher experienced group but not in the beginners. Similarly, the effect of information quality on behavioural intention is significantly different between experienced students ($\beta^{(1)} = -0.166$) and beginner students ($\beta^{(2)} = 0.299$), with the path being significant in the experienced group but not in the beginner's category. Finally, the relationship between social influence and actual use is significantly ($p < 0.10$) different for experienced students ($\beta^{(1)} = 0.234$) versus less experienced users ($\beta^{(2)} = 0.570$). However, the relationship between social influence and actual use is significant for both advanced and novices' group. The other relationships of the model do not indicate a major difference between advanced and beginner groups.

TABLE V. THE MODERATING EFFECT FOR EXPERIENCE

Paths	High Experience		Low Experience		Test
	β	R^2	β	R^2	p-Values
BI -> AU	0.383		0.046		0.018
FC -> AU	0.181	0.447	0.258	0.559	0.610
SI -> AU	0.234		0.570		0.018
EE -> BI	0.108		0.039		0.686
ESI -> BI	0.227		0.040		0.330
FC -> BI	0.158		0.067		0.502
IA -> BI	-0.021		-0.164		0.377
IQ -> BI	-0.166		0.296		0.003
PE -> BI	0.489	0.582	0.415	0.66	0.628
SI -> BI	0.120		0.032		0.438
SL -> BI	-0.011		0.113		0.613
SN -> BI	0.029		0.300		0.183
VD -> BI	0.008		-0.276		0.080
VD -> BI	0.008		-0.276		0.080
EE -> PE	0.205		0.143		0.731
IQ -> PE	0.244		0.310		0.687
ESI -> PE	0.176		0.403		0.098
IA -> PE	0.174	0.392	-0.202	0.568	0.059
VD -> PE	-0.238		-0.260		0.901
SL -> PE	0.114		0.190		0.778
SN -> PE	0.088		0.228		0.550
IA -> EE	0.135	0.452	-0.141	0.558	0.114
ESI -> EE	-0.083		0.073		0.330
IQ -> EE	-0.060		0.248		0.114
SL -> EE	0.579		0.666		0.697
SN -> EE	0.102		0.181		0.698
VD -> EE	0.034		-0.329		0.046

Table VI illustrates the path coefficients for each training categories, the explained variance (R^2) along with the permutation p-value for both groups. It can be seen from the data in Table VI that the only moderating effect of training is the association between the information quality and performance expectancy. These relationships were significant. Nonetheless, trained students exhibited higher perceptions (β = 0.416) of the LMS information quality and its effect on the system usefulness than did the untrained counterpart (β = 0.196).

TABLE VI. THE MODERATING EFFECT FOR TRAINING

Paths	Trained Students		Untrained Students		Test
	β	R^2	β	R^2	p-Values
BI -> AU	0.565	0.318	0.577	0.331	0.843
EE -> BI	0.255		0.104		0.089
ESI -> BI	0.134		0.102		0.746
IA -> BI	-0.103		0.047		0.076
IQ -> BI	0.075	0.674	-0.076	0.601	0.088
PE -> BI	0.550		0.625		0.376
SL -> BI	0.029		0.047		0.879
SN -> BI	-0.002		0.078		0.407
VD -> BI	-0.010		-0.033		0.785
EE -> PE	0.275		0.211		0.514
ESI -> PE	0.200		0.246		0.606
IA -> PE	0.058		0.076		0.863
IQ -> PE	0.417	0.611	0.196	0.385	0.043
SL -> PE	-0.030		0.134		0.209
SN -> PE	0.092		0.010		0.477
VD -> PE	-0.098		-0.090		0.940
ESI -> EE	-0.101		-0.081		0.814
IA -> EE	0.115		0.149		0.728
IQ -> EE	-0.038	0.643	0.061	0.506	0.315
SL -> EE	0.698		0.605		0.368
SN -> EE	0.236		0.087		0.150
VD -> EE	-0.131		-0.077		0.601

V. DISCUSSION

A. Experience

The permutation test, presented in Table V, reveals that LMS experience moderated three relationships: BI -> AU, IQ -> BI and SI->AU. This is similar to the Ameen et al. [8] and Binyamin et al. [50] conclusion in which not much difference was found between students with low or high levels of LMS experience. Nonetheless, LMS experience has moderated the effect of BI on students usage behaviour of the LMS in Saudi Arabia. This is consistent with results obtained by Taylor & Todd [27] where the path from intention to usage behaviour was stronger for experienced users than for inexperienced users. The results are also in line with the findings of Sun & Zhang [13]. In contrast with UTAUT findings, the students with prior experience seem to be more motivated to use LMS than less experienced users [10]. The results also contradict the study of Venkatesh et al. [30] in which the behavioural intention effect on technology use was stronger with less experienced users. It may be that these participants benefitted more from the LMS, as PE->BI was stronger for experienced users than for the beginners, supporting previous findings of Tarhini, Hone, & Liu [51]. Besides, the EE->PE was significant in the advanced group only, indicating a greater inclination to system ease of use and this might add further insight to the students affirmed the intention to use LMS. This finding is in compliance with the Venkatesh & Bala [26]'s conclusion in which the influence of perceived ease of use on usefulness will be stronger with advanced users. Thus, with increasing experience, Saudi use of LMS appears to be more for pragmatic purposes, such as gains in efficiency and effectiveness. That eventually will reinforce the actual behaviour. Therefore, LMS experienced users utilize their prior experience to form their intentions so, the more experience students acquire in the use of LMS, the more the affirmation of the usage behaviour.

The experience also moderated the IQ -> BI relationship. It is an inverse relationship. This means that the quality of the content of the LMS, its relevancy, completeness and timeliness contents negatively impact the students' willingness to use the LMS. It is rather an unanticipated finding and it merits further exploration. The negative interaction of experience on the effect of IQ on BI could be interpreted such that, more experienced individuals possess stable perceptions about the LMS usefulness and ease of use irrespective of the LMS content. This then translated into affirmed intention to use the LMS. Another plausible explanation might be related to that highly experienced students might find that the information of LMS is overwhelming, discouraging them from using the system.

Finally, the relationship between social influence and actual use was moderated by experience. It is evident that the less experienced users of LMS tend to be more susceptible to referents' opinions and the effect did not attenuate with increased experience. The results in this investigation were consistent with those of other studies [10], [25] in which in the mandatory settings, social influence appears to be important only in the early stages of individual experience with the technology. A similar finding was demonstrated by Calisir, Altin Gumussoy, & Bayram [52] who asserted that less experienced respondents showed high social influence toward the individuals' intention to use the system ERP system in Turkey. Besides, it was demonstrated that the social influence effect on perceived usefulness and behavioural intention was weaker with increased hands-on experience on the system [26]. Therefore, our result is expected in Saudi higher education as students comply with other expectations, especially in the early stages of experience where students' opinions are relatively ill-informed.

Regarding the explained variance of the experience moderators, the results demonstrated that the shared variance in advanced group for AU, BI, EE, PE is 0.447 (45%), 0.582 (58%), 0.452 (45%) and 0.392 (39%) respectively. The less experienced student sample the explained variance for AU, BI, EE, PE is 0.559 (56%), 0.660 (66%), 0.558 (56%) and 0.568 (57%) respectively. As it can be seen, the proposed model explained more variance in the less experienced category. This is in agreement with a recent study in the Saudi context, where lower-level experienced usage behaviours were well predicted by the independent variables [50]. The results are in parallel with the semnial study of Taylor & Todd [27] which demonstrated that the inexperienced users' intentions were better predicted by the antecedent variables in the model than were the intentions of experienced users. This indicates a better model fit for younger students in the dependent variables AU, BI, EE, PE. A plausible explanation for this difference might be the fact that our study sample comprises students from newly established universities where LMS has been recently introduced, so the students might have been more encouraged to use the system. Changes of perceptions are anticipated as the individuals gained more experience and knowledge about the system [41].

B. Training

The results of the permutation algorithm, presented in Table VI, established that LMS training moderates a single relationship: the information quality influence on performance expectancy. The lack of support in other relationships might be explained by the fact that around half of the participants in the study sample did not receive any training in the use of the LMS. This was supported in the previous studies in which a number of researchers acknowledged the lack of training in the use of LMS in Saudi universities [12], [32], [33]. However, significant differences in the group-specific path coefficients were noted. The trained students exhibited higher perceptions of the LMS information quality and its effect on the system usefulness than did their untrained counterparts. These relationships were significant in both groups. This means that trained students found information in the LMS platform to be accurate, relevant, timely, sufficient and complete. Those attributes subsequently contribute to the system usefulness more than the effect on the untrained students. These findings are unsurprising as the training given about the use of LMS seems not only to improve the students' technical skills but also the related pedagogical knowledge (i.e. LMS content). This is consistent with previous research [41] in which some relationships were intensified over the course of the training.

Regarding the model's explanatory power. Overall, the model was able to account for a substantial part of the variances in students' acceptance decisions: 67% with training and 60% without training. In a comparison of the R^2 values of performance expectancy and effort expectancy, the trained model explained 61% of the variances for performance expectancy and 64% for effort expectancy. Whereas there was 39% for the variance of performance expectancy and 51% for the variance for effort expectancy in the untrained model. This is in line with the Hu et al. [41] finding in which the model's explanatory power appeared to increase over the course of the training. Clearly, the model's explained variances appeared to increase with the training, indicating the important moderation effect of training in the students' acceptance and use of LMS in Saudi higher education.

VI. Conclusion

This study investigated the impact of moderating effect on the students' use of LMS in Saudi higher education. Specifically, experience and training received variables were posited to affect the extended UTAUT model relationships. The findings revealed three relationships (BI -> AU, IQ -> BI and SI->AU) were impacted by experience whereas only IQ -> PE was influenced by the training given to the students. It can be deduced that the two demographic moderators have little impact on the students' use of LMS in Saudi higher education. Still, the study substantiates the students' demographic differences regarding path significance and intensity. Lecturers and administrators should pay more consideration to recognized differences between the groups. It is important to note that less experienced and trained students place more emphasis on the determinants of intention and usage behaviour, evidenced by the explained variance of each categories. University policymakers are expected to benefit from this research as to find an effective approach for e-learning system acceptance in an academic setting and eliminate any impediments to its implementation. That in turn will improve their future strategic initiatives of technology implementation considering the different groups of students preferences and the usability factors relevant to their use. Thus, a key policy priority should therefore be to enhance the strategic plan for e-learning systems implementation at universities.

Before drawing definitive conclusions from these results, it is important to consider the study's limitations. Firstly, this cross-sectional study analysed data at a specific point in time. Several lines of evidence suggest that longitudinal research is recommended in which the same students are observed over the study period. This would appreciate the time and the dynamics of students' usage behaviour. The students' perceptions and preferences about technology may change as they gain more experience in LMS so a continuous improvement of LMS is advised to address any issues and shortfalls. Secondly, apart from the intra-cultural context limitations, the scope of this study was limited to higher education in Saudi Arabia so the generalisation at a cross-cultural level is undetermined. Thus, it is desirable to include geographically distributed universities around the Gulf region which might improve the generalizability of our research outcomes. Thirdly, the current research targeted students' experience of the Blackboard system. So an issue that was not addressed in this study was whether other platforms e.g. Moodle and Desire2Learn would lead to similar conclusions. Students have different motivation and experience in using different types of platforms, thus, this would be a fruitful area for further work.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors have contributed to this work. Ahmed Alshehri conducted the research; Malcolm and Sally have proofread the paper and provided valuable feedback. All authors had approved the final version.

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The Effects of Gender and Age on Students' Use of a Learning Management System in Saudi Arabia

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***Abstract*—The success of an e-learning intervention relies, to a considerable extent, on the student's acceptance of the system. Still, the challenge for educational institutions is to determine the factors that influence the user's acceptance of a Learning Management System (LMS) particularly, the demographic variables of age and gender, which would allow for effective approaches to implementation. Therefore, this study aims to analyse the moderating effects of gender and age in the acceptance and use of an LMS. Furthermore, the study is located in a Saudi tertiary learning context where students have unique psychological and social characteristics and where LMS are being rolled out on a national level. To this end, the study utilised a UTAUT (Unified Theory of Acceptance and Use of Technology) model as a base model, with an additional six usability variables, to investigate empirically the variables that influence the students' use of an LMS in Saudi higher education. By using a quantitative research approach and a sample size of 605 students, data were collected from students in five Saudi universities. Partial Least Squares Structural Equation Modelling (PLS-SEM) in conjunction with multigroup analysis techniques were employed to assess the model. The findings revealed that both gender and age moderated a single association between the facilitating conditions and actual use where female and younger students exhibited higher perceptions of the association than did their counterparts. The research has several implications for decision-makers, administrators and designers of e-learning systems. In light of the study findings, the limitations and future research avenues were discussed.**

***Index Terms*—Demographics, Technology acceptance, UTAUT, LMS, E-learning system, Saudi Arabia.**

I. Introduction

The implementation and use of LMS is a topic of intense interest germane to emerging nations such as Saudi Arabia. An educational LMS is a common e-delivery medium within academic institutions, possessing robust capabilities for delivering online courses in distance learning as well as augmenting on-campus courses in blended learning [1], [2]. Educational institutions implement LMSs such as Blackboard to administer their curricula with various types of functionalities, such as announcements, discussion boards, online assessment and document sharing. In Saudi Arabia, most universities are equipped with the Blackboard system as the main application for learning and teaching. A recent statistic indicated that the Blackboard system is by far the most prevalent LMS in Saudi higher education used by 90% of kingdom public universities [3]. Nonetheless, having access to an LMS does not necessarily mean that effective learning has occurred [4]. Despite the apparent usefulness, the issue of effective use of an LMS is an intriguing one [4]. The efficiency of LMSs will not be fully utilised if the students are not inclined to accept and use the system [5]. In fact, the decisions about the integration of LMS into universities are often at a higher management level. Yet, it is the individual adoption patterns that illustrate successful implementation [6]. Therefore, understanding the individuals' demographic differences can lead to a more favourable environment for greater adoption, as well as enhance the students' learning experience.

A survey of prior literature on moderators has not been addressed in existing works on e-learning in Saudi Arabia [7]–[9]. It is established that moderating factors have profound effects on user technology acceptance [10]. However, the influence of moderating effects on the LMS use might be different from the more developed nations such as the US and Europe. In the UTAUT model, the amalgamation of the core constructs and the moderating inputs have improved the predictive efficiency to 70% of the variance in behavioural intention to use technology [11]. Agarwal and Prasad [12] also explicitly criticized the absence of moderating influences in the Technology Acceptance Model (TAM). They called for more research that examines the moderating effect on the use and perception of an Information System (IS) [12]. As an illustration, when including gender as a moderating variable, the explanatory power of TAM increases to 52% compared to approximately 35% without moderators [10]. Demographic variables such as age and gender have been reported as salient moderators in technology acceptance [13]. Therefore, the present research explores the effects

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of moderating effect: age and gender in the use of LMS in Saudi tertiary education.

Saudi Arabia has many valid motives to encourage the implementation and use of LMS as a means to create an effective learning environment. Saudi Arabia, among many developing countries, has been characterised by distinct cultural traditions that are different from the West [13]. As an illustration, Saudi Arabian education is gender-segregated, both in primary and higher education. Males usually have more chances to enrol in many more available educational areas than women. Engineering education for females is deficient in Saudi Arabia and the study is typically restricted to medical science, education, humanities, natural science and Islamic studies [14], [15].

Besides, the Saudi population growth must be addressed to understand the potential of investigating the influence of the age variable in online learning. The latest statistics disclosed that the population growth rate is high and has reached more than 33.4 million [16]. It is important to mention that young people constitute the overwhelming majority of the Saudi population. In fact, a recent statistical analysis shows that the Saudi population under 20 grew by 52.88% over the last ten years [16]. A surge in Saudi students has been observed in the latest statistics. In general, the effect of age has not been treated in much detail, particularly within technology acceptance models [10], [17]. Nonetheless, as can be observed, the factor of age is considered important, especially in Saudi higher education.

As age and gender play a significant role in Saudi higher education, their moderating effects on the model relationships have been explored as main themes within this paper.

II. Theoretical Model

The UTAUT model has been extended with six usability attributes to measure students' behavioural intention and actual use of an LMS in Saudi higher education. The selection of the UTAUT framework was due to its comprehensiveness and powerful explanatory power [9]. Furthermore, the presence of demographics moderators in the UTAUT framework has added another significant value to the model. It is now well established from a variety of studies that usability attributes and user acceptance variables are essential to the uptake of a given technology [18], [19]. In this research, the UTAUT model was extended with six usability dimensions namely: system navigation, system learnability, visual design, information quality, instructional assessment and system interactivity. These six usability variables have been validated extensively in prior studies in the domain of usability, e-learning and educational technologies [20]–[22]. Along with that, the two moderators of students' gender and age were posited to influence all the model relationships. In this endeavour, the focus is on the influence of the moderating effect of student age and gender on the model relationships. The proposed model is depicted in Fig. 1.

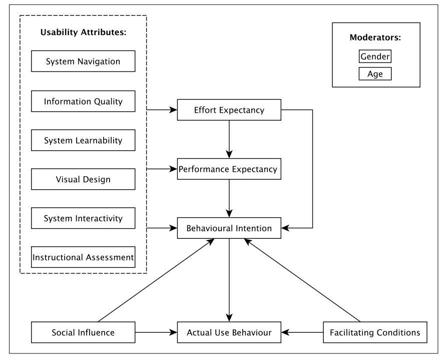

Figure 1. The proposed model

A. *Gender Moderating Effect*

Many researchers have acknowledged the role of gender in predicting the individual usage behaviour of technology [5], [11], [23]. Prior research has demonstrated that males and females are different in their decision-making processes, so their differences in perceptions of system usefulness and ease of use are evident in technology acceptance [24], [25]. For instance, it was found that men seem to utilize computers more than women [26]. A key study comparing male and female students' perceptions of information technology is that of He and Freeman [27], in which they found that females feel less confident with computers because they have learned less and practised less, and feel more anxious about using computers when compared with male counterparts. In the UTAUT model, gender significantly moderates the influence of the UTAUT independent variables on the behavioural intention to use technology [11]. The prior research on gender has shown that males tend to be more task-oriented than females [11], thus , placing more emphasis on work, accomplishment and rank whereas women seem to place more importance on the social influence, being more expressive, more aware of others' feelings, and more compliant compared with men [24]. As an illustration, performance expectancy is found to be significant in males as they are motivated by achievement needs whereas females are more concerned with effort expectancy aspects in the technology adoption and use [11]. Concerning social influence, females tend to be more sensitive to others' opinions, so the peer influence and affiliation needs are more salient to women in the study of technology adoption and use [11]. In fact, the explanatory power of the TAM model increased considerably at 52% when gender was included as a moderator [10], [11].

Gender differences also occur across cultures [10], [28]. This is evident in the Arab cultures as it was shown that women tend to be less powerful and less independent than men [29], and they are more reserved [30]. Women have fewer chances of obtaining a job, with historically less participation in the labour force, so the gender divide was expected to moderate in the Arab world [30]. There are also variations between males and females in the use of technology. In an investigation into technology usage among Saudi Arabian undergraduate students, Alothman et al., [31] found that location and gender influences the duration of the use of technology: students in small towns spend less time on technology compared with their counterparts in the capital city. The study also revealed that the use of computers or laptops at university is considerably less than at home. Students spent only four hours per week using computers or laptops at university and some female colleges forbid their students' to bring and use laptops and smartphones [31]. Similarly, Al-Harbi [32] concluded that Saudi male students like to use an e-learning system more than female students. Still, the influence of gender role in technology acceptance is far from conclusive [27], [33], and even less in relation to e-learning systems [25] This study postulates that:

H1: Gender will moderate all relationships in the proposed model.

B. Age Moderating Effect

Literature has shown that age is an important factor in technology and acceptance research [5], [11], [17]. The age has exhibited a moderating effect on behavioural intention and use of a technology [11], [26]. In the UTAUT model, Venkatesh et al., [11] reported that age showed a substantial moderation in the relationship between performance expectancy, facilitating conditions and behavioural intention. As an illustration, younger age groups appear to be more willing to adopt and use the system than older groups. In contrast, increased age was associated with difficulties in processing complex tasks and allocating attention to content [11]. Likewise, the relationship between effort expectancy, social influence and the behavioural intention was stronger for older employees in technology acceptance and use [11]. In England, age was found to moderate the relationship between perceived ease of use, perceived usefulness, self-efficacy and behavioural intention [5]. However, no differences were detected in terms of social influence on behavioural intention to use an LMS [5]. Khechine et al., [34] conducted a UTAUT study of the effects of moderators gender and age, on the acceptance of a Webinar system in a blended learning course. They found that age had a salient moderating influence on intention while gender did not. In a similar line of evidence, Chawla & Joshi [35] discovered that students aged 25 and under have a more favourable perception of e-learning systems than those over 25. However, the study of Julie, Becker, & Newton [36] has been unable to demonstrate the effect of age on users' intention and satisfaction with an e-learning system in an Australian organisational context. In Saudi higher education, the age variable was demonstrated to influence the utilization of the Jusur LMS [37]. Nonetheless, research on the subject has been mostly restricted to limited contexts other than Saudi Arabia. Overall, there remain questions as to whether the age variable has an influence on the students' use of LMS in Saudi higher education. Hence, it is hypothesised

H2: age will moderate all relationships in the proposed model.

III. Methodology

The target sample for this study was taken from students in Saudi higher education. The researcher targeted students in Saudi higher education from geographically dispersed universities. Due to the large sample frame of Saudi students, a sampling technique was necessary. Hence, the study approaches this concern using a multi-stage cluster sampling technique as suggested by [38].

Quantitative research in the form of an online questionnaire-based survey was performed to test the hypotheses. The instrument was divided into three main sections. The first section included information about the respondents' characteristics. In this section, the students select their gender identity and insert their age. In consideration of the cultural context of Saudi Arabia, the decision was taken to offer only a binary male/ female response for the gender question. The second section is concerned with UTAUT constructs. This section comprises 25 positive statements divided into six subscales using a five-point Likert scale, based on LMS use in higher education. The last part elicits students' perception of the six usability variables, containing 31 positive statements.

Three thousand emails, providing a hyperlink the Web-based survey, were distributed to students in five public universities. Specifically, the online survey was employed to reach the wider population of the female colleges as female students study in gender-segregated campuses. A total of 861 (28%) were returned and 256 (30%) questionnaires were incomplete and considered unusable due to the excessive missing data. Those instances had to be discarded before the process of data analysis. After the preliminary examination for outliers, normality and unengaged responses, 605 responses (20% response rate) were used for data analysis. The results indicated that males represent 46.1% (279 participants) and females 53.9% (326 participants).

IV. Data Analysis

This study employed the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach to test the measurement and structural model using SmartPLS 3 [39]. The multigroup analysis (MGA) technique was used to test the moderating effects. Many researchers emphasise the importance of using multigroup analysis using PLS-SEM technique, to analyse the effects of moderation across multiple relationships rather than standard moderation [40]–[42].

A. Measurement Model Assessment

1) Gender Moderator

The gender moderator was examined based on a nominal scale. Therefore the refinement strategies were not required [43]. The first step was to assess the measurement model for male and female groups. In this study, males represent 46.1% (279 participants) and females 53.9% (326 participants). The researcher began with the measurement model and structural model analyses.

Table I provides the summary statistics of the measurement model for male and female subpopulations. The analysis of male and female groups indicate that all constructs achieved composite reliability values of .7 and higher. Moreover, all Average Variance Extracted (AVE) values exceeded the recommended value of 0.50. In terms of factors loadings, all indicators exhibit loading above 0.70 except the AU2 for both male (0.554) and female (0.602) subsamples. However, Hair et al. [44] recommended that items with factor loadings between 0.4 to 0.7 should be removed only when removal leads to an increase in the composite reliability or in the average variance extracted above the cut-off value [44]. Also it is suggested to retain item loadings above .5 in exploratory research [43]. Hence, these items were retained for further multigroup analysis.

Regarding the convergent validity for each group, the AVE values for each construct, presented in Table I, exceeded the cut-off of 0.50 as recommended by Fornell and Larcker [45]. The results confirm that all loadings of the measurement model are highly significant as required for convergent validity (see Table I). Hence, adequate evidence of convergent validity is established.

TABLE I. THE MEASUREMENT MODEL ASSESSMENT FOR GENDER GROUPS

	Female Group			Male Group		
Construct	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
Actual Use (AU)	0.758	0.848	0.587	0.728	0.829	0.554
E-learning System Interactivity (ESI)	0.897	0.949	0.822	0.855	0.898	0.689
Behavioural Intention (BI)	0.928	0.949	0.822	0.918	0.942	0.803
Effort Expectancy (EE)	0.913	0.939	0.793	0.878	0.916	0.732
Facilitating Conditions (FC)	0.813	0.868	0.570	0.771	0.833	0.502
Instructional Assessment (IA)	0.917	0.935	0.707	0.897	0.921	0.662
Information Quality (IQ)	0.940	0.954	0.807	0.909	0.932	0.732
System Learnability (SL)	0.870	0.906	0.659	0.882	0.914	0.681
System Navigation (SN)	0.861	0.899	0.642	0.846	0.891	0.621
Performance Expectancy (PE)	0.85	0.899	0.692	0.821	0.882	0.654
Social Influence (SI)	0.776	0.855	0.597	0.772	0.854	0.595
Visual Design (VD)	0.921	0.939	0.72	0.905	0.928	0.682

CA: Cronbach's alpha, CR: composite reliability, AVE: average variance extracted

2) Age Moderator

TABLE II. THE MEASUREMENT MODEL ASSESSMENT FOR AGE GROUPS

	Senior Age Group			Young Age Group		
Construct	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
Actual Use (AU)	0.777	0.871	0.693	0.744	0.854	0.662
E-learning System Interactivity (ESI)	0.893	0.924	0.753	0.863	0.904	0.703
Behavioural Intention (BI)	0.925	0.947	0.817	0.920	0.944	0.807
Effort Expectancy (EE)	0.880	0.918	0.736	0.907	0.935	0.783
Facilitating Conditions (FC)	0.813	0.867	0.566	0.776	0.843	0.520
Instructional Assessment (IA)	0.918	0.936	0.710	0.897	0.921	0.661
Information Quality (IQ)	0.926	0.944	0.773	0.928	0.945	0.776
System Learnability (SL)	0.889	0.919	0.693	0.864	0.902	0.650
System Navigation (SN)	0.862	0.895	0.63	0.853	0.895	0.631
Performance Expectancy (PE)	0.820	0.881	0.651	0.852	0.900	0.693
Social Influence (SI)	0.757	0.846	0.580	0.788	0.862	0.609

CA: Cronbach's alpha, CR: composite reliability, AVE: average variance extracted

In this research, age was coded as a continuous variable, in compliance with previous studies [11], [24]. It has been suggested that when a metrically scaled variable is used, it should be transformed into a categorical variable ("high" and "low") [42]. The transfer can be created using median splits based on simulation studies as suggested in [46]. Other researchers also recommended using median splits on the variable measured on a continuous scale to create groups for comparison of the moderator's effects [42], [47]. Hence, using the median-split procedures (median = 21), the data were divided into two age groups; younger age (281) and senior age (324) groups. The younger age group is undergraduates aged between 17 and 21 years old. The senior age group is the students whose age is 21 and over. It has been stated that the validity of variables, including, construct reliability, construct validity and indicator loadings remain a requirement for all group estimations [48]. In this study, the researcher ran the PLS algorithm for both younger and senior age groups and found all the item ranges were acceptable except one item (AU2 "I have been using Blackboard regularly in the past" = 0.35) in the younger group, which did not conform to the standard factor reliability cut-off of .7 and above. That also affected the actual use's Cronbach's Alpha and the researcher had to delete the AU2 indictor for all groups and re-estimate the model. Similarly, the assessment of compositional invariance was conducted using a permutation test. Results of MICOM represented a problem in the analysis that the visual design score was significantly different from one which did not support the partial measurement invariance. In short, measurement invariance (measurement equivalence) refers to whether measurement operations yield measures of the same attribute. Since visual design composites differ regarding their composition across the groups, the researcher eliminated the construct that did not achieve compositional invariance from both groups as suggested by Hair et al. [40] and Henseler et al. [48].

The PLS algorithm and permutation test were repeated for both age groups. Table II illustrates the measurement model results for senior and younger age groups. As can be seen from the Table II, the results indicated that all Cronbach's Alpha, composite reliability and average variance extracted for the models of both groups were satisfactory.

In recent years, there has been an increasing amount of literature on IS which used only the criterion of Fornell-Larcker for reporting the discriminant validity [49]. Thus, the constructs' discriminant validity for both male and female groups was assessed using the Fornell-Larcker criterion [45]. The elements in the matrix diagonals, presented in Table III indicate that for all the constructs, AVE is greater than its squared correlation with other constructs. Hence, discriminant validity is established for male and female subpopulations. Overall, these results provide clear support for the measures' reliability, and discriminant and convergent validity of the constructs.

Similarly, Table IV showed that the levels of square root of the AVE for each construct is greater than the correlation involving the constructs for young and senior age groups [44]. Hence discriminant validity has been established for both groups. Based on these results, the construct validity, evidenced by convergent and discriminant validity, have been established.

TABLE III. THE FORNELL-LARCKER CRITERION FOR MALE AND FEMALE

Male Students												
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**	**VD**
AU	**0.744**											
BI	0.573	**0.896**										
EE	0.404	0.541	**0.855**									
FC	0.494	0.532	0.593	**0.709**								
IQ	0.452	0.546	0.543	0.554	**0.856**							
IA	0.429	0.549	0.531	0.575	0.623	**0.814**						
ESI	0.380	0.59	0.423	0.485	0.572	0.695	**0.830**					
SL	0.511	0.574	0.733	0.666	0.703	0.643	0.550	**0.825**				
SN	0.449	0.548	0.620	0.599	0.617	0.637	0.607	0.762	**0.788**			
PE	0.528	0.756	0.507	0.51	0.599	0.56	0.559	0.570	0.541	**0.809**		
SI	0.560	0.486	0.359	0.502	0.444	0.424	0.418	0.466	0.466	0.536	**0.772**	
VD	0.428	0.463	0.500	0.505	0.671	0.638	0.549	0.655	0.698	0.473	0.459	**0.826**
Female Students												
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**	**VD**
AU	**0.766**											
BI	0.568	**0.907**										
EE	0.551	0.619	**0.890**									
FC	0.610	0.594	0.647	**0.755**								
IQ	0.479	0.533	0.518	0.595	**0.899**							
IA	0.561	0.506	0.557	0.656	0.697	**0.841**						
ESI	0.416	0.491	0.409	0.547	0.58	0.671	**0.873**					
SL	0.594	0.605	0.779	0.718	0.684	0.678	0.59	**0.812**				
SN	0.561	0.535	0.645	0.711	0.618	0.647	0.585	0.763	**0.801**			
PE	0.568	0.792	0.609	0.611	0.64	0.578	0.564	0.631	0.551	**0.832**		
SI	0.628	0.536	0.447	0.527	0.54	0.531	0.395	0.52	0.421	0.553	**0.772**	
VD	0.464	0.401	0.468	0.576	0.607	0.609	0.558	0.68	0.701	0.442	0.386	**0.849**

TABLE IV. THE FORNELL-LARCKER DISCRIMINANT VALIDITY FOR AGE GROUPS

Young Age											
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**
AU	**0.814**										
BI	0.558	**0.898**									
EE	0.503	0.590	**0.885**								
FC	0.610	0.618	0.611	**0.721**							
IQ	0.410	0.570	0.532	0.541	**0.881**						

IA	0.504	0.570	0.555	0.635	0.641	**0.813**					
ESI	0.370	0.568	0.408	0.523	0.573	0.667	**0.839**				
SL	0.516	0.626	0.775	0.624	0.661	0.659	0.563	**0.806**			
SN	0.470	0.585	0.636	0.676	0.593	0.641	0.592	0.772	**0.794**		
PE	0.567	0.815	0.594	0.625	0.644	0.604	0.590	0.629	0.576	**0.833**	
SI	0.617	0.529	0.404	0.515	0.469	0.479	0.387	0.472	0.378	0.564	**0.781**
Senior Age											
	AU	**BI**	**EE**	**FC**	**IQ**	**IA**	**ESI**	**SL**	**SN**	**PE**	**SI**
AU	**0.830**										
BI	0.580	**0.900**									
EE	0.460	0.560	**0.860**								
FC	0.500	0.520	0.640	**0.750**							
IQ	0.520	0.510	0.530	0.620	**0.880**						
IA	0.490	0.490	0.540	0.610	0.690	**0.840**					
ESI	0.420	0.500	0.420	0.520	0.580	0.700	**0.870**				
SL	0.560	0.550	0.740	0.690	0.720	0.660	0.570	**0.830**			
SN	0.520	0.480	0.630	0.650	0.640	0.650	0.590	0.680	**0.790**		
PE	0.550	0.710	0.520	0.510	0.600	0.540	0.530	0.570	0.510	**0.810**	
SI	0.620	0.530	0.420	0.530	0.530	0.480	0.430	0.520	0.520	0.550	**0.760**

B. Structural Model Assessment

1) Gender Moderator

Since the results support partial measurement invariance, the standardized path coefficients differences across both groups can be computed with confidence using a multigroup analysis [40], [48]. Since the permutation test is non-parametric, two-tailed, more conservative, and recommended by researchers [40], [50], the researcher employed them in the analysis. The results obtained from the permutation test, summarised in Table V show the path coefficient for male and female, followed by the coefficient of determination (R squared) and the final column represent the permutation p-value. It can be seen from the data that most structural model relationships do not differ between male and female subsamples. The only exception is the correlation between the facilitating conditions and actual use which showed a statistical difference between the two groups at 0.05 significance level. This is evident by the permutation p-value of 0.04. Females exhibited higher perceptions (β = 0.302) of facilitating conditions to use the e-learning system than did their male counterparts (β = 0.154).

In Table V, the R^2 values were communicated. For the males group, the R^2 values of AU, BI, EE, PE were 0.442 (44%), 0.626 (62%), 0.542 (54%) and 0.457 (46%) respectively. For the females group, the R^2 values for AU, BI, EE, PE were 0.519 (52%), 0.662 (62%), 0.624 (62%) and 0. 0.545 (55%) respectively. There is a clear indication that females explain more variance compared to their male counterparts.

TABLE V. THE MODERATING EFFECT FOR GENDER

Paths	Female		Male		Test
	β	R^2	β	R^2	p-Values
BI -> AU	0.191	0.519	0.336	0.442	0.083
FC -> AU	0.302		0.154		0.044
SI -> AU	0.368		0.32		0.565
EE -> BI	0.168	0.662	0.134	0.626	0.693
IA-> BI	-0.069		-0.01		0.501
ESI -> BI	0.053		0.192		0.159
FC -> BI	0.08		0.069		0.872
IQ -> BI	-0.044		-0.014		0.745
SL -> BI	-0.001		0.024		0.835
SN -> BI	0.05		0.015		0.705
PE -> BI	0.605		0.528		0.38
SI -> BI	0.113		0.044		0.309
VD -> BI	-0.03		-0.024		0.938
VD-> PE	-0.11	0.545	-0.078	0.457	0.745
EE -> PE	0.329		0.143		0.057
IQ -> PE	0.335		0.287		0.678
IA-> PE	0.021		0.113		0.39
SN -> PE	0.012		0.078		0.58
SL -> PE	0.055		0.064		0.94
ESI -> PE	0.243		0.217		0.768
SN -> EE	0.139	0.624	0.154	0.542	0.89
SL -> EE	0.77		0.589		0.076
IA-> EE	0.137		0.108		0.762
IQ -> EE	-0.03		0.038		0.488
ESI -> EE	-0.116		-0.061		0.535
VD -> EE	-0.154		-0.056		0.326

2) Age Moderator

Having established configural and compositional invariance, it is important to compare the path coefficients of young and senior groups using a permutation technique. In Table VI, the results of path coefficients of both groups were presented. As it can be seen, most structural model relationships were insignificant, as most of the p values are considerably larger than 0.05 with a single exception: the relationship between facilitating conditions and actual use behaviour of the LMS, which differ significantly on p.value < 0.05. The relationship between facilitating conditions and the actual use is significantly different among young students ($\beta^{(1)} = 0.319$) versus those who are senior ($\beta^{(2)} = 0.139$).

It can be concluded that the freshman and sophomores have more tendency to use LMS if the universities provide proper support to use the system more than the senior students.

In Table VI, the R^2 values were presented. For the young group, the R^2 values of AU, BI, EE, PE were 0.508 (51%), 0.704 (70%), 0.606 (61%) and 0.550 (55%) respectively.

For the senior group, the R^2 values for AU, BI, EE, PE were 0.477 (48%), 0.572 (57%), 0.553 (55%) and 0. 0.437 (44%) respectively. As can be seen, the young students' explained variances of the outcomes outperformed the senior students and the R^2 values for the young students' model appeared to range between medium and high.

TABLE VI. THE MODERATING EFFECT FOR AGE

Paths	(Young_Age)		(Senior_Age)		Test
	β	R2	β	R2	p.value
BI -> AU	0.167	0.508	0.308	0.477	0.097
FC -> AU	0.319		0.139		0.016
SI -> AU	0.365		0.379		0.871
EE -> BI	0.082	0.704	0.231	0.572	0.094
PE -> BI	0.632		0.474		0.068
SI -> BI	0.062		0.149		0.187
FC -> BI	0.067		0.054		0.870
IQ -> BI	-0.038		-0.026		0.901
ESI -> BI	0.086		0.135		0.609
SL -> BI	0.028		0.013		0.904
IA-> BI	-0.024		-0.038		0.865
SN -> BI	0.066		-0.067		0.144
ESI -> EE	-0.117	0.606	-0.084	0.553	0.711
IA-> EE	0.106		0.14		0.718
SL -> EE	0.681		0.642		0.696
IQ -> EE	0.023		-0.061		0.405
SN -> EE	0.097		0.123		0.799
SN -> PE	0.023	0.550	-0.02	0.437	0.693
SL -> PE	0.041		0.06		0.889
IQ -> PE	0.278		0.308		0.790
EE -> PE	0.257		0.210		0.653
IA-> PE	0.088		0.039		0.635
ESI -> PE	0.231		0.211		0.827

V. DISCUSSION

A. Gender Moderator

The standardized path coefficient differences between males and females show that most structural model relationships do not differ between male and female subsamples with one exception: the facilitating conditions effect on actual use. It is somewhat surprising that in this research no other significant relationships were noted in Saudi higher education, as females are separate in terms of education and location. The results overlap with several e-learning studies in which male and female students are equally motivated to use an LMS [25], [51]–[54].

The results indicate, however, that gender moderated the FC->AU path and is significant for male and female sub-groups. The female group exhibited a stronger effect (β = 0.302) than did their male counterpart (β = 0.154). In line with this, the Alshehri et al. [55] study (using a different data set) found that facilitating condition was the highest path coefficient that affected the LMS use in Saudi higher education (β = 0.511). In tandem with our results, the gender differences were found to have an impact on technology acceptance where women place more emphasis on facilitating conditions, which was more pronounced with increasing age [56]. Besides, Kibelloh & Bao [57] focused on the female perceptions of e-learning system and revealed key concerns regarding the poor and costly internet connectivity in developing countries. This outcome is compatible with that of Ameen [30] who found that gender was insignificant in moderating the effect of FC on AU to use a mobile phone in three Arabian countries, Iraq, Jordan and United Araba Emirates (UAE). This can be interpreted by the cultural influence of gender segregation; where females' segregated colleges are more demanding of organisational resources (e.g. technological support and technical ICT infrastructure) to support the use of LMS in Saudi higher education. Females have dispersed campuses and the availability of support might be limited. In the context of the study, some universities might not have the appropriate ICT infrastructure, especially those who were recently established, so female students might find limited avenues for help and support at the universities' campuses.

Regarding the explained variance for gender, the female group model accounted for 52% of the variance in actual use behaviour, and 62% for behavioural intention compared with 44% for usage behaviour and 62% for the behavioural intention to use. Similarly, in the female sub-sample, 62% of the variability in the effort expectancy variable is explained the predictors and 55% of the variability in the performance expectancy construct is explained by the predictors (refer to Table V). There is a clear indication that females explain more variance compared to their male counterparts. Thus, females exhibited more variance in the dependent variables than males. This is in line with the study of [23], [51] in which the female group explained more variance than males in the acceptance of mobile learning.

In this regard, universities should create strategies for ongoing enhancement of their LMS organizational and technical infrastructure to support the learners' use of the system, especially for female colleges. Services such as online support, response time, training provided and resource availability have been suggested as fundamental to successful e-learning implementation [58], [59].

B. Age Moderator

As it can be seen in Table VI, the age moderating variable did not affect the young and senior population except for one path: facilitating conditions on actual use. The moderating factor of age did not moderate most of the relationships in the model. This is consistent with the Ameen et al. [53] study in the Iraqi context. Similarly, the age moderating effect did not play an important role in the relationships between the psychological constructs of the UTAUT model and the intention to use a technology in Saudi Arabia higher education [60]. Likewise, Altawallbeh, Thiam, Alshourah, & Fong [61] demonstrated that age does not moderate the students' acceptance and use in Jordanian universities. Similar results were concluded by Baker et al. [13] where age and gender were non-significant in the IT adoption in their Saudi Arabian sample. Overall and considering the single moderating effect, the results could be attributed to an increasing awareness of LMS among students, no matter their age group.

FC->AU is the only path coefficient where the p.value is less than 0.05. The influence of FC on AU is significant for both groups. However, the relationship is significantly different among young students ($\beta^{(1)} = 0.319$) versus those who are senior ($\beta^{(2)} = 0.139$). Considering the system usage behaviour, the age attribute was more significant for older workers with more experience [11], [24]. Nonetheless and unlike our results, age moderated all of the key relationships in the Venkatesh's UTAUT model [11]. Age was shown to affect the willingness of students to use an LMS [34]. In this research and similar to the gender moderator, it is evident that young students are more focused on the available IT support and infrastructure (FC) than older students. A possible explanation for these results may be the lack of adequate support and poor Internet access, especially in the newly established universities, as confirmed in the previous studies in Saudi education [62], [63]. As most of the respondents are undergraduates, young students may require more IT support and available Internet access based on higher expectations, especially in the recently established universities. Furthermore, it seems possible that these results are due to the lack of training on LMS platforms. The descriptive statistics showed that the majority of students had no previous training in the use of LMS (47.8%). Thus young students might be more in need of LMS training at the universities campuses.

Regarding the explained variances' differences, the R^2 values of the young group AU, BI, EE, PE was (51%), (70%), (61%) and (55%) respectively. The percentages of 48%, 57%, 55%, 44% accounted for AU, BI, EE, PE in the senior group respectively. Thus, the young students outperformed the senior group, meaning a better model fit for younger students in the dependent variables AU, BI, EE and PE. Similar conclusion was reached by Chawla & Joshi [35].

The impact of social influence on intention was significant for older students, which is consistent with previous research [11], [24]. This implies that senior Saudi students place more importance on the opinion of others in the use of LMS, in which social influences change over time. This indicates its important role in driving behaviour in Saudi education. Overall, the senior model has more statistically significant relationships in the model, indicating the LMS implementation might have more significance for mature students (refer to Table VI).

VI. Conclusion

The present study was designed to determine the effects of gender and age on the students' acceptance and use of LMS in Saudi universities. The results have shown that both gender and age moderating variables affected only one path: the facilitating conditions on actual use. These findings suggest that in general, the gender and age, that have been reported to be significant in other cultural settings e.g. [11], were found to be less significant in the Saudi Arabian sample. It might be that the recent fast changes associated with the vision 2030 [64], has created a more LMS-friendly environment in Saudi universities. In light of the evident need to focus on education, the effect of vision 2030 on the equality of access to education has begun to materialise. The initiative emphasised that the demand and focus on the quality of education should be set out to ensure that all students, with different age and gender, would be equipped with the required skills and knowledge to compete in the globalised society [64].

These findings have significant implications for the universities' management regarding future LMS policy. System designers and administrators may now have a better understanding of the age and gender-related differences on students' use of LMS, specifically in a Saudi context where students have unique psychological and social characteristics. Possibly, a key policy priority should therefore be to enhance the strategic plan for e-learning system implementation at universities, considering the effect of age and gender on the students' use of LMS. Whilst this study did confirm only a single moderation (FC->AU), it did partially substantiate the students' demographic differences regarding path significance and intensity. There is a clear indication that the predictors have more effect on the female and senior subsample's outcomes, as evidenced by the more statistically significant relationships in the female and senior groups. This means that LMS implementation and use might have more significance for female and mature students.

The generalisability of these results is subject to certain limitations. The scope of this study was limited in terms of using a quantitative methodological approach. The study was grounded on the inquiry-based survey to collect data from the target population. Even though the survey method is the most common approach used in technology acceptance and usability research, more information derived from qualitative methods (e.g. interviews and focus groups) would also help to establish an in-depth understanding of the research problems and the surrounding issues towards students' attitudes and perceptions. Likewise, this study focused on the students' perspective, a natural progression of this work would be to involve other e-learning stakeholders (teachers and administrators). This could enrich the research by providing a better understanding of other issues, offering different views about the implementation and use of an e-learning system in Saudi Arabia.

There are two suggested directions for further studies: firstly, to increase the scope and cover data from a larger student population (e.g. private institutions), with different demographic characteristics such as income, cultural aspects and level of education. A second direction might be to consider other technological attributes such as other system functionalities, service qualities e.g. privacy, to investigate their effects on the students' use of LMSs. This is expected to add valuable insights to inform decision-making processes at university higher management and administrative level.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors have contributed to this work. Alshehri conducted the research; Malcolm and Sally have proofread the paper and provided valuable feedback. All authors had approved the final version.

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THE EFFECTS OF UTAUT AND USABILITY QUALITIES ON STUDENTS' USE OF LEARNING MANAGEMENT SYSTEMS IN SAUDI TERTIARY EDUCATION

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ABSTRACT

Aim/Purpose	This study proposes a theoretical framework that amalgamates Unified Theory of Acceptance and Use of Technology (UTAUT) variables with usability metrics to investigate the impact on students' intention and use of the Learning Management System (LMS) in Saudi higher education.
Background	There is a dearth of academic research on Saudi higher education to examine the effects of usability factors on students use of LMSs, so significant issues have not yet been examined.
Methodology	Based on survey data from 605 respondents, the Partial Least Squares Structural Equation Modelling (PLS-SEM) technique was employed to assess the model.
Contribution	The findings of the study may help colleges and universities to gain insights into the best way to promote e-learning system perceived usefulness and acceptance among students.
Findings	The results confirmed that the UTAUT parameters are valid and robust in the context of LMS in Saudi Arabia. The dimension of social influence emerged to significantly influence the students' intention and usage behaviour. The performance expectancy was affected by information quality and the system interactivity whereas the effort expectancy was influenced by system navigation, system learnability, and instructional assessment. The usability feature of

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	interactivity was also demonstrated to influence students' willingness to use the system.
Recommendations for Practitioners	University policymakers are expected to benefit from this research for e-learning system acceptance in an academic setting and eliminate any impediments to its implementation. University students will be able to identify the factors and motivations driving their adoption of the system. In particular, usability, social, and organisational factors that affect their use of an e-learning system would be better understood.
Recommendations for Researchers	The study should aid the research community in technology acceptance and usability studies to determine the students' perceptions and experiences towards e-learning usability, social, and organisational factors that influence their acceptance, specifically in a Saudi context where students have unique psychological and social characteristics. Administrators and designers could also better understand areas of improvement for usability issues and develop design solutions based on the findings of this study.
Impact on Society	The suggestions have been offered in order to accelerate and increase the use of e-learning services in Saudi higher education. System designers and administrators should have a better insight into the user interface design, considering system-independent metrics that could enhance user acceptance of e-learning systems.
Future Research	The study focused on the students' perspective, a natural progression of this work is to involve other e-learning stakeholders (teachers and administrators). This could enrich the research by providing a better understanding of undisclosed issues, offering different views about the implementation and use of an e-learning system in Saudi Arabia.
Keywords	UTAUT, technology acceptance, usability, e-learning systems, LMS, PLS-SEM, developing country

INTRODUCTION

The rapid improvement in information and communication technologies has shaped opportunities in many fields. While the progress of technological innovations is continuing, the transfer and integration of these advances into education has become a current topic of debate. The successful experience of e-services around the world has led to a redefinition of the role of educational institutions through the adoption of e-learning services and techniques. The goal is to create a lifelong learning environment through cost-efficient, flexible, and accessible education, regardless of geographic and time boundaries.

Since the ultimate goal of using an e-learning system is the improvement of effective learning, its benefits cannot be achieved if the students' adoption rate is low. Although higher education is investing heavily in e-learning system development, to stay competitive, educational officials have requested an assessment of the students' perceptions of e-learning systems and whether a system is effective and efficient in facilitating students' learning (Halawi & McCarthy, 2008). Thus, the focus of students' acceptance and utilization of LMSs has come to prominence.

The issue might be exacerbated when implementing a learning technology without an adequate understanding of the target audience. Various e-learning systems have been deployed in educational settings; some create a pleasurable and informative experience; others inflict frustration and unfavourable interaction. An LMS supports or hinders active engagement, easy communication, and formative feedback for all educational stakeholders (Rubin et al., 2010). If the e-learning system is difficult to use, the learners might find themselves disoriented, skip vital content, be reluctant to engage in the course, or be unwilling to communicate with a course coordinator and other peers using the e-learning system (Koohang & Paliszkiewicz, 2016). Thus, it becomes imperative to examine the students' experience of an e-learning system, with much emphasis on the factors that influence the use of these applications.

This is relevant to e-learning solutions in which further enhancements might be needed to suit individuals in unique settings such as the Saudi Arabian environment. In Saudi universities, the majority of students are still unwilling to use e-learning systems (Alenezi et al., 2011). Furthermore, recent studies have examined the use of e-learning systems in a Saudi higher institution and found that more than half of university students only use LMS either rarely or occasionally (Binyamin et al., 2016, 2017). Prior studies disclosed that there is a dearth of academic research on Saudi higher education to examine the effects of usability factors on students use of LMSs, so significant issues have not yet been examined (Al-Asmari & Khan, 2014; Al-Harbi, 2011a; Alshammari et al., 2016; Alshehri et al., 2019a; Salloum & Shaalan, 2019; Yamani, 2014). Issues associated with system technical support, self-efficacy and instructional design, perceived accessibility, perceived flexibility, and subjective norm have been examined in the acceptance and use of LMSs (Al-Harbi, 2011a; Alshammari et al., 2016). Yet, other system characteristics such as navigation, visual design, learnability, information quality, assessment, and interactivity are important usability qualities (Asarbakhsh & Sandars, 2013; Koohang & Paliszkiewicz, 2016; Zaharias & Poylymenakou, 2009). Thus, academic institutions would benefit more from these technologies if they could examine the factors that encourage effective use of LMS in Saudi Arabia (Alenezi et al., 2011; Binyamin et al., 2017).

In particular, organizational, technological and social barriers have been recognized as the main inhibitors for the utilization and adoption of an e-learning system in Saudi universities (Asiri et al., 2012). An integral step in filling this knowledge gap is to conduct a quantitative evaluation of the e-learning system and identify the drivers for effective utilization of the software (Decman, 2015; Koohang & Paliszkiewicz, 2016). Hence, this research fills the gap by determining empirically the effects of usability, social, and organizational factors on the use of LMS in Saudi university from students' standpoints. The researchers propose a theoretical framework by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) model to include the system usability features such as navigation, learnability, visual design, information quality, instructional assessment, and interactivity for investigating students' perceptions towards the use of the LMS in Saudi tertiary education. The overall aim of this research is to identify the significant usability, social, and organisational factors that influence students' use of learning management systems in Saudi state universities.

The remainder of the paper is structured as follows: the next section provides a brief description of the UTAUT model. The third section explores the theoretical framework, the UTAUT variables, the usability dimensions and the research hypotheses. This is followed by the research methodology. The model testing results are provided in the next section and finally there is discussion, implication and conclusions.

THEORETICAL BACKGROUND

As a result of previous technology acceptance research, Venkatesh and colleagues (2003) developed a UTAUT model based on a comprehensive review of diverse theories for computer use prediction. The model unifies the theoretical models in information system studies and integrates human and social constructs to form a unique extensive model (Venkatesh et al., 2003). The model established a unique measure with four essential constructs of user behavioural intention and usage: Performance Expectancy (PE), Effort Expectancy (EE), Social Expectancy (SE), and Facilitating Condition (FC). All these elements are direct determinants of user intention and behaviour. Demographic characteristics such as age, experience, gender, and willingness to use are posited to moderate the influence of the four key constructs on behavioural intentions. The amalgamation of the core constructs and the moderating inputs has improved the predictive efficiency to 70% of the variance in behavioural intention to use technology (Venkatesh et al., 2003).

Furthermore, it is essential to identify the usability variables desired for a learning management system in the educational environment in Saudi higher education. It is often believed that choosing usability attributes is difficult, especially with the different variety of factors available (Hornbæk, 2006). It has thus been suggested to explore the current studies and check for measures that are relevant in an e-learning context (Hornbæk, 2006). Yet, the usability factors pertaining to e-learning-system evaluation have been diverse, and there is no consensus between scholars and experts about the dimensions and factors that should be utilised in the educational environments. Table 1 presents a summary of the relevant usability studies in the e-learning context and demonstrates the diverse usability attributes employed to evaluate different e-learning systems. This is supported by Orehovački et al. (2013), who claim that there is no agreement about the quality standards that reflect the e-learning system. Hence, there is abundant room for further progress in determining the significant and relevant usability factors in the e-learning system usability assessment.

In this research, the UTAUT theory was extended with six usability dimensions: System Navigation (SN), Visual Design (VD), System Learnability (SL), Information Quality (IQ), Instructional Assessment (IA), and the E-learning System Interactivity (ESI). There are four reasons why these six attributes have been specifically employed in the research's theoretical framework. The variables have already been validated extensively in prior studies of e-learning system evaluation (Alshehri et al., 2019b; Althobaiti & Mayhew, 2016; Binyamin et al., 2019; Reeves et al., 2002; Zaharias & Koutsabasis, 2011; Zaharias & Poylymenakou, 2009). The heuristics have been employed specifically in the design and evaluation of e-learning systems and were found to identify common areas of usability problems across web-based learning applications. Secondly, a study was carried out to identify the most important usability metrics in e-learning system evaluation from Saudi students' point of views (Alshehri et al., 2019b), and the six usability criteria were found to be important in the use of the e-learning system in Saudi higher education. Thirdly, the selected usability principles were tested in Saudi tertiary education, confirming the validity and reliability of the variables in a new context. As outlined previously by many experts (Althobaiti & Mayhew, 2016; Oztekin et al., 2010; Zaharias & Poylymenakou, 2009), considerably more work will need to be done to validate the usability attributes in diverse contexts, with different systems and users; hence this was another motivation to apply the variables in the Saudi Arabian educational context. Finally, the proposed model has been tested using PLS-SEM, a sophisticated multivariate analysis. This not only enhances the validity of the variables in Saudi Arabia using PLS-SEM but also adds to the novelty and originality to the current study.

Table 1. Domain-Specific Usability Evaluation Studies

Study	Context	Methodology	Attributes	Validation
Koohang and Paliszkiewicz (2016)	e-learning system	Literature review	Developed a theoretical model of four interrelated components: Fundamental (simplicity, comfort, user friendly, control, navigability and load time) Appearance (recognition, visual appearance, consistency, and well-organized) Information presentation (understandability, relevancy, adequacy, and right to the point) Communication (technical communication, direction/instruction, feedback, visual models of all content,	A Likert-scale instrument was tested using a variance-based Structural Equation Modeling (SEM) package that uses Partial Least Square (PLS) in the USA

Study	Context	Methodology	Attributes	Validation
			provision of basic information via Q&A, and search/inquiry)	
Orfanou et al. (2015)	e-learning system	Literature review	System Usability Scale (SUS)	Inquiry-based method. They conducted eleven studies with 769 students.
Mtebe & Kissaka (2015)	LMS	Existing heuristics and studies	10 Nielsen's heuristics Instructional materials, collaborative learning, learner control, feedback and assessment, accessibility, motivation to learn	heuristics evaluation with five experts in Africa
Granić & Ćukušić (2011)	e-learning system	End users' assessment and expert inspection (quantitative and qualitative analysis)	Memorability: Memory test for System functions Attitude questionnaire: SUS Interview Usability criteria: accuracy of task completion, task completion time and satisfaction	Students, teachers and experts of several European countries
Davids et al. (2013)	e-learning system	Heuristics evaluation and user testing	10 Nielsen's heuristics Intuitive visual layout	Six inspectors to identify usability problems and end users are directly observed while using the application
Oztekin et al. (2010)	e-learning system	Existing heuristics in usability and quality-related checklist	Error prevention, visibility, flexibility, course management, interactivity, feedback and help, accessibility, consistency, assessment, memorability, completeness, aesthetics, reduce redundancy	Learner-based questionnaires, factor analysis and Structural Equational Modelling in the USA
Alsumait & Al-Osaimi (2009)	Child e-learning application	Guidelines and existing heuristics	10 Nielsen's heuristics Multimedia representations, attractive screen layout, appropriate hardware, challenge the child, evoke child mental imagery, support child curiosity, learning content design, assessment, motivation to learn, interactivity, accessible	Using four experts and user testing in Kuwait
Zaharias (2009)	e-learning application	Literature review	Learnability, accessibility, consistency, navigation, visual design, interactivity, content and resources, feedback, instructional assessment, media use, learner guidance and support, learning strategies design	None

Factors Influencing the Students' Use of LMSs

Study	Context	Methodology	Attributes	Validation
Zaharias & Poylymenakou (2009)	e-learning application	Literature review	Content, learning support, visual design, navigation, accessibility, interactivity, self-assessment and learnability, motivation to learn	Two empirical studies of learner-based questionnaires and factor analysis in corporate settings
Ssemugabi & De Villiers (2007)	Web-based e-learning application	Existing heuristics, model and learning theories	10 Nielsen's heuristics Navigation, relevance of content, clarity of objectives, collaborative learning, learner control, support significant approaches to learning, cognitive error recognition, diagnosis and recovery, feedback, context meaningful to domain and learner motivation	Student-based questionnaires and focus groups in South Africa
Dringus & Cohen (2005)	e-learning system	Expanded existing heuristics	Visibility, functionality, aesthetics, feedback and help error prevention, memorability, course management, interactivity, flexibility, consistency, efficiency, reducing redundancy and accessibility	Faculty and students testing of online courses to produce an adaptable usability checklist

RESEARCH FRAMEWORK AND RESEARCH HYPOTHESES

The current study explores the UTAUT theory with the usability attributes on an LMS in Saudi Arabia. The model extends UTAUT to include navigation, learnability, visual design, information quality, instructional assessment, and interactivity for investigating students' perceptions towards the use of the LMS in Saudi tertiary education. The proposed research model is shown in Figure 1. The next sub-sections explain the model hypotheses.

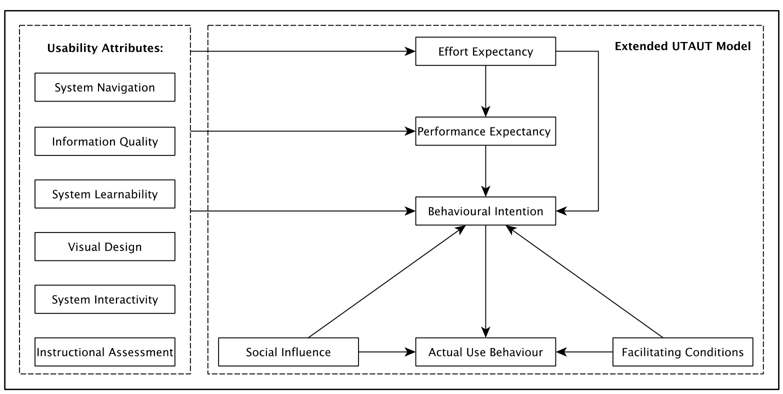

Figure 1. Research Theoretical Framework

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UTAUT VARIABLES

The theoretical framework begins by discussing the base model (UTAUT) variables as follows:

Performance expectancy (PE)

Performance expectancy is concerned with individuals' beliefs that a system use will enhance their job performance to perform various tasks (Venkatesh et al., 2003). In this study, it is the extent to which students believe that using LMS will enhance the learning outcomes by accomplishing the learning activities. The presumption that learners form about the promising usefulness of the LMS, the more chances that they will use or continue to use the system in the future (Halawi & McCarthy, 2008). In the absence of this PE, the system might be not utilized even if it easy to use, easy to learn, and satisfying to use. Many studies have shown that PE is a significant determinant of behavioural intention (BI) to use an e-learning system (Alrawashdeh et al., 2012; Alshehri et al., 2019a; Bellaaj et al., 2015; Bouznif, 2018; Salloum & Shaalan, 2019; Usoro et al., 2013). Similarly, in the Saudi higher education context, the studies of Alshehri et al. (2019a) and Bellaaj et al. (2015) found that performance expectancy has a remarkably positive impact on the students' intention to use an LMS. Thus, these findings suggest that the students are driven to accept the e-learning system primarily on the basis of its usefulness. Based on the above discussion, it is hypothesized:

H1: *Performance expectancy has a direct positive influence on students' behavioural intention to use an LMS.*

Effort expectancy (EE)

Effort expectancy is defined as the degree of ease associated with the use of the system (Venkatesh et al., 2003). In this context, it is the students' perception of the LMS usage ease or difficulty (Chiu & Wang, 2008). Venkatesh et al. (2003) claim that the users' acceptance of an application is determined by users' perceived ease of use. Meta-analysis such as that conducted by Khechine et al. (2016) have shown that effort expectancy is a significant determinant of behavioural intention to use an LMS. Although data from several sources have identified a significant association between effort expectancy and behavioural intention to use learning technologies (Alrawashdeh et al., 2012; Bellaaj et al., 2015; Usoro et al., 2013), the claim was not the case in other studies (Alshehri et al., 2019a; Attuquayefio & Addo, 2014; Jong & Wang, 2009; Park, 2009; Salloum & Shaalan, 2019; Šumak et al., 2010). Thus, in order to further assess the relationship and confirm whether it is valid in the Saudi e-learning context, we propose that effort expectancy leads to improved performance and willingness to use, i.e., that effort expectancy has a positive effect on performance expectancy and behavioural intention to use LMS. This claim has been demonstrated by several empirical investigations e.g. Ameen et al. (2019) and Moreno et al. (2017). So, when students see that the LMS is free of effort, that will lead them to perceive it to be useful which further encourage them to use it. Therefore, it is hypothesized:

H2: *Effort expectancy has a direct positive influence on students' behavioural intention to use an LMS.*
H3: *Effort expectancy has a direct positive influence on performance expectancy.*

Social influence (SI)

This construct relates to whether important people (friends, colleagues, and family members) influence an individuals' intention to use the system (Venkatesh et al., 2003). In this study, it is the students' perceptions of the influence of university officials, lecturers, and peers on motivating students to use LMS. So, when students in the educational environment think they should adopt the system, they tend to conform to the opinions of others (e.g., university officials, lecturers, and peers) and adopt the system (specific behaviour) (Eckhardt et al., 2009). The construct has been recognized as fundamental to technology adoption as the influence of peers, change agents, organizational pressure, and societal norms are inevitable (Rogers, 1995; Venkatesh et al., 2003).

In the context of e-learning technologies, there has been a positive significant association between SI and behavioural intention to perform a focal behaviour with LMS (Chu & Chen, 2016; Khechine et al., 2014; North-Samardzic & Jiang, 2015; Salloum & Shaalan, 2019; Šumak et al., 2010; Williams et al., 2015). In recent studies, social influence was found to be an important factor for the individuals' intended behaviour towards usage of LMS in Saudi universities (Alshehri et al., 2019a; Soomro, 2018). Following the guidelines of UTAUT and since the e-learning system use is mandatory in the context of the study (i.e., students have to use the system to complete the course), this research will study the direct effect of SI on behavioural intention as well as on the system usage behaviour.

***H4**: Social Influence has a direct positive influence on students' behavioural intention to use an LMS.*
***H5**: Social Influence has a direct positive influence on students' actual usage behaviour.*

Facilitating conditions (FC)

This construct refers to the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system (Venkatesh et al., 2003). In this context, ensuring technological infrastructure is rich, reliable, and capable of providing the needed support for stakeholders is a critical element for e-learning success (Selim, 2007). It is also believed that the availability of environmental resources and organizational and technical infrastructures would help students to employ them in their learning activities, thereby promoting their use of the e-learning system (Venkatesh et al., 2003). Thus, some theoretical foundations acknowledge the effect of facilitating conditions on behavioural intention (Ajzen, 1991; Taylor & Todd, 1995), and this was supported by many empirical findings (Ain et al., 2015; Dwivedi et al., 2017; Eckhardt et al., 2009; Lewis et al., 2013; Venkatesh et al., 2012). These lines of evidence reinforced the association between FC and BI; in contrast to the original model (Dwivedi et al., 2017). Furthermore, many prior studies have demonstrated a significant positive influence between facilitating conditions and actual use of an e-learning system (Alshehri et al., 2019a; Buchanan et al., 2013; Deng et al., 2011; Khechine et al., 2014; Salloum & Shaalan, 2019; Šumak et al., 2010). Based on the prior literature, the following hypotheses are proposed:

***H6**: Facilitating condition has a direct positive influence on students' behavioural intention to use an LMS.*
***H7**: Facilitating condition has a direct positive influence on students' actual use of an LMS.*

Behavioural intention (BI)

BI is defined as the probability that individuals will perform the behaviour in question (Venkatesh et al., 2003). BI is proposed to be a direct antecedent of the actual behaviour (Ajzen, 1991), so the greater intention that an individual forms about a certain behaviour, the more likely that performance is to occur (Ajzen, 1991). There is a large volume of published studies confirming the relationship between BI and usage behaviour (Davis, 1989; Taylor & Todd, 1995; Venkatesh & Davis, 2000; Venkatesh et al., 2003). In the e-learning environment, the vast majority of studies on technology acceptance have proved that behavioural intention has a significant positive influence on LMS use (Ain et al., 2015; Alshehri et al., 2019a; Lewis et al., 2013; North-Samardzic & Jiang, 2015; Salloum & Shaalan, 2019; Šumak et al., 2010; Williams et al., 2015). Therefore, based on the findings in the literature, the following hypothesis is proposed:

***H8:** Behavioural intention to use LMS has a direct positive influence on the actual usage behaviour.*

Usability Variables

The following describes the usability parameters of the framework:

System navigation

The LMS navigation quality concerns the visible navigational structure such as menus and links that grant learners many options over the system elements (Zaharias & Poylymenakou, 2009). The navigation is considered as a map that connects the components of a system and is expected to enable users to move within the system in a clear and easy way (Binyamin et al., 2019). If the navigation structure is complicated and contains broken links, users might become disorientated when navigating and experience heavy cognitive load.

In the e-learning context, the navigational tools enable students to locate specific content items and instructional elements as well as to identify their position in the sequence of commands to enhance the amount of learners' control (Naveh et al., 2012). Furthermore, students' perceptions of usability formed the central focus of a study by Selim (2007) in which the author found navigation in an e-learning system impacted the decision to adopt and use the e-learning system. Similarly, in a Saudi higher education study, learners encountered difficulties navigating through the e-learning system content and other features in the menu (Alturki et al., 2016). Furthermore, Alelaiwi and Hossain (2015) found that the majority of Saudi university students reported inconsistency in the e-learning navigation format and even the results of clicking links might be confusing.

In a study which set out to determine the effects of usability attributes on the website acceptability in an e-commerce context, Y. Wu et al. (2009) reported that navigation is a key indicator that promotes the behavioural intention to use the system, and so did Green and Pearson (2011), in whose work navigability was found to be a significant predictor of perceived ease of use. In educational settings, Theng and Sin (2012) found that the navigation of LMS has a positive influence on the students' perceived ease of use. This also corroborates with the research of Tsai et al. (2017). As for antecedents to the learners' belief of ease of use and usefulness, the Cheng (2015) study revealed that e-learning system navigation has the greatest impact. In the Saudi universities, Binyamin et al. (2019) demonstrated the significant effect of LMS navigation on students' perceptions of ease of use, yet the effect of navigation on the students' perception of the system usefulness was not confirmed. This combination of findings provides some support for the premise that a relationship of e-learning navigation is evident. Hence, we hypothesise that:

H9: *System Navigation has a direct positive influence on performance expectancy.*
H10: *System Navigation has a direct positive influence on effort expectancy.*
H11: *System Navigation has a direct positive influence on students' behavioural intention to use an LMS.*

Visual design (VD)

This attribute focuses on the aesthetic aspects of the system through considering the effects of images, colours, fonts, and general layouts (Usability.gov, 2013). This includes the arrangement of the content: layouts, colours, icons, buttons, paragraph formats, and the line spacing as well as the websites' consistency (Graham et al., 2005). The structural design of the interface offers features and support whereby users can interact with the system components. A well-designed and user-friendly user interface for an e-learning system is the most significant driver for students' utilization (Shee & Wang, 2008). It is argued that the more simple and flexible the system user interface is, the less effort the students need to use the system, and that it promotes accessibility and adds further enhancement to the e-learning system's usefulness (Cho et al., 2009). That lessens the students' effort to access the functions and will help them to find information with ease and speed, and ultimately learn in an effective manner (Cho et al., 2009).

Visual design of e-learning systems is often overlooked and, in many cases, treated as a minor cosmetic detail (Horton, 2011; Reyna, 2013). Previously published studies on the effect of visual design on technology acceptance seem to be limited (Binyamin et al., 2019) and, in many cases, tend to be indeterminate. It was demonstrated that visual cues play a key role in the consumers' intention in an e-commerce context (Shaouf et al., 2016). In an empirical finding, the overall perception of visual interface design was determined to be a critical factor in the students' acceptance and use of the e-learning system (Cho et al., 2009). It was also found that the LMS interface design affected considerably the usefulness of the system (Cho et al., 2009; Khedr et al., 2011; Mouakket & Bettayeb, 2015). However, Binyamin et al. (2019) were unable to demonstrate the effect of visual interface design on the students' perception of the LMS ease of use and usefulness in the Saudi context while Al-Aulamie (2013) has proved the effect to be on the LMS ease of use, rather than usefulness. Using UTAUT, Almaiah and Alyoussef (2019) found visual design has a significant effect on performance expectancy as well as students' usage behaviour of LMS in a Saudi university. However, in other contexts, Theng and Sin (2012), Khedr et al. (2011), Cheng (2012) and Liu et al. (2010) have demonstrated the influence of interface design on the perceived ease of use. In this paper, it is assumed that LMS user interface design will enable students to accomplish their goals, affect the ease of use the system and subsequently influence their intention and use of the system. Hence, the following hypotheses are proposed:

H12: *Visual design has a direct positive influence on performance expectancy.*
H13: *Visual design has a direct positive influence on effort expectancy.*
H14: *Visual design has a direct positive influence on students' behavioural intention to use an LMS.*

System learnability (SL)

The learnability dimension is related to the ease of learning: the degree to which students can learn how to use the LMS without difficulty (Holden & Rada, 2011; Nielsen, 1993). There is a consensus among researchers that learnability is an essential component of usability (Dix et al., 2004; Nielsen, 1993; Shackel, 2009; Shneiderman et al., 2017). Most researchers acknowledge that learnability is particularly important in e-learning systems due the system complexity, intricate pedagogy, and the diversity of users (Junus et al., 2015). E-learning systems with high learnability enable learners to start using the system with a minimum of training, help, and orientation (Marzanah et al., 2013).

Few lines of evidence have investigated the impact of learnability on students' ease of use and usefulness. Using the Structural Equation Modelling technique, Scholtz et al. (2016) verified that learnability significantly influenced the Technology Acceptance Model (TAM) perceived usefulness and perceived ease of use which in turn increased the usage of the ERP system. Likewise, Aziz and Kamaludin (2014) revealed that the learnability of a Malaysian university website positively influenced students' perception of system ease of use and usefulness. Yet, in the study of Lin (2013), the correlation between learnability and perceived ease of use was not evident. In Saudi higher education, the effect of LMS learnability was demonstrated with the system ease of use but not for usefulness (Binyamin et al., 2019). Up to now, far little attention has been paid to the influence of the learnability variable on the students' intention and use of an e-learning system in the Saudi Arabian context. In this research, the concern is whether the learnability variable influences students' performance expectancy and effort expectancy as well as their intention to use the system. Thus, the following hypotheses are proposed:

H15: *System Learnability has a direct positive influence on performance expectancy.*
H16: *System Learnability has a direct positive influence on effort expectancy.*
H17: *System Learnability has a direct positive influence on students' behavioural intention to use an LMS.*

Information quality (IQ)

Information quality refers to the information and content that is provided by the e-learning system (Ameen et al., 2019; Aparicio et al., 2017). IQ is considered an important factor for measuring the effectiveness of an e-learning system because the students' materials for learning are contained in the system (Alsabawy et al., 2016; Aparicio et al., 2017). DeLone and McLean (2003) in their information systems' success model, asserted that information quality is a crucial variable that influences user satisfaction and intention. It is also an important measure for the system success (Freeze et al., 2010;

Petter et al., 2008), and among the most important qualities component in the evaluation of the e-learning system (Alla & Faryadi, 2013).

Empirical evidence has shown that information quality influences the effectiveness of computer-mediated learning (Ameen et al., 2019; Aparicio et al., 2017; Binyamin et al., 2019). Recently, researchers have shown that information quality has a significant effect on the intention to use an LMS in the Thai context (Thongsri et al., 2019). It was verified that students' high perceptions of the system information quality will lead to a higher level of perceived usefulness (Al-Fraihat et al., 2019; Alsabawy et al., 2016; Ameen et al., 2019; Aparicio et al., 2017; Lee et al., 2014; J.-H. Wu et al., 2010) and is positively correlated with learners' satisfaction (Al-Fraihat et al., 2019; Chiu et al., 2007; Mohammadi, 2015). Among the factors influencing the students' intention to use an e-learning system, the IQ factor had a remarkable positive effect in an Iranian context (Mohammadi, 2015). In an Arab context, it was confirmed that there is a positive relationship between information quality and the continued intention to use an e-learning system (Almahamid & Rub, 2011) and on students' perceived ease of use and on perceived usefulness (Alkandari, 2015; Salloum, 2018). Specifically, in Saudi higher education, it was empirically found that the IQ of an LMS is a determinant of students' perceived ease of use and usefulness (Binyamin et al., 2019). However, other researchers found different results. For instance, Al-Aulamie (2013) and Ameen et al. (2019) demonstrated the insignificance of the association between IQ and BI. To date few studies have examined the relationship between information quality and the willingness to use the system (Petter et al., 2008). Based on the previous discussion, the researchers consider that IQ will have an influence on the students' performance expectancy, effort expectancy, and their behavioural intention to use LMS. Therefore, the following hypotheses are proposed:

H18: *Information quality has a direct positive influence on performance expectancy.*
H19: *Information quality has a direct positive influence on effort expectancy.*
H20: *Information quality has a direct positive influence on students' behavioural intention to use an LMS.*

Instructional assessment (IA)

Instructional assessment is concerned with an e-learning system's provision of learning guidance through various assessment tools including test, quizzes, surveys, electronic submission of assignments, and the grade book (Zaharias & Poylymenakou, 2009). The construct also includes an evaluation of the effectiveness of e-learning system feedback facility to the online assessment. The e-learning assessment tool is an indispensable element in the students' learning process. The diversified evaluation methods within the e-learning systems stimulate students to interact with the assessment tools in order to gain better academic performance (Sun et al., 2008). Besides, the self-assessment tool can help students to understand the course educational materials (Kayler & Weller, 2007). This enables students to identify areas of difficulties and became more engaged with the course materials (Kayler & Weller, 2007).

Regarding the influence of IA on e-learning acceptance, one study conducted by Binyamin et al. (2019) examined the relationships of LMS instructional assessment on students' perception of LMS ease of use and usefulness. They found that both links were supported in Saudi higher education. Similarly, another recent research has revealed that course assessment has a significant positive effect on performance expectancy and the actual use of e-learning systems in a Saudi university (Almaiah & Alyoussef, 2019). To date, LMS system characteristics such as instructional assessment influence on UTAUT are far from conclusive, so the current research explored the role of assessment in students' intention as well as on performance expectancy and effort expectancy. Thus, we hypothesize the following:

H21: *Instructional assessment has a direct positive influence on performance expectancy.*
H22: *Instructional assessment has a direct positive influence on effort expectancy.*
H23: *Instructional assessment has a direct positive influence on students' behavioural intention to use an LMS.*

E-learning system interactivity (ESI)

Interactivity concerns the e-learning system's collaborative tools that facilitate the interaction among students and between students and instructors. This is evident in the LMS in which many collaborative functionalities such as announcements, mail, chat, and discussion are used, not only for student-student, student-instructor interaction but also as a convenience to communicate course matters and support instructional tasks (Junus et al., 2015). In an LMS, communication tools are fundamental and foster constructive and meaningful interaction among students and teachers (Rubin et al., 2010).

Several studies have demonstrated a direct relationship between system interactivity and perceived usefulness (Alkandari, 2015; Alrawashdeh et al., 2012; Baleghi-Zadeh et al., 2017; Binyamin et al., 2019; Cheng, 2012; Moreno et al., 2017; Pituch & Lee, 2006) and perceived ease of use Binyamin et al. (2019) and Cheng (2012) as well as the behavioural intention to use an e-learning system (Agudo-Peregrina et al., 2014; Uğur & Turan, 2018; Wrycza & Kuciapski, 2018). For instance, Pituch and Lee (2006) found that system interactivity had the greatest direct and total effect on perceived usefulness and e-learning system usage behaviour. A recent study in Iraq indicated that interactivity has a significant positive influence on students' perceived usefulness of an e-learning system (Moreno et al., 2017). Nonetheless, Abbad et al.'s (2009) analysis did not substantiate the effect of e-learning system interactivity on student's perception of usefulness and ease of use in a Jordanian university. In Saudi higher education, Alenezi (2012) indicated that interactivity constructs have a positive relationship with the perceived usefulness and perceived ease of use as well as the students' behavioural intention to use an e-learning system. Binyamin et al. (2019) performed a similar series of experiments and concluded that interactivity influenced the perceived usefulness and perceived ease of use of e-learning system in Saudi tertiary education. In tandem with that, Al-Harbi (2011b) found that perceived interactivity was a determinant for e-learning system usefulness in Saudi higher education.

More information on the influence of interactivity on the acceptance and use of LMS would help us to establish a greater degree of accuracy on this matter in Saudi higher education. Therefore, it is assumed that the higher the interactivity of the system, the stronger the students' belief about its usefulness and ease of use and accordingly, the more willingness to use the system. Thus, we hypothesize the following:

H24: *E-learning system interactivity has a direct positive influence on performance expectancy.*
H25: *E-learning system interactivity has a direct positive influence on effort expectancy*
H26: *E-learning system interactivity has a direct positive influence on students' behavioural intention to use an LMS.*

RESEARCH METHOD

POPULATION AND SAMPLE

The sample for this study was taken from students in Saudi higher education, targeting students in geographically dispersed universities. Due to the large sample frame of Saudi students, sampling techniques were necessary. This is a normal approach where it is difficult or infeasible to reach the total population due to geographical boundaries, time, and budget constraints (Saunders et al., 2012). Hence, the study approaches this concern using geographical cluster sampling of Saudi universities. Each cluster (university) represents a geographical province of Saudi Arabia based on cardinal directions; so five universities that have adopted LMS for student use were selected based on a simple random probability method. Within each of these universities, the researchers selected samples of students using a simple random probability technique. The sample design made provision for obtaining a suitable number of males and females who use or have used the LMS in their studies. This is particularly true when PLS-SEM is applied as large sample size increases the precision and consistency of the PLS-SEM estimation (Hair et al., 2017).

Instrument Testing

The UTAUT items were used according to Venkatesh et al. (2003). The usability items were adapted from various studies in the usability evaluation of e-learning systems (Al-Aulamie, 2013; Alshehri et al., 2019b; Binyamin et al., 2019; Cheng, 2012; Cho et al., 2009; Gilani et al., 2016; Khedr et al., 2011; Oztekin et al., 2010; Pituch & Lee, 2006; Zaharias & Poylymenakou, 2009). The indicators were set into the context of the main web-based LMS in Saudi higher education, the Blackboard system. All survey items were translated into the Arabic version using the back-translation method by bilingual professors to ensure linguistic equivalence. As a check, the pre-test questionnaire was conducted with four experts in the field. The received insights and suggestions showed that the items' logical consistency, meaningfulness, clarity, ease of understanding, and relevancy were satisfactory and also that the meaning was consistent with the conceptual value of the construct. After the pre-test, a pilot study of the questionnaire was conducted with fifty-five students. The researcher ensured that the students had registered for at least one web-based course. The purpose was to gain additional comments regarding the understanding and the clarity of questionnaire content. Feedback about the survey layout and questions' ambiguity were taken into consideration. Also, minor modifications in wording were applied before issuing the survey to the students.

Quantitative research in the form of an online questionnaire-based survey was performed to test the hypotheses. The theoretical framework items used a five-point Likert scale which was considered suitable for this study, because its main purpose was to evaluate the perceived usability variable influence on the e-learning system acceptance from a student's perspective. The 5-point Likert scale was used in the questionnaire of the study with a scale of: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. The instrument was divided into three main sections. The first section included information about the respondents' characteristics. The second section was concerned with UTAUT constructs. This section comprised 25 positive statements, divided into six subscales using a five-point Likert scale about LMS use in higher education. The last part elicits students' perception of the six usability variables. It contained 31 positive statements (refer to the Appendix for the study's instrument).

Data Collection

Three thousand emails, providing a hyperlink to the Web-based survey, were distributed to students who had had some experience of blended learning or distance learning courses. Specifically, the online survey was employed to reach the wider population of the female colleges, as female students study in gender-segregated campuses. A total of 861 (28%) were returned and 256 (30%) questionnaires were incomplete and considered unusable due to the excessive missing data (more than 50% missing values). Those instances had to be discarded before the process of data analysis. After the preliminary examination for outliers, normality, and unengaged responses, 605 responses (20% response rate) were used for data analysis. Table 2 summarizes the distribution of respondent's characteristics. The results indicated that males represent 46.1% (279 participants) and females 53.9% (326 participants). The dominating age group ranges from 18 to 25 years old, representing 87.7% (531 respondents) of the total study sample. The remaining 12.3% corresponds to the more senior age groups, 26-36 years old.

Table 2. Demographic Analysis of Respondents

Characteristics	Frequency	Percentage
Gender		
Male	279	46.1
Female	326	53.9
Educational Level		
Undergraduate	573	94.7
Postgraduate	32	5.3

Characteristics	Frequency	Percentage
Blackboard Experience		
Less than 1 year	68	11.2
1 – 2 years	324	53.6
2 – 7 years	213	35.2
Blackboard enrolled Courses		
1-3 courses	246	40.7
4-5 Courses	194	32.1
More than 6 Courses	159	26.3
I do not Use Blackboard in any Course	6	1
Blackboard Training		
1-3 hours	263	43.5
4 -6 hours	36	6
More than 6 hours	17	2.8
None	289	47.8

Data Analysis and Results

The data was analysed using SPSS 24 and SmartPLS 3 Partial Least Squares Structural Equation Modelling PLS-SEM. The SPSS 24 package was employed to perform the preliminary examination including missing data, collinearity, outliers, normality, and unengaged responses. The SmartPLS 3 software was used to analyse and test the research proposed model. PLS-SEM is convenient when the primary objective of the research is to extend an existing theory or identify key drivers (Hair et al., 2017). Since the goal is to identify the key drivers for student's acceptance of an LMS by extending the UTAUT model to include usability variables, PLS-SEM was used.

The analysis was conducted in two phases. In phase one, the estimations of internal consistency, convergent validity, and discriminant validity were established to prove the validity and reliability of the constructs and the measurement items. The second phase involved the structural model analysis and hypothesis testing using PLS-SEM techniques. PLS-SEM examination of the structural model involved the criterion of the coefficients of determination (R^2 values), as well as the size and significance of the path coefficients (Hair et al., 2017).

Analysis of the Measurement Model

Using the PLS algorithm with 5000 iterations, the researchers estimated the measurement model including outer loadings, composite reliability, Cronbach's alpha, Average Variance Extracted (AVE), convergent validity, and discriminant validity. As shown in Table 3, the reliability assessment of the measurement model ranges between 0.75 and 0.93 in which all variables were greater than the recommended benchmark value of 0.70 (Hair et al., 2014). Along with that, the composite reliability values demonstrate that all constructs have high levels of internal consistency reliability.

Convergent validity

Convergent validity evaluates the extent to which two measures of the same construct yield results that are highly correlated and whether the items can effectively reflect the corresponding constructs (Hair et al., 2014, 2017). In this study, the researcher began with evaluation of the convergent validity. To this end, the researcher estimated the factor loadings of the items and the Average Variance Extracted (AVE).

The assessment of items' factor loading was employed to examine the variability among correlated constructs. As illustrated in Table 3, most of the outer loadings of the reflective constructs are well above the threshold value of 0.70 (Hair et al., 2017). However, a few loadings estimate fall just below the 0.70 ideal standard. There are two indicators which are > 0.60 (e.g., FC3 (0.66), AU2 (0.61)) which were retained for further analysis in exploratory research. A number of researchers advised that values of 0.60 to 0.70 are acceptable in exploratory research, as is the case in this research (Hair et al., 2017). Besides, factor loadings less than 0.70 are anticipated in social science, especially when newly developed scales are utilized (Hair et al., 2017). Furthermore, these two were considered significant, and they were retained for further analysis on the basis of their contribution to construct content validity (Hair et al., 2014). In this research, all factors have an acceptable value which satisfies the requirement of the factor loadings (see Table 3).

Another common measure used to establish the convergent validity is the Average Variance Extracted (AVE) (Fornell & Larcker, 1981). The AVE calculates the amount of variance that each construct captures from its indicators relative to the variance contained in the measurement error. The measurement of the AVE for each construct should exceed the cut-off of 0.50 as recommended by Fornell and Larcker (1981). In this research, an AVE measure was estimated for each latent construct in a measurement model. The AVE values of the all constructs lie within the 0.54 to 0.81 range and are able to satisfy the explaining criteria of 50% of variance, as suggested by Fornell and Larcker (1981) (see Table 3). Thus, all measurement items converge highly on their own corresponding construct. Hence, adequate evidence of convergent validity is established.

Table 3. Results of Measurement Model

Construct	Indicator	Factor Loading (>0.5)*	Composite Reliability (>0.7)*	Cronbach Alpha (0.7)*	Average Variance Extracted (>0.5)*
Performance Expectancy (PE)	PE1	0.84	0.89	0.84	0.67
	PE2	0.86			
	PE3	0.88			
	PE4	0.70			
Effort Expectancy (EE)	EE1	0.85	0.93	0.9	0.76
	EE2	0.90			
	EE3	0.87			
	EE4	0.88			
Social Influence (SI)	SI1	0.76	0.86	0.77	0.60
	SI2	0.84			
	SI3	0.77			
	SI4	0.72			
Facilitating Conditions (FC)	FC1	0.72	0.85	0.79	0.54
	FC2	0.76			
	FC3	0.66			
	FC4	0.73			
	FC5	0.79			
Behavioural Intention (BI)	BI1	0.90	0.95	0.92	0.81
	BI2	0.92			
	BI3	0.88			
	BI4	0.91			
Actual Use (AU)	AU1	0.75	0.84	0.75	0.57
	AU2	0.61			
	AU3	0.88			
	AU4	0.77			
System Navigation (SN)	SN1	0.84	0.90	0.85	0.63
	SN2	0.78			
	SN3	0.83			
	SN4	0.75			
	SN5	0.77			

Factors Influencing the Students' Use of LMSs

Construct	Indicator	Factor Loading (>0.5)*	Composite Reliability (>0.7)*	Cronbach Alpha (0.7)*	Average Variance Extracted (>0.5)*
System Learnability (SL)	SL1	0.84	0.91	0.88	0.67
	SL2	0.81			
	SL3	0.87			
	SL4	0.81			
	SL5	0.76			
Visual Design (VD)	VD1	0.73	0.93	0.91	0.70
	VD2	0.77			
	VD3	0.88			
	VD4	0.90			
	VD5	0.86			
	VD6	0.88			
Information Quality (IQ)	IQ1	0.87	0.95	0.93	0.77
	IQ2	0.90			
	IQ3	0.89			
	IQ4	0.88			
	IQ5	0.86			
Instructional Assessment (IA)	IA1	0.79	0.93	0.91	0.69
	IA2	0.85			
	IA3	0.88			
	IA4	0.86			
	IA5	0.79			
	IA6	0.80			
E-learning System Interactivity (ESI)	ESI1	0.84	0.91	0.88	0.73
	ESI2	0.87			
	ESI3	0.84			
	ESI4	0.86			

* indicates the threshold level of reliability and validity.

Discriminant validity

Discriminant validity measures whether the items of the same construct are statistically different from other similar concepts (Anderson & Gerbing, 1988; Kline, 2016). In this research, the measure can be evaluated using two approaches, Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT), as suggested by Hair et al. (2017). The Fornell-Larcker criterion assessment compares the square root of the AVE values with the latent variable correlation (Chin, 1998; Hair et al., 2017). A successful evaluation of discriminant validity can be verified by comparing the correlation variances between any pair of variables with AVE square root in which the value of AVE square root should exceed the correlation coefficients among any pair of latent constructs (Fornell & Larcker, 1981). The elements in the matrix diagonals, presented in Table 4, indicate the square roots of the average variance extracted. The diagonal bold values confirmed that all the AVEs are higher than any other correlation. Therefore, the discriminant validity of the constructs is established.

Table 4. The Fornell-Larcker Criterion Result

	AU	BI	EE	FC	IQ	IA	ESI	SL	SN	PE	SI	VD
Actual Use	**0.76**											
Behavioural Intention	0.57	**0.90**										
Effort Expectancy	0.49	0.58	**0.87**									
Facilitating Conditions	0.55	0.56	0.62	**0.73**								
Information Quality	0.47	0.54	0.53	0.58	**0.88**							
Instructional Assessment	0.50	0.52	0.54	0.62	0.67	**0.83**						
E-learning System Interactivity	0.40	0.54	0.42	0.52	0.58	0.69	**0.85**					
System Learnability	0.55	0.59	0.75	0.65	0.69	0.66	0.57	**0.82**				
System Navigation	0.51	0.54	0.63	0.66	0.62	0.64	0.60	0.70	**0.79**			
Performance Expectancy	0.55	0.78	0.57	0.57	0.62	0.57	0.56	0.60	0.55	**0.82**		
Social Influence	0.58	0.51	0.40	0.51	0.50	0.48	0.40	0.49	0.43	0.55	**0.77**	
Visual Design	0.44	0.43	0.48	0.54	0.63	0.62	0.56	0.67	0.70	0.45	0.41	**0.84**

Henseler et al. (2015) proposed an alternative approach: the heterotrait-monotrait ratio (HTMT) assessment of correlations in variance-based SEM. The technique achieves high specificity and sensitivity rates across all simulations compared with the Fornell-Larcker criterion (Henseler et al., 2015). Specifically, the technique measures the average correlations of indicators across constructs, measuring different phenomena relative to the average of the correlations of indicators within the same construct (Henseler et al., 2015). An HTMT value close to 1 indicates a lack of discriminant validity. In this research, a more conservative threshold value of 0.85 was used (Hair et al., 2017; Henseler et al., 2015). It can be seen from the data in Table 5 that all the values are below the threshold of HTMT 0.85, hence, the discernment validity is established. Overall, based on the assessment of the Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT), the discriminant validity of the constructs was established.

Table 5. The HTMT Results

	AU	BI	EE	FC	IQ	IA	ESI	SL	SN	PE	SI
AU											
BI	0.683										
EE	0.593	0.637									
FC	0.668	0.614	0.678								
IQ	0.557	0.577	0.575	0.666							
IA	0.604	0.567	0.597	0.721	0.723						
ESI	0.468	0.559	0.447	0.62	0.617	0.762					
SL	0.678	0.648	0.845	0.827	0.767	0.739	0.641				
SN	0.636	0.604	0.710	0.786	0.693	0.728	0.675	0.795			
PE	0.684	0.771	0.638	0.660	0.703	0.652	0.624	0.694	0.638		
SI	0.753	0.597	0.481	0.642	0.586	0.566	0.474	0.593	0.532	0.671	
VD	0.537	0.460	0.529	0.643	0.686	0.684	0.608	0.751	0.793	0.519	0.491

STRUCTURAL MODEL ESTIMATION

Hypotheses testing results

In running the PLS-SEM algorithm, the hypothesized relationships among variables will be estimated. To this end, the researcher ran a bootstrapping technique, a non-parametric statistical approach that draws many sub-samples from the sample data and examines models for each sub-sample. 5000 bootstrap sub-samples were set as recommended by Hair et al. (2017). The critical t value should be above 1.96 with p value of 0.05 as the cut-off for significance (Hair et al., 2017). Table 6 illustrates all the study hypotheses, the path coefficients, t values, and p values. Among the factors influencing behavioural intention, performance expectancy (β = 0.571) exhibited the highest positive effect on students' intention towards using the LMS, followed by effort expectancy (β = 159), interactivity (β = 0.112), social influence (β = 0.081) and supporting, H1, H2, H4 and H26. It can be observed that all t values for these relationships are above the threshold of 1.96 with the significance level less than 0.05 (see Table 6). The other hypotheses that were proposed to have a direct influence on behavioural intention did not prove to be a significant determinant of the construct, hence H6, H11, H14, H17, H20 and H23 are not supported (P > 0.05) (see Figure 2).

Moving to the students' actual use of the e-learning system. as it can be seen from Table 6, the findings also reveal that usage behaviour is influenced positively by social influence at (β = 0.340) followed by behavioural intention (β = 0.266) and facilitating conditions (β = 0.229). These results provide support for hypotheses H5, H7 and H8 at 5% significance level.

Regarding the dependent variable of performance expectancy, the variable information quality displayed the primary positive correlation with the usefulness of the LMS (β = 0.309), followed by effort expectancy (β = 0.245) and interactivity (β = 0.228) with the t value greater than 1.96 and the p value less than 0.05. Hence, H18, H3 and H24 were supported. Since there was negative evidence of the relationship between visual design and performance expectancy (β = -0.102, p < 0.05), the findings leave H12 unproven. In line with that, H9, H15 and H21 hypotheses were not supported because of the p-value > 0.05.

Table 6. The Result of Path Analysis

Hypothesis number	Path	Path Coefficient β	T Value	P Values	Study Results
H1	PE -> BI	0.571***	13.574	0.001	Supported
H2	EE -> BI	0.159***	3.718	0.001	Supported
H3	EE -> PE	0.245***	5.021	0.001	Supported
H4	SI -> BI	0.081**	2.524	0.012	Supported
H5	SI -> AU	0.340***	8.312	0.001	Supported
H6	FC -> BI	0.065	1.814	0.07	Not Supported
H7	FC -> AU	0.229***	6.21	0.001	Supported
H8	BI -> AU	0.266***	6.414	0.001	Supported
H9	SN -> PE	0.05	0.895	0.371	Not Supported
H10	SN -> EE	0.157**	3.127	0.002	supported
H11	SN -> BI	0.037	0.792	0.428	Not Supported
H12	VD -> PE	-0.102**	2.153	0.031	Not Supported
H13	VD -> EE	-0.111**	2.24	0.025	Not Supported
H14	VD -> BI	-0.033	0.832	0.406	Not Supported
H15	SL -> PE	0.056	0.874	0.382	Not Supported
H16	SL -> EE	0.673***	13.376	0.001	Supported
H17	SL -> BI	0.009	0.155	0.877	Not Supported

Hypothesis number	Path	Path Coefficient β	T Value	P Values	Study Results
H18	IQ -> PE	0.309***	5.852	0.001	Supported
H19	IQ -> EE	0.003	0.071	0.944	Not Supported
H20	IQ -> BI	-0.029	0.673	0.501	Not Supported
H21	IA -> PE	0.068	1.295	0.196	Not Supported
H22	IA -> EE	0.129**	2.749	0.006	Supported
H23	IA -> BI	-0.034	0.788	0.431	Not Supported
H24	ESI -> PE	0.228***	5.225	0.001	Supported
H25	ESI -> EE	-0.092**	2.187	0.029	Not Supported
H26	ESI -> BI	0.112**	2.375	0.018	Supported

*P <0.1, **p<0.05, ***P<0.001

Coefficient of determination (R squared).

The coefficient of determination R^2 is a common measure to assess the structural model. R^2 is the proportion of the variance in the outcome variable that is predictable from the independent variables (Hair et al., 2014, 2017). Hair et al. (2017) proposed that R^2 value of 0.75, 0.50, or 0.25 for dependent variables can be respectively described as substantial, moderate, and weak. In this research, the adjusted coefficient of determination is used to avoid the bias toward a complex model as recommended by Hair et al. (2017) and Hair et al. (2014). The adjusted R^2 deals with a number of independent variables relative to the sample size, removing the need to include several independent variables that were nonsignificant in the regression equation to merely increase the R^2 (Hair et al., 2014). Following a Hair et al.'s (2017) recommendation, the adjusted R^2 values of actual use (0.48), effort expectancy (0.58), performance expectancy (0.51), and behavioural intention (0.65), can be considered moderate (Table 7, Figure 2). Overall, 48% of the variance in actual use is predictable from behavioural intention, facilitating conditions, and social influence. Also, students' intention to use is demonstrated to be well predicted by its independent variables which account for 65% of the variance in student behavioural intention to use an e-learning system in Saudi higher education.

Table 7. R^2 for the Dependent Variable

Constructs	R Square Adjusted
Actual Use	0.48
Behavioural Intention	0.65
Effort Expectancy	0.58
Performance Expectancy	0.51

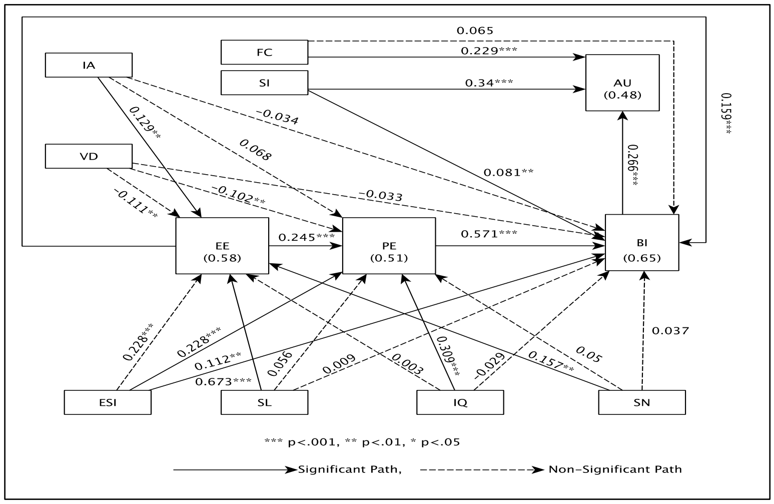

Figure 2. The Results of Path Analysis and R^2

DISCUSSION AND IMPLICATION

This section aims to interpret and describe the significance of the posed hypotheses and explain any insights that emerged from the analysis. Therefore, the results of the analysis of the UTAUT and usability model relationships, predictors, and outcomes will be discussed. It can be observed from the results that half of the proposed hypotheses were supported (see Figure 2). Specifically, the UTAUT variable (PE, EE, SI, FC, BI and AU) relationships were supported in Saudi higher education in accordance with the original results conducted by Venkatesh et al. (2003). However, the findings of the usability dimensions were mixed; around a third of the proposed hypotheses were supported. Below is a brief discussion of each proposed relationship.

PERFORMANCE EXPECTANCY (PE)

The first hypothesis (**H1**) postulated that PE will have a direct effect on the students' behavioural intention to use an e-learning system. The findings demonstrated that PE displayed a robust effect on the students' intention to use an LMS. The construct has the highest predictor ($\beta = 0.571$, $P < 0.05$) on students' behavioural intention to use the e-learning system in the Saudi universities in the study, explaining more than half of the variance in the student's behavioural intention to use e-learning system. In tandem with our findings, the Chiu and Wang (2008), Raman et al. (2014), Decman (2015) and Thongsri et al. (2019) studies of an LMS acceptance revealed that PE exhibited the maximum weight on the students' intention to use the system. Besides, in a number of meta-analysis investigations, the PE was the only construct in the complete list of analysed cases that showed substantial influence on BI among all relationships of the UTAUT model (Dwivedi et al., 2011; Khechine et al., 2016; Taiwo & Downe, 2013). In the Saudi higher education context, the studies of Alshehri et al. (2019a) and Bellaaj et al. (2015) found that performance expectancy has a remarkably positive impact on the students' intention to use an LMS. This finding suggests that the students are driven to accept the e-learning system primarily on the basis of its usefulness. In this respect, lecturers, course designers, system administrators, and students should work together to enhance the usefulness of the system, seeking to influence learners' perceptions. As an illustration, more detailed e-learning context and content, including course content, assessments, and delivery activity, could be planned and clearly presented in the e-learning system for the target students. That would help students to better realize the advantages of an e-learning system and increase the perception that using the system can enhance their learning performance and productivity.

EFFORT EXPECTANCY (EE)

The second and third hypothesized relationships were the paths of effort expectancy with behavioural intention **H2** and performance expectancy **H3** respectively. The current study found the link between EE and BI was significant ($\beta = 0.159$, $P < 0.05$) and supported by the research findings (**H2**) (refer to Table 6). The results indicated that the relationship EE->PE is statistically significant thus, **H3** was supported. In this respect, the predictive strength of EE-> PE ($\beta = 0.245$, $P < 0.05$) is stronger compared with the EE-> BI but weaker compared to that of performance expectancy in the previous discussion. This finding is in line with IS adoption studies (Islam, 2013; Venkatesh & Davis, 2000).

Several studies have demonstrated a positive effect of effort expectancy on performance expectancy. These results reflect those of Chiu and Wang (2008), who also found effort expectancy had a direct effect on performance expectancy. Similarly, Al-Gahtani (2016), whose EE was called PEOU (Effort expectancy pertains to perceived ease of use in TAM), found that the PEOU has a significant positive influence on students' perceived usefulness of an e-learning system in Saudi higher education. This is also consistent with many studies in the prior literature (Ameen et al., 2019; Binyamin et al., 2019; Davis, 1989; Davis et al., 1989; Moreno et al., 2017; Teo, 2009). Besides, many studies support the direct impact of effort expectancy on behavioural intention (Alrawashdeh et al., 2012; Usoro et al., 2013). In Saudi higher education, Bellaaj et al. (2015) reported a substantial positive impact of effort expectancy on the intention to use LMS. Prior research has indicated that effort expectancy is more salient for females (Venkatesh et al., 2003; Wang, 2016). Thus, since more than half of the participants were female in this study, this phenomenon explains why effort expectancy revealed a more noticeable effect on the students' behavioural intention. Overall, if a system is relatively easy to use, students will be more likely to have a perception of usefulness and be willing to learn about the e-learning system features and use them in their studies, and that leads them to form a positive intention to use it which influences their actual usage behaviour. Thus, the challenges facing developers and system administrators would become clearer: to improve the system's ease of use, clarity, and understanding (i.e., 'ease of understanding') to make the students' learning experience more efficient and effective.

SOCIAL INFLUENCE (SI)

This study hypothesized that social influence would have an influence on the behavioural intention **(H4)** and on the actual use behaviour of an e-learning system **(H5)**. Regarding the path of SI->BI, the findings illustrated that the social influence factor had a small but significant impact on behavioural intention ($\beta = 0.081$, $P < 0.05$) hence, H4 was supported. Similar to the study findings, the weights of social influence were classified as small on the intention to use the system (Chen, 2011; Taiwo & Downe, 2013). These results match those observed in earlier studies that social factors significantly affect the students' intention to adopt LMSs (Alrawashdeh et al., 2012; Chu & Chen, 2016; Khechine et al., 2014; North-Samardzic & Jiang, 2015; Raman et al., 2014; Salloum & Shaalan, 2019; Šumak et al., 2010; Thongsri et al., 2019). In Saudi tertiary education, social influence was found to be an important factor for students' willingness to use an LMS (Soomro, 2018).

In this research, the association of social influence with e-learning system actual usage behaviour was examined (**H5**). Remarkably, the construct had a significant positive effect on the student's actual usage behaviour ($\beta = 0.340$, $P < 0.05$). The relationship appeared to significantly influence the variance in the student's usage of the e-learning system (due to the direct relationship (0.34)). Our findings also showed that the explanatory power of the theoretical model improved significantly when social influence is explicitly theorized (i.e., from 40% of variance in usage behaviour without social influence to 48% of variance in usage behaviour explained with the construct in the model). However, very little was found in the literature that examined the association between SI and use behaviour (Eckhardt et al., 2009). Jong & Wang (2009) found that social influence had a significant impact on the students' system usage. In accordance with the present results, El-Masri and Tarhini (2017) in their comparative studies between Qatar and the US showed that the social influence association with the e-learning system use behaviour tended to be more influential in a non-western context, the Qatari sample, more than the US sample. The findings also corroborate the ideas of Al-Gahtani et al. (2007), who suggested that a low individualism culture such as Saudi Arabia might exhibit a significant relationship between social construct and the use of web-based technology. One plausible explanation could be that those living in a high collectivistic culture structure (e.g., Saudi Arabia) tend to regard social influence as a significant element in the usage behaviour towards technology (Al-Gahtani et al., 2007; Ameen et al., 2019). Therefore, the referents, e.g., university officials and teachers, should encourage the students in the use of the e-learning system. More importantly, they should develop initiatives to encourage awareness about the efficiency and the effectiveness of the e-learning system for teaching and learning, e.g., through social media such as the university official social networking site's Facebook, Twitter, and newspapers that might arouse young peoples' interest.

Facilitating Condition (FC)

To examine how the perceived organizational support influences students' intentions and usage behaviour, two hypotheses were proposed: **H6:** FC -> BI and **H7:** FC -> AU. In the FC -> BI path, the current study did find a significant link between FC and BI ($\beta = 0.065$, $P > 0.05$), leaving **H6** unproven. This matches with the study conducted by Hsu (2013), Ain et al. (2015) and Alshehri et al. (2019a). These results reported an insignificant relationship between facilitating conditions and students' behavioural intention to use the e-learning system. However, Venkatesh et al. (2003) anticipated that when performance expectancy and effort expectancy factors are present, the facilitating conditions construct becomes nonsignificant in predicting an intention to use technologies. Thus, the presence of performance expectancy and effort expectancy in our proposed model might explain the reason for this hypothesis to be unsupported, as confirmed by Venkatesh et al. (2003).

Nevertheless, our study reported that facilitating condition was found to be a strong predictor of the e-learning system's actual use ($\beta = 0.229$, $T= 6.21$, $P < 0.05$), indicating a support for **H7**. The facilitating condition has in the past been found to be the most significant factor for predicting the students' use of an LMS (Buchanan et al., 2013; Deng et al., 2011). The empirical evidence has supported the impact of the perceived organizational resources on the individuals actual utilization of the e-learning system (Buchanan et al., 2013; Deng et al., 2011; North-Samardzic & Jiang, 2015; Šumak et al., 2010). A plausible explanation for this could be that as students have experienced the e-learning system, they might become more familiar with the available organizational resources and they are more willing to find support to facilitate the actual use of the system. Thus, universities should encourage learners to take advantage of e-learning services by providing the necessary resources and support (e.g., enhance the ICT infrastructure, give timely, appropriate technical support, and deliver training by a qualified individual).

Behavioural Intention (BI)

As the theoretical foundation of TAM and UTAUT postulated that behavioural intention is a direct determinant of actual usage behaviour (Davis, 1989; Venkatesh et al., 2003), the study under discussion here also hypothesized the direct influence of BI on AU (**H8**). Our findings indicate that behavioural intention demonstrated a positive effect on the e-learning usage of students ($\beta = 0.266$, $T= 6.414$, $P < 0.05$), supporting **H8**. The vast majority of studies on technology acceptance have proved that behavioural intention has a significant positive influence on LMS use (Ain et al., 2015; Binyamin et al., 2019; Lewis et al., 2013; North-Samardzic & Jiang, 2015; Salloum & Shaalan, 2019; Šumak et al., 2010). Weight analysis of the relationship between BI and AU was found to be positively correlated in 82% of studies, qualifying for the best predictor category of usage behaviour (Williams et al., 2015). Also, the use of LMS is mandatory for students in Saudi higher education so it is logical to consider the connection between the two dependent variables.

System Navigation (SN)

In this study, it was hypothesized that SN has a direct positive influence on students' PE and EE and BI of the LMS use, representing **H9**, **H10**, and **H11** respectively. Regarding the path of SN->PE, the analysis revealed that the SN factor had an insignificant effect on performance expectancy ($\beta = 0.05$, $P > 0.05$) hence, **H9** was not supported. This result was unexpected and is contrary to prior research findings, e.g., Khan and Qutab (2016) in which the system navigation significantly predicted the users' perceived usefulness. Nonetheless, in an e-library system, navigation was found to have an insignificant influence on the perceived usefulness (Jeong, 2011). Similarly, Binyamin et al. (2019) in Saudi Arabian universities demonstrated that SN is not a significant predictor of the students' perception of usefulness in the context of an e-learning environment. This result might be attributed to a lack of awareness of e-learning system features such as navigational structure. This might explain the inadequate exploitation of e-learning system tools in Saudi higher education as outlined by Alotaibi (2019).

In the current study, it was also hypothesized that SN has a direct positive influence on students' effort expectancy of LMS. The results confirmed that SN had a significant positive effect on the students' perception of effort expectancy ($\beta = 0.157$, $P < 0.05$). Thus, **H10** was supported. The findings are in parallel with previous investigations of Cheng (2015), Binyamin et al., (2019), and Theng and Sin (2012) who established a significant influence between e-learning interface navigation and the students' perceived ease of use. A possible explanation for this might be that the ease of navigational structure between the course content along with the operating links might encourage students to consider the LMS system easy to use, and ultimately to use it. In general, therefore, it seems that the ease in finding the information, correctness of navigation buttons, menu, site map, and links are significant elements for the students' perception of ease of use of an e-learning system.

The last hypothesized relationship in the construct is SN->BI. The findings indicated that navigation had no effect on student's behavioural intention ($\beta = 0.037$, $P > 0.05$) to use LMS, leaving **H11** unproven. There is a dearth of research into the causal impacts between the navigation factor and the intention and usage behaviour, especially in e-learning settings (Binyamin et al., 2019). Therefore, more research is needed to investigate the SN->BI especially in Saudi higher education.

Visual Design (VD)

The SEM results in Table 6 provided empirical evidence that the path VD->PE was insignificant ($\beta = -0.102$, $p < 0.05$), and accordingly **H12** was rejected. Even though it is a weak correlation, this indicates an inverse relationship. Contrary to the conceptualized path model, the students' perception of the system visual design is negatively associated with the students' perception of the system usefulness. This observation is similar to the findings of Binyamin et al, (2019) and Al-Aulamie (2013) in a Saudi educational context while other researchers evidenced otherwise (Cho et al., 2009; Khedr et al., 2011; Mouakket & Bettayeb, 2015). Contrary to the previous research, the effect of VD on EE was found to be insignificant ($\beta = -0.111$, $p < 0.05$), failing to support **H13**. These results also corroborate the findings of a Binyamin et al. (2019) in a Saudi context. However, this result disagrees with Al-Aulamie (2013) Khedr et al. (2011), Cheng (2012), Liu et al. (2010), and Cho et al. (2009) in which the e-learning system interface design was confirmed to be an important determinant that affects perceived ease of use. A possible explanation for the unsupported relation of VD on PE and EE can be attributed to the fact that 89% of the respondents acknowledged moderate and advanced levels of e-learning system experience. Thus, the students' familiarity with the system and their high exposure to it might minimize the effect of the interface's visual appearance.

Regarding VD -> BI, it was hypothesized that BI is directly affected by VD of LMS. The results in Table 6 showed empirical evidence that hypothesis **H14** was not proven ($\beta = -0.033$, $P > 0.05$). This also accords with the study of Shaouf et al. (2016), which did not find a direct effect between visual design and users' behavioural intention to use an e-commerce system. Even though this not in an educational context, the overall pattern of the findings failed to demonstrate the support of the visual aesthetics in system acceptance and use. Therefore, in Saudi tertiary education, the aesthetics aspects of the system stimuli such as colours, images, shapes, font style, and graphical information as well as screen design consistency across pages, appeared to be less attention-grabbing and are not congruent with the student's beliefs of usefulness or ease of use as well as their willingness to use the system.

SYSTEM LEARNABILITY (SL)

In the proposed model, it was hypothesized that the system learnability construct would have a significant positive influence on performance expectancy (**H15**), effort expectancy (**H16**), and the students' behavioural intention to use the system (**H17**). Regarding SL -> PE, it was thought that PE would be directly influenced by the SL of the LMS. However, the observed p value of the relationship between SL and PE in this study was not significant, ($\beta = 0.056$, $P > 0.05$) and thus, **H15** was rejected. This result concurs with the result published by Binyamin et al. (2019) in which the system's ease of learning, in time or effort, does not play a significant role in the students' decisions of the LMS usefulness in Saudi higher education. In contrast to earlier findings (Aziz & Kamaludin, 2014; Gul, 2017; Scholtz et al., 2016), evidence of a positive and significant relationship between SL and system usefulness was detected. It is worth mentioning that the above studies were conducted in different contexts with different systems, e.g., an ERP system.

The results of the model testing in Table 6 supported the positive and significant relationship between SL -> EE ($\beta = 0.673$, $P < 0.05$), indicating an acceptance for **H16**. The findings demonstrated that SL showed the strongest effect on the conceptual model. The construct also had the highest predictor on the students' perception of the LMS ease of use in Saudi tertiary education. This result is aligned with the result found by Binyamin et al. (2019), and Scholtz et al. (2016). The rationale behind the significant association between SL and EE could be that the effort expectancy of the system can be explained by learnability. In this respect, the system designers have a significant role in making the LMS easy to learn: the clarity of wording, the familiarity and predictability of commands and buttons, the availability of on-line help manuals, the site maps availability with a reasonable hierarchy. Incorporating these into an LMS design not only facilitates the students' learning but also maximises the speed of the learning process.

The last hypothesized relationship between SL and BI was not supported ($\beta = 0.009$, $P > 0.05$), leaving **H17** unproven. The result is consistent with a previous study in which lack of ease of learning did not correlate with usage behaviour (Mendoza et al., 2010). Therefore, it can be concluded that the study findings reject the direct influence of SL on students' intention to use LMS in Saudi higher Arabia.

INFORMATION QUALITY (IQ):

In this study, it was hypothesized that IQ has a direct positive influence on students' PE and EE and BI of the LMS use, representing **H18**, **H19** and **H20** respectively. The results revealed that IQ has a significant influence on performance expectancy ($\beta = 0.309$, $p < 0.05$), indicating a support for **H18**. Across the significant factors, IQ->PE exhibited one of the strongest effects in the proposed framework. Comparison of the findings with those of other studies confirms that the path IQ->PE has been demonstrated in an e-learning context (Alkandari, 2015; Ameen et al., 2019; Binyamin et al., 2019; Cheng, 2012; Lee et al., 2014; Mohammadi, 2015; Shah et al., 2013), and IQ was found to be an important predictor of the system usefulness in an e-commerce context (Green & Pearson, 2011). Thus, the quality of information provided by the e-learning system, being understandable, useful, clear, relevant, sufficient, and up-to-date, is a significant determinant of whether the students perceive the system to be useful. A plausible explanation for this is that students seem to enjoy multiple learning resources and materials in different forms such as books, lecture slides, online quizzes, and discussion, that enhance their education. These resources appeared to be useful, sufficient, and appropriate for the student learning in which they can access materials anytime and from everywhere.

The results of the structural model assessment unexpectedly disclosed the lack of a direct positive influence of information quality on effort expectancy ($\beta = 0.003$, $p > 0.05$), leaving **H19** unconfirmed. This outcome is contrary to those of Shah et al. (2013), Lee et al. (2014), Alkandari (2015), and Binyamin et al. (2019) who found that the quality of e-learning information directly affected students' perceived ease of use. This rather contradictory result may be because that students consider the e-learning system to be more convenient and less complex nowadays, especially with recent technological advances and the greater sophistication of information technology products.

The SEM results showed no statistical influence between IQ and BI ($\beta = -0.029$, $P > 0.05$), leaving **H20** unproven. The insignificant findings between the IQ and the student's intention to use the e-learning system are in accordance with those studies of Al-Aulamie (2013), Ameen et al. (2019), and Terzis & Economides (2011). That said, the correlation between IQ and intention and use behaviour is lacking, so more research is needed to investigate the association between information quality and behavioural intention in an e-learning system context (Terzis & Economides, 2011).

Instructional Assessment (IA)

In the current study, it was thought that IA would have a significant positive influence on performance expectancy **H21**, effort expectancy **H22**, and the behavioural intention **H23** to use the LMS. The parameter estimates for these hypothesized relationships are ($\beta = 0.068$, $P > 0.05$), ($\beta = 0.129$, $P < 0.05$), and ($\beta = -0.034$, $P > 0.05$), respectively. These results indicate that hypotheses **H21** and **H23** were rejected, whereas only hypothesis **H22** with this construct was supported.

The current study found that the LMS assessment tools seem to influence only the ease of use, whereas no influence was found regarding usefulness and the willingness to use. So once students are provided with effective assessment tools, they are more likely to perceive the LMS as being easy to use. In Saudi higher education, supporting the IA->EE path accords with that of Binyamin et al. (2019) whereas the IA->PE relationship contradicts the finding of Binyamin et al. (2019). However, the literature seems to be limited in investigating such associations. The most likely explanation for this surprising result is the students may differ in the awareness and utilization of the assessment tools. There might be a lack of maturity among students regarding the use of the diversity of assessment features that are offered by the LMS (e.g., test, quizzes, and surveys feedback facilities). So, students might be not aware of the complete assessment and feedback functionalities in the LMS. In Saudi universities, the system tends to be used mainly for assignment submission. The other e-learning system features such as test, quizzes, surveys, and given feedback are practically unused in the students' learning process, which also might be a plausible explanation for this discrepancy. This finding is unexpected and suggests that the matter should be explored further in future research.

E-learning System Interactivity (ESI)

The theoretical model hypothesized that perceived LMS interactivity would have a significant positive effect on performance expectancy (**H24**), effort expectancy (**H25**), and student's behavioural intention (**H26**) to use the LMS.

The hypotheses testing results showed that ESI->PE ($\beta = 0.228$, $P < 0.05$) path was significant, hence **H24** was supported. In accordance with the present results, previous studies have demonstrated that system interactivity has a significant positive influence on the students' performance expectancy (Alkandari, 2015; Alrawashdeh et al., 2012; Baleghi-Zadeh et al., 2017; Binyamin et al., 2019; Cheng, 2012; Moreno et al., 2017; Pituch & Lee, 2006). The interactivity feature had the most significant direct effect in the e-learning context (Pituch & Lee, 2006). Thus, the higher the student's perception of system interactivity is, the stronger they believe the LMS to be useful as a means to assist them to achieve their educational objectives. This can be interpreted to mean that the students have experienced using a wide spectrum of features in the LMS (email, discussion board, chat room) that increase their performance.

Among all antecedents examined in this study, ESI exhibited a small negative direct impact on EE ($\beta = -0.092$, $P < 0.05$) and thus, **H25** is rejected. This study supports evidence from previous observations, e.g., Pituch and Lee (2006), Abbad et al. (2009), Baleghi-Zadeh et al. (2017), and Uğur and Turan (2018). Nonetheless, other scholars, e.g., Binyamin et al. (2019) and Cheng (2012), demonstrated a positive significant relationship between system interactivity and perceived ease of use. Thus, and contrary to expectation, Saudi students tend to not perceive that the LMS communication tools' effectiveness has an impact on their effort to use the system. This may be caused in part by a lack of training and support. In our study, nearly 50% of the students have not received any training in the use of an e-learning system. This concurs with the research conducted by Alenezi (2018) that inadequate training was among the main challenges of LMSs adoption in Saudi Arabian universities.

As expected, the significant and positive influence of the system interactivity on the student's behavioural intention ($\beta = 0.112$, $P < 0.05$) **H26** was supported. Even the previous literature is limited on interactivity (J. Sun & Hsu, 2013) , few have demonstrated such an effect, e.g., Uğur & Turan (2018) and more significant direct impact, e.g., Wrycza and Kuciapski (2018) while others revealed indirect influence in an e-learning context, e.g., Alrawashdeh et al. (2012). Some also found no influence, e.g., Abbad et al. (2009). This result indicated that students' willingness to use the LMS is affected by their perception of the interaction between students and the interaction between lecturers and students as well as the effectiveness of the system's communication tools. A possible explanation for this is that previous and current research has demonstrated that the social influence construct appeared to be important in the students' use of the e-learning system (Alshehri et al., 2019a). Hence the social communication between the learners themselves and also between learners and their teachers tended to be more effective and more engaging, contributing to efficiency in learning. Thus, system designers should ensure that a system's components are highly interactive and intuitive to use, so students are involved and willing to learn. Instructors should also motivate the collaboration between students and facilitate better communication with the help of activity streams.

Conclusion

The use of an LMS has become important in education to provide recipients with information content and instruction resources. In fact, the incorporation of technology in the learning and teaching environment is no longer an option, but a necessity. However, assessment of learner's perceptions and adoption of LMSs are becoming an essential element in improving educational inputs and outcomes. This research has attempted to amalgamate the unified acceptance model, UTAUT, with six usability factors to investigate empirically the influence on students' intentions and usage behaviour for an LMS in Saudi tertiary education. The UTAUT model was extended with six usability features (navigation, visual design, learnability, information quality, instructional assessment, and interactivity) to formulate a new theoretical framework of LMS acceptance. Using the PLS-SEM technique, the results confirmed that the UTAUT parameters are valid and robust in the context of LMS in Saudi Arabia. In particular, the empirical results concluded that social influence is fundamental in determining the students' acceptance as well as the usage behaviour of LMS in Saudi Arabia. While the findings of this research show that effort expectancy was influenced directly by system navigation, system learnability, and instructional assessment, the performance expectancy was affected by information quality and system interactivity. The usability feature of interactivity was also shown to influence students' willingness to use the system.

These findings provide a new theoretical basis with empirical support to further understand the individuals' intention and usage behaviour. Based on this interpretation, developers and practitioners can determine how to improve the learners' intention and usage of LMS to their full potential. The refinement strategies must not only focus on UTAUT inputs but also consider the important usability design characteristics in technology adoption and usage behaviour. The validated research model can not only be applied to examine the student's acceptance of LMS but can also serve as a diagnostic measure for further enhancements and improvements to the system. This is an important finding for future research in which usability testing or expert evaluation can be conducted to further improve the existing design of LMS and maximize its effective utilization. This is expected to add valuable insights to inform the decision-making processes at the university higher management and administrative level.

Before drawing definitive conclusions from these results, it is important to consider the study's limitations. To begin with, this cross-sectional study analysed data at a specific point of time. Several lines of evidence suggest that longitudinal research is recommended in which the same students are observed over the study period (Roca et al., 2006; Venkatesh et al., 2003). Secondly, since the study was limited to five regions of Saudi universities, it was not feasible to include another educational institution within the allocated region, considering the study time and resource constraints. In fact, there are 30 public universities distributed throughout the Saudi area where various cultures, nationalities, and backgrounds might be significant. Thus, the validity and reliability of the developed model might improve if different universities were surveyed, especially those more recently founded. Apart from the intra-cultural context limitations, the scope of this study was limited to higher education in Saudi Arabia, so the generalisation at a cross-cultural level is undetermined. Thus, it is desirable to include geographically distributed universities around the Gulf region which might improve the generalizability of our research outcomes.

There are three suggested directions for further studies. Firstly, increase the scope and cover data from a larger student population (e.g., private institutions) with different demographic characteristics such as income, cultural aspects, and level of education. A second direction might be to consider other technological attributes such as other system functionalities, service qualities, e.g., privacy, to investigate their effects on the students' use of LMSs. Finally, since the study focused on the students' perspective, a natural progression of this work is to involve other e-learning stakeholders (teachers and administrators). This could enrich the research by providing a better understanding of undisclosed issues, offering different views about the implementation and use of an e-learning system in Saudi Arabia.

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APPENDIX: QUESTIONNAIRE (ENGLISH)

Part 1: Demographic Details:

1. Gender : □ Male □ Female
2. Age: [ ] Years
3. University: □ King Khalid University □ Saudi Electronic University
   □ Al Jouf University □ King Abdelaziz University
   □ Imam Abdulrahman Bin Faisal University
4. Education level: □ Undergraduate □ Graduate
5. Blackboard Experience: □ Less than a Year □ 1-2 years □ More than 2 years
6. Blackboard Usage Frequency: □ Daily □ Weekly □ Monthly □ Almost never
7. Blackboard Taught Courses: □ 1-3 courses □ 4-5 Courses □ More than 6 Courses
   □ I do not use Blackboard in any course.
8. Blackboard Training: □ None □ 1-3 hours □ 4-6 hours □ More than 6 hours

Part 2: Perceptions of UTAUT variables towards Blackboard:

Performance Expectancy (PE)

1. I find Blackboard useful in my courses.
2. Using Blackboard enables me to accomplish tasks more quickly.
3. Using Blackboard increases my academic productivity.
4. If I use Blackboard, I will increase my chances of getting high grades.

Effort Expectancy (EE)

5. I find Blackboard clear and understandable.
6. It would be easy for me to become skilful at using Blackboard.
7. Learning to operate Blackboard is easy for me.
8. Overall, I find Blackboard easy to use.

Social Influence (SI)

9. People who influence my behaviour think that I should use Blackboard.
10. My classmates and friends think that I should use Blackboard.
11. My instructors encourage the use of Blackboard.
12. In general, the university encourages students to use of Blackboard.

Facilitating conditions (FC)

13. I have the resources necessary to use Blackboard.
14. I have the knowledge necessary to use Blackboard.
15. The e-learning support staff are available when I face any problem with Blackboard.
16. Training and manuals for Blackboard is available.
17. The management would provide the necessary help for using Blackboard.

Factors Influencing the Students' Use of LMSs

Behavioural Intention (BI)

18. I intend to continue using Blackboard in the future.
19. I would prefer my instructors use Blackboard more frequently.
20. I would like to use Blackboard in all future courses.
21. I would recommend using Blackboard to others.

Actual Use (AU)

22. I have used Blackboard this semester.
23. I have been using Blackboard regularly in the past.
24. I have used Blackboard frequently in my studies.
25. I usually use Blackboard for my learning activities.

<u>Part 3: Perceptions of Usability variables towards Blackboard:</u>

System Navigation (SN)

26. The navigational structure of Blackboard is easy for me.
27. Hyperlinks in Blackboard are working satisfactorily.
28. Navigation options are visible in each page.
29. Learners always know where they are in the course.
30. I can leave Blackboard at any time and easily return.

System Learnability (SL)

31. Learning how to perform tasks using Blackboard is easy.
32. I can predict the general result of clicking on each button or link.
33. The Blackboard system provides clarity of wording for easy learning.
34. I can learn how to use Blackboard without a long introduction.
35. There is sufficient on-line help to support the learning process.

Visual Design (VD)

36. Texts, fonts and colours are easy to read.
37. The most important information on the screen is placed in the areas most likely to attract attention.
38. Blackboard layout follows a good structure.
39. Terminology, symbols, and icons are used consistently throughout Blackboard.
40. Blackboard operates consistently throughout my courses.
41. Blackboard visual design is attractive and appealing to the learner's senses.

Information Quality (IQ)

42. Blackboard provides easy to understand information for my study.
43. Blackboard provides complete information for my study.
44. Blackboard provides sufficient information for my study.
45. Blackboard provides accurate, free form error information for my study.
46. Blackboard provides up-to-date information for my study.

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Instructional Assessment (IA)

47. Blackboard contains self-assessment tools (i.e. exams, quizzes, case studies… etc.) that advance my achievement.
48. It is easy for me to use the self-assessment tools in Blackboard.
49. Assessment features in Blackboard are effective to help understanding the material.
50. The self-assessment tools in Blackboard measure my achievements of learning objectives.
51. Blackboard provides learners with opportunities to access extended feedback from instructors, experts, peers, or others.
52. Blackboard provides informative feedback to online assessments.

E-learning System Interactivity (ESI)

53. The communicational tools in Blackboard (email, discussion board, chat room, etc.) are effective.
54. Blackboard enables interactive communication between instructor and student.
55. Blackboard enables interactive communication among students.
56. Blackboard makes my learning process more engaging.

BIOGRAPHIES

Ahmed Alshehri is a lecturer within the School of Computer Science and Information Technology at Albaha University, Saudi Arabia. He has over 7 years of experience in project management, business continuity for IT services as well as various responsibilities in academia. Mr Alshehri graduated with a master's degree in Information Technology from the University of Western Australia (2011) and a bachelor's degree in Education, majoring Computer Science from King Khalid University (2007). His primary research interests include issues related to IS/IT adoption and implementation, human computer interaction, usability, and e-learning systems.

Dr. Malcolm J. Rutter trained as a communications engineer. His research experience started with his PhD in adaptive digital filtering. In the PhD, Dr. Rutter was working on mathematical algorithms, of the sort that are nowadays found inside integrated circuits in applications such as mobile phones and sea divers' communication equipment. In Napier, he worked with optics projects. He mainly worked on fibre-optics for communications and the use of passive infra-red detection for identifying people by their gait. In the School of computing, Dr. Rutter has done a lot of teaching in the field of HCI, which interests him greatly, and web design. He has published on the topic of student communications in education, which combines his interests in HCI, education and communication. More recently he has become involved in evaluating e-government, involving his interests in web design and HCI.

Prof. Sally Smith has an MA in mathematics from Aberdeen University, an MSc in computer science from City University, London and a DBA from Edinburgh Napier University. She is the dean of Computing at Edinburgh Napier University and project director of e-placement, Scotland. Prior to joining academia in 1992, she was a software engineer in the telecoms industry. She is also the director of the Computing Education Research Centre and her research interests are digital skills development and graduate employability. Prof. Smith is a Fellow of the British Computer Society and a Principal Fellow of the Higher Education Academy.