Using the Technology Acceptance Model to Measure the Effects of Usability Attributes and Demographic Characteristics on Student Use of Learning Management Systems in Saudi Higher Education

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ABSTRACT

Learning management systems (LMS), which allow education at the student's choice of place and time, have been widely adopted in higher education worldwide. In the case of Saudi Arabia, LMS have been recently introduced in Saudi universities at the request of the Ministry of Education. The effectiveness of these systems ultimately depends on whether students use them. However, previous literature suggests that student utilisation of LMS remains low in some educational contexts. Addressing this problem, this thesis proposes and examines a theoretical framework that might help explain the factors affecting student use of LMS in higher education. More specifically, the proposed model was developed based on the technology acceptance model (TAM), previous literature on the perceived usability of education technology, and student demographic characteristics. Using the probability multi-stage cluster-sampling technique, quantitative online surveys were sent by email to 2,000 students at three public universities in Saudi Arabia: King Abdulaziz University, King Saud University, and Imam Abdulrahman Bin Faisal University. A total of 851 surveys were submitted by students, and 833 surveys were employed for data analysis. The data were coded, cleaned, and preliminarily analysed using the Statistical Package for Social Science (SPSS) package. Furthermore, the proposed model and hypotheses were examined using the partial least squares structural equation modelling (PLS-SEM) technique and SmartPLS software. The results reveal the significant drivers of student use of LMS, the differences in the acceptance of LMS based on the student demographic characteristics (namely gender, age, education level, and experience), and the moderating effect of these demographics on the proposed relationships. This study is relevant for scholars, university leaders, and e-learning developers working to enhance student use of LMS, in particular where there is not yet widespread adoption.

DECLARATION

I, Sami Saeed Binyamin, declare that the work presented in this thesis is my own independent work and has not been submitted for any other degree or professional qualification at Edinburgh Napier University or any other institution. Further, I confirm that some parts of this thesis have been published (or under review) as:

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Signed: Sami Saeed Binyamin
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DEDICATION

To my parents, wife, and children.

إلى والداي نجاة وسعيد
إلى زوجتي ريم
إلى أبنائي وسام وحسام وباسل

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ABBREVIATIONS

Acronym	**Definition**
A-TAM	Augmented TAM
AU	Actual use
AVE	Average variance extracted
BI	Behavioural intention
CA	Cronbach’s alpha
CBT	Computer-based training systems
CB-SEM	Covariance-based structural equation modelling
CITC	Communications and Information Technology Commission
CQ	Content quality
CR	Composite reliability
D^2	Mahalanobis distance
EDU	Level of education
EOA	Ease of access
ERP	Enterprise resource planning
EXP	Experience
GoF	Goodness-of-fit
GPA	Grade point average
HCI	Human-computer interaction
HTMT	Heterotrait-Monotrait ratio
IA	Instructional assessment
ICT	Information and communication technology
ITU	International Telecommunication Union
LMS	Learning management systems
LS	Learning support
MCIT	Ministry of Communications and Information Technology
MGA	Multigroup analysis
MICOM	Measurement invariance of composite models
NCeL	National Centre for e-Learning
NFI	Normed fit index.
PEOU	Perceived ease of use
PLS	Partial least squares
PLS-SEM	Partial least squares structural equation modelling
PU	Perceived usefulness
Q^2	Cross-validated redundancy
R^2	Coefficient of determination
RMS_{theta}	Root mean square residual covariance
SDL	Saudi Digital Library
SEM	Structural equation modelling
SEU	Saudi Electronic University

SI	System interactivity
SL	System learnability
SN	System navigation
SPSS	Statistical package for the social sciences
SRMR	Standardised root mean square residual
TAM	Technology acceptance model
TAM2	Extended technology acceptance model
TAM3	Technology acceptance model 3
TPB	Theory of planned behaviour
TRA	Theory of reasoned action
UI	User interface
UTAUT	Unified theory of acceptance and use of technology
UTAUT2	Unified theory of acceptance and use of technology 2
VD	Visual design
VIF	Variance inflation factor
VLE	Virtual learning environments

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CHAPTER 1: INTRODUCTION

1.1 Introduction

Chapter 1 introduces the current PhD thesis entitled 'Using the Technology Acceptance Model to Measure the Effects of Usability Attributes and Demographic Characteristics on Student Use of Learning Management Systems in Saudi Higher Education'. This introduction includes the research problem, the motivation of this study, the research questions, the thesis aim and objectives, the research activities and process, the context of this study, and the thesis structure.

1.2 Research Problem

With the remarkable development of information and communication technologies, higher-educational institutions have widely adopted technology to improve the effectiveness of learning (Huang, Lin, & Huang, 2012; Kabassi, et al., 2016). The field of education has certainly been affected by this development, which has given rise to the emergence and expansion of new learning approaches, such as e-learning (Asiri, bt Mahmud, Abu Bakar, & bin Mohd Ayub, 2012; Sheerah & Goodwyn, 2016). E-learning refers to a learning approach that benefits from utilising computer networks to deliver education to users (Abdul Rahman, Ghazali, & Ismail, 2010). Furthermore, e-learning is a flexible learning method that greatly enables education that is not limited by place and time (Islam, Abdul Rahim, Liang, & Momtaz, 2011). Unquestionably, e-learning cannot be implemented without the utilisation of technology. Learning management systems (LMS) – web-based systems that allow teachers to develop course content – which share content with students, create course activities, and assess student progress, are a typical example of such educational technology (Hussein, 2011).

Learning management systems are the most popular technology for facilitating e-learning and are the most commonly used technology in education (Swart, 2016; Zanjani, Edwards, Nykvist, & Geva, 2017). An American study (Dahlstrom, Brooks, & Bichsel, 2014) revealed that 99% of educational institutions in the United States (US) have adopted LMS. The value of the LMS marketplace is more than $3 billion per year and is expected to grow by 24% between 2016 and 2020 (Docebo, 2016). The field of education in academic settings in Saudi Arabia has also been influenced by this evolution (Al-Youssef, 2015). Aljuhney and Murray (2016) demonstrated that 87% of Saudi higher-educational institutions have adopted LMS, with Blackboard being the dominant system. Furthermore, the introduction of LMS across all Saudi universities is in accordance with the request of the Saudi Government and the Vision 2030 initiative, which supports the adoption of e-learning to provide equity of access to education (Vision 2030, 2016).

The considerable adoption of LMS in higher education is attributed to its perceived advantages (see Section 2.2.3) and contributions to student academic performance. Macfadyen and Dawson (2010) tracked the log files of 118 students who use Blackboard for an online undergraduate course at a single university in Canada. The study concludes that the students' final grade was positively correlated with 13 variables in relation to the use of Blackboard (the total number of discussion messages posted, the number of new discussion messages posted, the number of reply discussion messages posted, the number of discussion messages read, the total number of online sessions, the time spent online, the number of files viewed, the number of assessments started, the number of assessments finished, the number of assignments submitted, the number of mail messages read, the number of mail messages sent, and the number of web links viewed). Similarly, previous research in developing countries (Elmahadi & Osman, 2013; Nicholas-Omoregbe, Azeta, Chiazor, & Omoregbe, 2017) demonstrated a correlation between the use of LMS and student final grades. Elmahadi and Osman (2013) found a positive correlation between the Sudanese students' use of forum and wiki tools of Moodle and their final grades. Nicholas-Omoregbe et al. (2017)

examined the influence of performance expectancy, attitude, social influence, technology culturation, and power on both behavioural intention to use LMS and student final grades in Nigeria. They revealed that performance expectancy and behavioural intention are positively associated with students' final grades. Regarding Saudi Arabia, a recent study (Basri, Alandejani, & Almadani, 2018) investigated the effects of student use of Blackboard, gender, student academic major, and GPA (grade point average) on academic performance in four Saudi public universities. Based on 629 responses, Basri et al. (2018) provided quantitative evidence that student academic performance is likely to improve with the use of Blackboard.

Despite the massive adoption and perceived advantages of LMS, this success does not necessarily indicate student uptake of such systems (Kanwal & Rehman, 2017). The effectiveness of e-learning systems ultimately relies on student use (Teo, 2016), and the benefits of these systems are minimised if students do not use them (Alenezi, 2012; Kattoua, Al-Lozi, & Alrowwad, 2016; Park, 2009; Pituch & Lee, 2006; Tarhini, Hone, Liu, & Tarhini, 2017; Tarhini, Hone, & Liu, 2014a; Teo, 2016). The effective implementation of LMS is dependent on whether the students use the system or not (Hwa, Hwei, & Peck, 2015). Al-Gahtani (2008) argues that systems are not beneficial unless they are used to their full capability. Therefore, it is important for university leaders to discover the factors that affect student use and acceptance of LMS to improve their learning experience (Abdullah & Ward, 2016; Liaw, 2008; Kanwal & Rehman, 2017).

However, the utilisation of LMS is still not as expected (Ayub, Tarmizi, Jaafar, Ali, & Luan, 2010; Alsaied, 2016; Dube & Scott, 2014; Alharbi & Drew, 2014; Alshammari, Ali, & Rosli, 2016; Juhary, 2014). Previous literature regarding developing countries (Baroud & Abouchedid, 2010; Tarhini, 2013), and Saudi Arabia in particular (Alenezi, 2012; Al-Jarf, 2007; Al-Aulamie, 2013), found that the rich features of LMS are not widespread. Back et al. (2016) investigated the use of Blackboard by medical students and revealed that only 7% of the students used discussion boards. Zanjani et al. (2017)

and Zainuddin, Idrus, and Jamal (2016) empirically found that students primarily use LMS for downloading materials and submitting assignments. Ariffin, Alias, Abd Rahman, and Sardi (2014) and Ooi (2014) evaluated student use of LMS features at a university in Malaysia. They demonstrated that the communication features of LMS and discussion boards were used poorly. Thus, Saudi Arabia is not an exception. This study, for example, discovered relatively few uses of rich features, such as discussion boards, virtual classes, and announcements, by students in Saudi public universities (see Section 5.7). Notably, students have made little use of the advanced features. The evidence from this study indicates the existence of issues that discourage LMS use, which necessitates examining variables that encourage effective utilisation (Tarhini, Hone, & Liu, 2014b).

System usability is one of the important characteristics that attracts students to use LMS (Alkhattabi, 2015; Dobozy & Reynolds, 2010). Beck (2017) concludes that perceived usability is positively associated with the use of self-directed e-learning programs. In South Africa, Booi and Ditsa (2013) examined the effect of interaction, appeal, application robustness, and invisibility on student acceptance of a university web-portal. Booi and Ditsa (2013) demonstrated the presence of a correlation between perceived usability and student acceptance. Furthermore, Dağhan and Akkoyunlu (2016) revealed that, in Turkey, student intention to use online learning environments is affected by perceived usability in addition to utilitarian value, satisfaction, and perceived value. From a practical perspective, Venkatesh and Davis (1996) emphasise the importance of understanding the determinants of technology use, because a large amount of money is spent on systems that are later rejected due to poor design. Theng and Sin (2012) investigated the influence of usability attributes (system interaction, system navigation, user interface, and personalisation) on student perceived satisfaction with e-learning systems and reported that the examination of perceived usability and its attributes have been disregarded. This observation is supported by previous literature regarding technology acceptance (see Section 3.5) and by researchers of information systems (Naqvi, Chandio, Abbasi, Burdi, & Naqvi, 2016;

Scholtz, Mandela, Mahmud, & Ramayah, 2016). As usability is an important factor in technology acceptance, this study primarily aims to investigate the influence of usability attributes on student use of LMS within the context of Saudi higher education.

1.3 Research Motivation

One important motivational factor is that education and e-learning are supported by the Saudi Government and educational institutions. The Saudi Arabian Government requires all public and private universities to create departments for e-learning and distance education to provide learning programmes in various fields (Aldiab, Chowdhury, Kootsookos, & Alam, 2017). Additionally, the new direction of the Saudi Ministry of Education is to support e-learning by establishing the National Centre for e-Learning (NCeL), which is responsible for controlling the quality of e-learning programmes provided by higher-educational institutions (NCeL, 2017). Furthermore, the Ministry of Education encouraged universities in Saudi Arabia to reduce student attendance hours by adopting blended learning using LMS (Sheerah & Goodwyn, 2016). Moreover, e-learning is an important part of the new Saudi Vision 2030 initiative, which emphasises quality and diversity of learning resources in higher education (Vision 2030, 2016). Thus, LMS have been introduced across all universities in Saudi Arabia at the request of the Government (Unnisa, 2014). This initiative represents a significant investment, including the cost of licences, staff development, and new roles as learning technologists. Therefore, exploring student perceptions toward LMS is an important topic that will help university leaders in Saudi Arabia to make the necessary decisions in this regard.

Although many studies have used the technology acceptance model (TAM) to understand student use of LMS, the majority of those studies were conducted in North America, Europe, and Eastern Asia (Al-Gahtani, 2016; Jamil, 2017; Tarhini, Hone, Liu, & Tarhini, 2017). More specifically, the Arab territory, with Saudi Arabia as its centre (see Section 3.2), is considered to be under-researched regarding student acceptance of LMS (Tarhini, Hone, Liu, & Tarhini, 2017; Al-Azawei, Parslow, & Lundqvist, 2017; Tarhini, Hone, & Liu, 2013a; Tarhini, Hone, & Liu, 2013b; Kanwal & Rehman, 2017). In addition, extrapolating results from one culture to another is questionable, as culture affects research findings (El-Masri & Tarhini, 2017). Consequently, it cannot be asserted that the findings of studies that investigated factors influencing student acceptance and use of LMS in developed countries are relevant to Saudi Arabia (Alkharang, 2014; Al-Gahtani, 2008). Supporting this argument, Tarhini (2013) compared student acceptance of Blackboard in both Lebanon and England and found that the examined factors were perceived differently between the countries. Hence, generalising the findings of these studies to Saudi Arabia is questionable due to cultural differences. This problem suggests a need for further investigation of the variables that might influence student acceptance and use of LMS in Saudi Arabia.

Little research has been conducted to understand student acceptance of LMS in Saudi Arabia (see Section 3.2), and the vast majority of these studies did not consider demographic differences between students (Abdel-Maksoud, 2018; Al-Harbi, 2011; Al-Mushasha, 2013; Alenezi, 2012; Almarashdeh & Alsmadi, 2016; Alotaibi, 2017; Muniasamy, Eljailani, & Anandhavalli, 2014). User demographics are important regarding student acceptance of e-learning systems, and understanding the effect of demographics can help in technology uptake (Tarhini, Hone, & Liu, 2014a; Ramírez-Correa, Arenas-Gaitán, & Rondán-Cataluña, 2015; Brinson, 2016; Islam, Abdul Rahim, Liang, & Momtaz, 2011; Tarhini, Hone, & Liu, 2014b; Smeda, 2017). Regarding Saudi Arabia, previous literature (Al-Aulamie, 2013; Al-Harbi, 2010; Alenezi, 2011) revealed that student attitudes toward e-learning systems differ between their demographic groups. From a methodological viewpoint, researchers usually do not consider heterogeneity in the dataset, which influences the validity of the analysis and contributes to erroneous conclusions (Hair, Hult, Ringle, & Sarstedt, 2017; Sarstedt, Henseler, & Ringle, 2011; Hair, Sarstedt, Ringle, & Mena, 2012). Therefore, understanding the differences in student acceptance of LMS helps decision-makers in Saudi Arabia to develop and tailor policies appropriate for a specific group of students, which, in turn, improves their utilisation of LMS. This factor encouraged the researcher to investigate the acceptance of LMS by students at both a national and individual level based on their personal characteristics.

Although the TAM (Davis, 1989) is one of the most popular theories in technology acceptance, several limitations of the model are discussed in the literature. First, the TAM is criticised for producing inconsistent results when tested in non-Western cultures (Sun & Zhang, 2006; Tarhini, Hone, & Liu, 2014b). For example, Muniasamy et al. (2014) examined the acceptance of LMS by female students at a single university in Saudi Arabia and found that attitude does not affect student intention to use LMS. The findings of Muniasamy et al. (2014) are predictable, as Davis (1989) did not consider cultural differences when he developed the model (Abbasi, Tarhini, Elyas, & Shah, 2015). Hence, it is important to investigate the TAM across different cultures to ensure its applicability and reliability (Sun & Zhang, 2006). This issue is relevant for Saudi Arabia because it has unique cultural differences, such as gender segregation in education and the work place. Another limitation is that the TAM explains only around 40% of variance in user intention, which is considered low (Abbasi, Tarhini, Elyas, & Shah, 2015; Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Davis, 2000; Venkatesh & Morris, 2000; Claar, Dias, & Shields, 2014; Holden & Rada, 2011). This problem is attributed to the two constructs of TAM, which are perceived ease of use and perceived usefulness. These constructs alone are insufficient to explain user intention to use technology (Al-Aulamie, 2013; Waehama, McGrath, Korthaus, & Fong, 2014). This issue highlights the importance of using the TAM with additional factors (e.g. usability) to improve its explanatory power. In addition, the TAM itself has been criticised by researchers (Al-Gahtani, 2008; Venkatesh & Morris, 2000; Venkatesh, Morris, Davis, & Davis, 2003) because it does not include moderating variables. Moderators help to understand the effects of personal characteristics on user acceptance to explain inconsistency in results across cultures (Sun & Zhang, 2006) and to improve the model's explanatory power (Venkatesh, Morris, Davis, & Davis, 2003). Nevertheless, the importance of moderators on technology acceptance has been overlooked by researchers studying Saudi e-learning acceptance (Abdel-Maksoud, 2018; Al-Harbi, 2011; Al-Mushasha, 2013; Alenezi, 2012; Almarashdeh & Alsmadi, 2016; Alotaibi, 2017; Muniasamy, Eljailani, & Anandhavalli, 2014). Therefore, this study attempts to overcome these limitations by extending the TAM by using personal moderators and additional factors and by examining the model in a non-Western culture and a developing country, Saudi Arabia.

Various studies have investigated the factors that affect student acceptance of LMS, such as organisational factors (Alenezi, Abdul Karim, & Veloo, 2011; Al-Mushasha, 2013; Al-Harbi, 2011); technical factors (Alenezi, 2012; Fathema, 2013; Hashim, 2011); personal factors (Alenezi, Abdul Karim, & Veloo, 2010; Al-Aulamie, 2013; Radif, 2016); and cultural factors (Tarhini, 2013; El-Masri & Tarhini, 2017; Tarhini, Hone, Liu, & Tarhini, 2017). The importance of perceived usability on user behaviour is confirmed in the literature regarding information systems (Aziz & Kamaludin, 2014; Booi & Ditsa, 2013; Gül, 2017; Lacka & Chong, 2016; Scholtz, Mandela, Mahmud, & Ramayah, 2016). Nevertheless, the effects of usability attributes on student use of LMS have not received enough attention from researchers (Holden & Rada, 2011; Theng & Sin, 2012). Moreover, the TAM is criticised for not considering the technical characteristics (e.g. usability) of the system under examination (Venkatesh & Davis, 1996). This shortcoming is to be expected, as the TAM was developed prior to the increasing demand for system usability (Holden & Rada, 2011). Such a limitation indicates a need to extend the TAM with usability attributes related to the investigated technology. On the other hand, previous research regarding cultural usability (Alamri, Cristea, & Al-Zaidi, 2014; Wallace, Reid, Clinciu, & Kang, 2013; Al-Wabil & Al-Khalifa, 2009; Clemmensen, Hertzum, Hornbæk, Shi, & Yammiyavar, 2009; Hsieh, 2011; Zaharias, 2008; Frandsen-Thorlacius, Hornbæk, Hertzum, & Clemmensen, 2009) indicates that culture influences perceived usability, implying that user attitude toward system usability varies depending cultural background (see Section 2.3.4). Thus, the scarcity of usability studies regarding technology acceptance and the concept of cultural usability highlights the necessity for a theoretical framework that incorporates usability factors and that investigates their effects on student acceptance of LMS in Saudi Arabia.

Having explained the research problem and the motivational drivers of this study, the next section outlines the research questions.

1.4 Research Questions

Saudi Arabia, like most developing countries, has a shortage of scientific research on student acceptance of educational technology, including LMS (Al-Aulamie, 2013; Al-Gahtani, 2016). Furthermore, LMS have massively penetrated educational environments in Saudi higher education (Aljuhney & Murray, 2016), but without achieving the expected student utilisation level (Asiri, Mahmud, Abu Bakar, & Mohd Ayub, 2012; Al-Aulamie, 2013; Alenezi, 2011). Consequently, this study primarily aims to identify the significant usability attributes and demographic characteristics that affect student use of LMS in Saudi public universities. The TAM is employed and extended to achieve the research aim (see Chapter 3). To attain this goal, the following questions have been formulated:

- RQ1. What are the usability attributes that have significant and positive effects on student acceptance and use of learning management systems in Saudi public universities?
- RQ2. To what extent do the effects of the usability attributes on student acceptance and use of learning management systems in Saudi public universities differ between students based on their demographic characteristics of gender, age, level of education, and experience?
- RQ3. To what extent do the demographic characteristics of gender, age, level of education, and experience significantly moderate the effects of the usability attributes on student acceptance and use of learning management systems in Saudi public universities?

1.5 Research Aim and Objectives

This thesis was initially conducted to identify the significant usability attributes and demographic characteristics that affect student use of LMS in Saudi public universities. To successfully achieve the primary aim of this study and provide answers for the research questions, the following objectives have been formulated:

1. Review the recent literature and situation regarding LMS, usability, and technology-acceptance theories for the following reasons:
    a. To determine student use of LMS within the context of higher education in Saudi Arabia.
    b. To identify the usability attributes and factors that are appropriate for usability evaluation of LMS from the perspective of students.
    c. To understand the positives and negatives of technology models and select an appropriate model to be extended and used as the theoretical framework for this research.
2. Develop a novel conceptual model that incorporates the relevant usability attributes as independent variables and demographic characteristics as moderators to explain their effects on student use of LMS in Saudi higher education.
3. Empirically validate the direct relationships between the independent and dependent variables in the proposed research model. This validation helps the researcher to answer the first research question.
4. Compare the similarities and differences regarding the acceptance and use of LMS between the students based on their demographic characteristics of gender, age, level of education, and experience. This comparison is important to answer the second research question.
5. Statistically examine the significant differences in the acceptance and use of LMS between the students based on their demographic characteristics of gender, age, level of education, and experience. This examination helps the

researcher to answer the third research question and explain the moderation effect of the students' demographic characteristics on the relationships in the proposed research model.

6. Based on the findings, recommendations and implications are provided for practitioners to improve student use of LMS in Saudi higher education.

The next section addresses the activities carried out to answer the research questions and achieve the aforementioned objectives of this study.

1.6 Research Process

The research design or process refers to the blueprint that comprises all the activities performed by the researcher from the beginning of the study until its conclusion (Bryman & Bell, 2015). However, there is no research design that is optimum for every type of study; therefore, researchers should develop a design that is appropriate for their work (Sekaran & Bougie, 2016). The flow chart of this present research process is depicted in Figure 1.1. The study begins by forming the research problem, aim, and objectives (Chapter 1). Then, the literature is reviewed (Chapter 2), the research questions are formulated (Chapter 1), the research model and hypotheses are proposed (Chapter 3), and the research methodology is identified (Chapter 4). The data from the online surveys are then analysed (Chapter 5), and the model is tested (Chapter 6). Finally, the findings are discussed (Chapter 7), and the conclusion is addressed (Chapter 8).

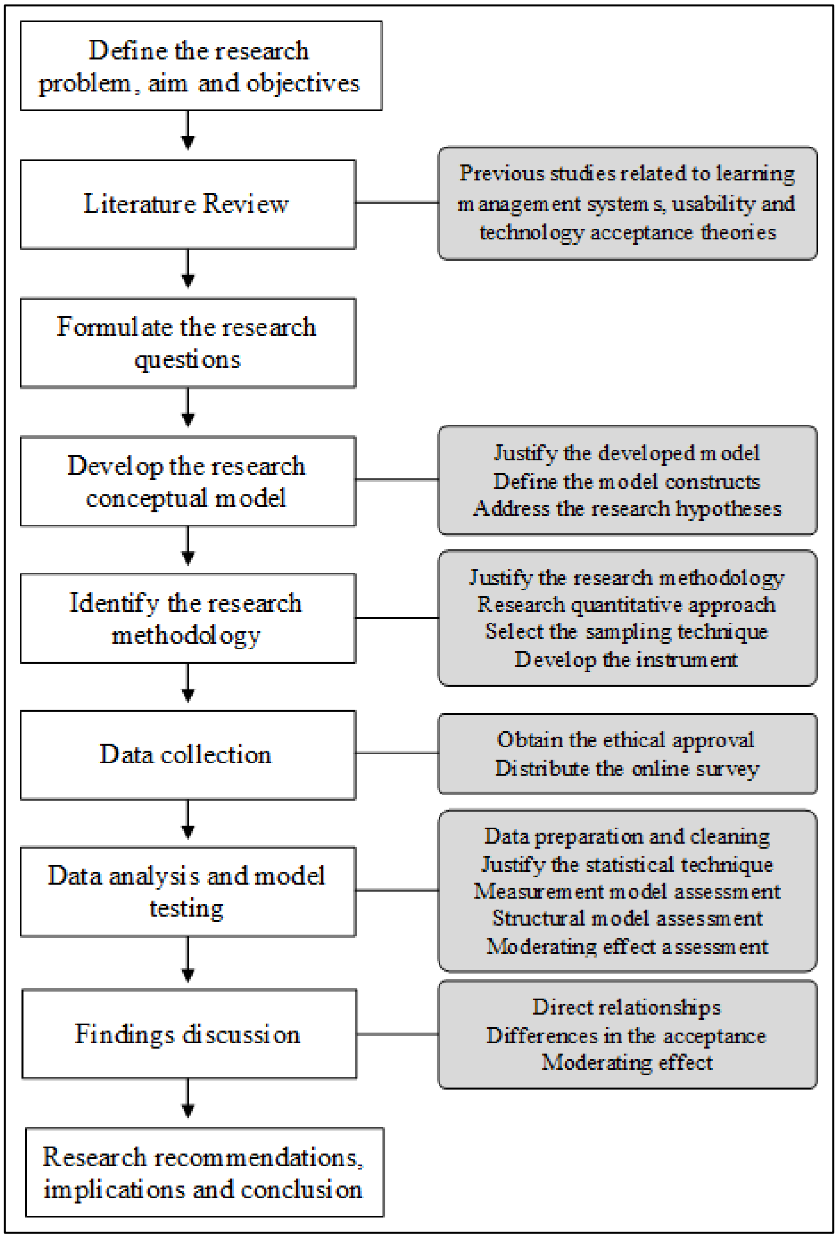

Figure 1.1 Flow Chart of Research Process

1.7 Research Context

This section offers glimpses over 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. This section presents information about culture, the new vision, Internet access, Government support and benefits of e-learning for Saudi society.

1.7.1 Profile of Saudi Arabia

The Kingdom of Saudi Arabia is located in the Southwestern part of Asia and considered the largest land in the Arabian Peninsula with 2.15 million km² and 13 administrative regions (General Authority for Statistics, 2010). Saudi Arabia shares land borders with eight Arab countries, United Arab Emirates, Bahrain, Kuwait, Yemen, Jordan, Oman, Iraq, and Qatar, and has the largest contiguous sand desert in the world, Rub' al Khali (see Table 1.1 and Figure 1.2). The latest report published by the General Authority for Statistics in Saudi Arabia indicated that the population growth rate is high and reached more than 33.4 million in 2018 (General Authority for Statistics, 2018). The mother tongue in Saudi Arabia is Arabic, while English is the second language and spoken in business organisations, educational institutions and hospitals. Saudi Arabia heavily depends on oil to support its economy, has the largest oil reserves, is the largest exporter of oil, and plays a leading role in the OPEC organisation (OPEC, 2018).

Table 1.1 Population Distribution in Administrative Regions

Regions	Male	Female	Total
Western Region	3,914,225	3,000,781	6,915,006
Central Region	3,983,358	2,793,788	6,777,146
Eastern Region	2,423,669	1,682,111	4,105,780
Aseer	1,038,284	875,108	1,913,392
Al-Madinah Al-Monawarah	985,534	792,399	1,777,933
Jazan	736,888	628,222	1,365,110
Al-Qassim	693,893	521,965	1,215,858
Tabuk	438,541	352,994	791,535
Hail	326,466	270,678	597,144
Najran	278,316	227,336	505,652
Al-Jouf	248,610	191,399	440,009
Al-Bahah	218,191	193,697	411,888
Northern Borders	174,172	146,352	320,524

Source: (General Authority for Statistics, 2010)

Figure 1.2 Map of Saudi Arabia
Source: (General Authority for Statistics, 2010)

1.7.2 Saudi Vision 2030 and Education

Prince Mohammed bin Salman, Crown Prince and Chairman of the Council of Economic and Development Affairs in Saudi Arabia, instigated the new Saudi Vision 2030 initiative on April 25, 2016. The vision proposes a future that mainly depends on three pillars, the heart of Middle East, an investment power and a hub that links three continents, and on three themes, vibrant society, thriving economy and ambitious nation (Vision 2030, 2016). The vision's objectives are planned to be achieved by implementing 12 programmes, so-called vision realisation programmes (e.g. national transformation, quality of life, privatisation and housing). A significant goal of the ambitious vision is to transfer the economy from an over-reliance on oil and diversify income sources by growing non-oil exports and sectors. The Vision 2030 initiative is centred around many endeavours related to economic reinforcement, cultural promoting, and investment maximisation (Vision 2030, 2016). However, it is not possible to successfully accomplish the endeavours of this vision without focusing on the quality of education (Yusuf, 2017).

The Saudi vision aimed to improve several aspects of Saudi society, and a well-developed educational system comes at top of this list. On October 5, 2018, Bloomberg News broadcasted an interview with the Saudi Crown Prince, Mohammed Bin Salman, declaring that Saudi Arabia has a plan to reduce its unemployment rate from 13% to 7% by 2030 (Bin Salman, 2018). Hence, the Vision 2030 initiative targets a thriving economy and an increase in the employment rate by developing human capital in accordance with job market requirements (Vision 2030, 2016). Achieving this goal requires significant efforts from the Ministry of Education in Saudi Arabia to reform education in order to accomplish the vision’s educational objectives, such as providing equal access to education, improving education quality, aligning university graduates with labour market needs and improving the ranking of five universities to top 200 (Vision 2030, 2016). Past models and curriculum are no longer appropriate for the growing society, and, thus, the Saudi universities curriculum should be changed to prepare graduates with the skills needed for this endeavour (Yusuf, 2017). Furthermore, the population of Saudi Arabia is widely distributed across the kingdom, and, therefore, shifting to more digital education (e.g. e-learning) and employing distance education technologies (e.g. LMS) might help the Saudi Government to accomplish the vision’s goal related to equity of access to education, especially in rural areas. Accordingly, the topic of this research, understanding the factors affecting student use of LMS, is important with respect to the Vision 2030 initiative as it would lead to the achievement of the vision’s objectives and boost the number of distance learning students in Saudi universities.

As the implementation of many aspects of the Vision 2030 initiative and the topic of this thesis are related to the use of Internet in Saudi Arabia, it is necessary to understand the current status of Internet use by Saudis.

1.7.3 Internet Use in Saudi Arabia

Access to the Internet in Saudi Arabia was made available to the public as late as1999 (MCIT, 2018). It is noteworthy that higher-educational institutions were first, even before public institutions, to connect to the Internet in 1993 prior to King Abdulaziz City for Science and Technology and King Faisal Specialist Hospital and Research Centre (Alshahrani, 2016). This may indicate that the education sector is a top priority to the Government in Saudi Arabia. Nevertheless, a recent report published by Communications and Information Technology Commission (CITC) in Saudi Arabia showed an enormous growth in the number of Internet users (CITC, 2017). The report demonstrated that the total percentage of Internet users has increased dramatically from 63.7% in 2014 to 82 % in 2017. This implies that every person included in the 82 % has access to the Internet through a computer, tablet or mobile phone to benefit from Internet services. Regarding the amount of time spent on the Internet, the percentage of those who use the Internet for more than four hours a day has grown from 52% in 2014 to 63% in 2017. Based on the number of subscriptions, 94% of the country's total population has subscribed to mobile broadband services, and 34% of all residential units are subscribed to fixed broadband services. Similarly, Figure 1.3 and Figure 1.4 represent the results published by the International Telecommunication Union (ITU) and demonstrate that the percentage of Internet users and the number of fixed broadband subscriptions in Saudi Arabia have been increasing since 2005 (ITU, 2017). In terms of e-commerce, CITC (2017) revealed that 93% visited online stores through smartphones, and eight million, mostly women, had completed at least one purchase transaction via the Internet. The successful projects in IT infrastructure conducted in the last two decades by the Saudi Government in collaboration with the private sector facilitated Internet connection and contributed to the rise in Internet users in Saudi Arabia (MCIT, 2018). Notwithstanding, IT infrastructure in the country is still lagging behind those in developed countries and requires concerted efforts from public and private organisations within the country to improve the quality of broadband services (Nurunnabi, 2017).

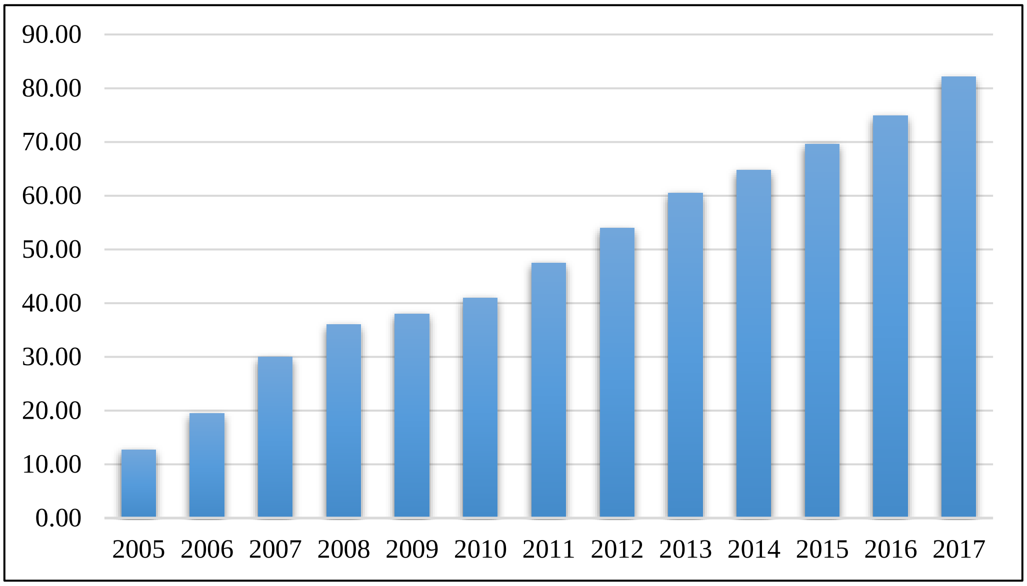

Figure 1.3 Percentage of Internet Users in Saudi Arabia
Source: (ITU, 2017)

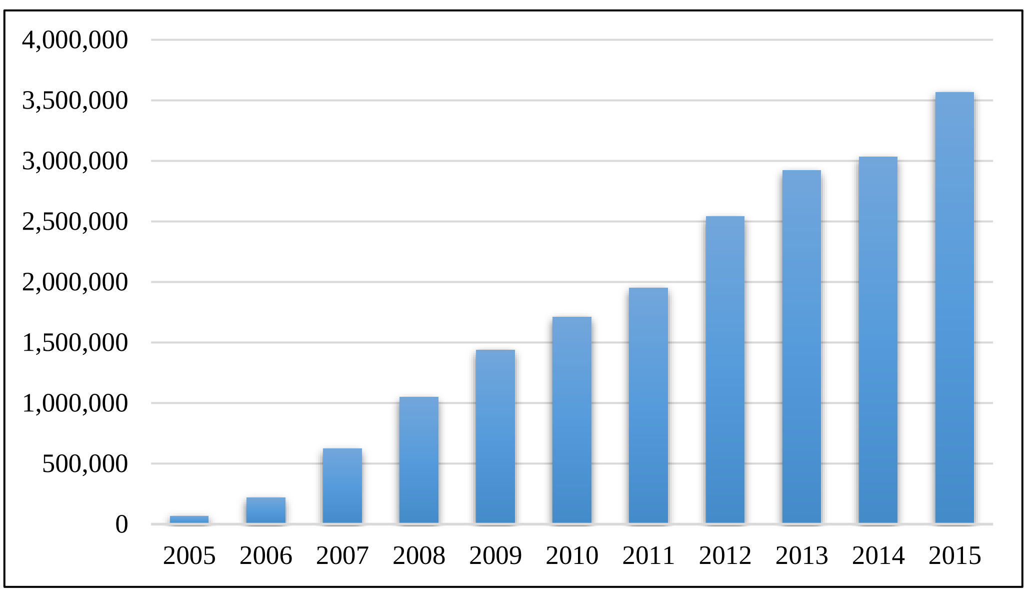

Figure 1.4 Fixed Broadband Subscriptions in Saudi Arabia
Source: (ITU, 2017)

CITC conducted a study that aimed to understand the current status of individual use of technology, Internet, and social media across Saudi Arabia including both genders and various age groups from 12 to 65 years old (CITC, 2015). The study revealed that 91% of respondents use the Internet, and 87% of them use the Internet for two or more hours every day. The remaining 9% do not use the Internet mainly because they do not know how to use it and do not know what the Internet is. Home is the first place for using the Internet as 78% of respondents reported that they use the Internet at home. The main activities of using the Internet are web browsing (90%), social media (85%), emails (53%), video games and movies (50%), reading news and newspaper (43%) and education purposes (26%). Regarding social media, their study found that 91% of all participants use social media, and more than 42% of them are always connected and respond as much as needed. Notably, the findings of the CITC's study, related to number of users, time spent on Internet, and social media, uncovered that the Internet and online services are becoming an important aspect of the modern Saudi Arabia.

1.7.4 Government Initiative of E-learning

Education in Saudi Arabia has a priority in the financial support provided by the Government, which represents a substantial portion of the national budget each year (Ministry of Education, 2017b). The Government of Saudi Arabia has announced its largest ever budget for the year 2019 with a planned expenditure of SAR 1.106 trillion ($295 billion) (Ministry of Finance, 2018). As education is a significant pillar of the new vision of Saudi Arabia (Vision 2030, 2016), education received the largest amount of the national Saudi budget with 17.5%, SAR 193 billion ($51.5 billion). This budget is expected to be spent on the development of the education sector, and online learning is one area of investment. Most Saudi universities heavily invested resources, money and time to establish new departments to provide online and blended learning courses as requested by the Government (Aldiab, Chowdhury, Kootsookos, & Alam, 2017; Almarashdeh & Alsmadi, 2016).

The Custodian of the Two Holy Mosques King Salman bin Abdul Aziz approved the establishment of The National Centre for e-Learning (NCeL) on October 4, 2017. The Centre is financially and administratively independent and directly linked to the Ministry of Education in Saudi Arabia. The National Centre for e-Learning was established with the objective of controlling the quality of e-learning programmes and employing educational technology to improve the efficiency of education and training in Saudi Arabia. The centre sets up regulations and policies for the quality standards of e-learning programmes provided by educational institutions in Saudi Arabia. The Centre is also responsible for granting licenses to organisations providing e-learning programmes, conducting research in Saudi e-learning and representing the Kingdom abroad in e-learning (NCeL, 2017).

In the era of digital technology, the Saudi digital library (SDL) is another prominent support resource provided by the Saudi Ministry of Education to facilitate and modernise access to information (SDL, 2015). The library is the largest electronic library in the Arab world and is free for the staff, researchers, faculty and students of higher-educational institutions in Saudi Arabia. The Saudi digital library has access to the content of more than 310,000 digital resources and 300 international publishers in various disciplines (e.g. ScienceDirect, Springer Link, ProQuest, ACM digital library). The library has also undertaken the responsibility of spreading the skills of scientific research to those interested in academic society by providing training courses about scientific research (e.g. philosophy, methodology, publishing, translation and technology).

Another initiative of the Government toward e-learning is the establishment of The Saudi Electronic University (SEU) in 2011. The university represents the flexibility of higher education that supports self-learning skills and offers knowledge to the whole country by delivering e-learning, distance learning and blended learning courses (Saudi Electronic University, 2011). The university is the only public university in Saudi Arabia specialised in distance learning that provides undergraduate (bachelor's degree) and postgraduate (master's degree) qualifications along with life-long learning. The university has more than 13,399 undergraduate and 519 postgraduate students from both genders, and the number is increasing (Ministry of Education, 2017a). While e-learning is still in its early stages in Saudi Arabia, the popularity of e-learning is increasing.

The motivation of the Saudi Government for these e-learning initiatives can be understood from the advantages that e-learning provides for Saudi society, which are presented in the next section.

1.7.5 Benefits of e-Learning

The advantages of e-learning are closely relevant to the context of Saudi Arabia, especially from its culture. Saudi society does not allow men, excluding close relatives, to see or meet women without a veil due to Islamic rules and the local culture. This regulation has been extended to affect the educational environment in Saudi universities and made it a gender-segregated environment. In fact, a sexually segregated university is the only available system in all public and private universities in Saudi Arabia except King Abdullah University of Science and Technology, which was severely criticised by Saudi society. Consequently, female students are not allowed to attend face-to-face classes with male faculty staff (Aldosemani, Shepherd, & Bolliger, 2018). Given the current insufficiency of female faculty members (Aljaber, 2018) and the increasing number of female secondary school graduates joining universities (Alhareth, Al-Dighrir, & Al-Alhareth, 2015; Nurunnabi, 2017), many female students thereby are taught by male faculty staff via closed-circuit television with one-way video and two-way audio communications. This setting might complicate the learning process and restrict female students from fully participating in class activities (Alkhalaf, 2013). Further, this places more pressure on university facilities and the limited number of human resources (Unnisa, 2014). Therefore, e-learning is a convenient medium for delivering education with a socially acceptable interaction, in terms of the Saudi culture, allowing female students to equally participate (Aldosemani, Shepherd, & Bolliger, 2018; Al-Youssef, 2015).

The statistics of higher education published by the Saudi Ministry of Education showed that the population of students attending institutions of higher education has been increasing each year (Ministry of Education, 2017a). The number has increased from 1.2 million in 2012 to 1.7 million in 2017 (see Figure 1.5). Moreover, the country's population has been expanding with approximately 50% of the population younger than 30 years old (General Authority for Statistics, 2018). The rise in the students' demand for higher education and the population of young people contributed to capacity pressure on Saudi universities (Al-Youssef, 2015). As such, it was decided that higher-educational institutions should increase the number of available places on face-to-face classes to emulate the growth in the students' population, which is associated with enormous costs. This necessitates higher-educational institutions to offer additional learning channels (e.g. e-learning) to accommodate the increasing number of higher-education students and the younger population.

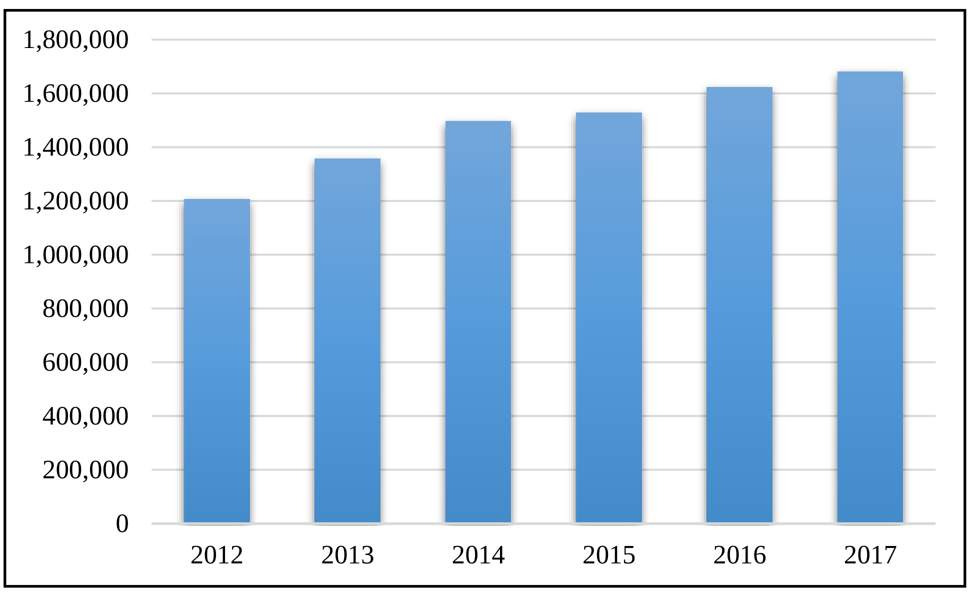

Figure 1.5 Number of Students in Saudi Higher Education
Source: (Ministry of Education, 2017a)

Saudi Arabia is the second largest country, in terms of geographical area, among the Arabian countries with 2.15 million km² and more than 33.4 million people (General Authority for Statistics, 2018). The report of General Authority for Statistics, summarised in Table 1.1 in Section 1.7.1, showed that around two thirds of the population in Saudi Arabia is distributed in three of the 13 administrative regions: Western Region (located in the western area of Saudi Arabia), Central Region (located in the centre of Saudi Arabia), and Eastern Region (located in the eastern area of Saudi Arabia) (General Authority for Statistics, 2010). Further, the distribution of university campuses is not proportionate for those regions with a high-density population (Aldiab, Chowdhury, Kootsookos, & Alam, 2017). Moreover, the very remote districts in Saudi Arabia are difficult to reach due to high mountains (Al-Harbi, 2010). These environmental barriers have affected the access of remote and rural districts to the institutions of higher education. Considering the Saudi Vision 2030 initiative, aiming to provide equal access to education for all citizens, adopting e-learning systems provides the potential to deliver education to these remote and rural districts and reduces the differences between the regions in order to provide equity of access to education (Aldiab, Chowdhury, Kootsookos, & Alam, 2017; Unnisa, 2014).

Online learning is especially important for women in Saudi Arabia. The Saudi Crown Prince, Mohammed Bin Salman, announced in a 2018 Bloomberg News interview that the Government is planning to reduce the female unemployment rate as part of Vision 2030 (Bin Salman, 2018). According to the local culture, Saudi women take the most part in the roles that influence inside the household, such as childcare and upbringing, cooking, washing and cleaning. E-learning provides students with more flexible education as they can learn at their convenience (Chaubey & Bhattacharya, 2015; Chu, et al., 2010; Althobaiti & Mayhew, 2016). The e-learning method is consistent with the objective of the vision and allows Saudi female workers to balance their lives between education, career and household duties (Aldosemani, Shepherd, & Bolliger, 2018; Sheerah & Goodwyn, 2016).

1.8 Thesis Structure

The structure of this thesis is organised into eight chapters. A summary of each chapter is provided, below:

- *Chapter 1 Introduction:* The roadmap of the entire thesis is presented. More specifically, the chapter justifies why the topic was selected, and explains the purpose of this study. Also, the chapter discusses the research context, including Saudi culture, new changes and developments, and education and technology in Saudi Arabia.
- *Chapter 2 Research Background:* This chapter provides an overview and background information about the three areas that underpin this study: LMS, usability, and the TAM. The chapter begins by describing the technology of LMS. Then, literature about the usability of LMS is presented from the perspective of students to choose appropriate usability factors. Finally, technology adoption theories are introduced to select an appropriate theoretical framework for the research.
- *Chapter 3 Conceptual Framework:* The primary objective of this chapter is to frame and justify the proposed model based on the gaps in the existing literature and the current state of knowledge. The development of the proposed conceptual model of this study is explained in detail. Furthermore, the rationale underlying the adoption of usability attributes, the TAM, and personal moderators is provided, and the research hypotheses are listed.
- *Chapter 4 Research Methodology:* This chapter justifies the selection of the methodological approaches used for the data collection and analysis to examine the proposed model in Chapter 3. Six subsections are included: research paradigm, research design, population and sampling, instrument development, data collection, and data analysis technique.
- *Chapter 5 Data Analysis:* The researcher primarily introduces and analyses the results of the collected data. First, the chapter covers the preliminary

examination of data, including missing data, outliers, normality, and unengaged responses. A detailed explanation of the response rate and non-response bias test follow. The final section presents the profile of the respondents, the descriptive statistics of the variables, and the LMS features.

- *Chapter 6 Model Testing:* This chapter contains the results of testing and validating the proposed model in Chapter 3 using the PLS-SEM technique and SmartPLS software. The results include multi-stage procedures as follows: (1) measurement model assessment; (2) structural model assessment; (3) goodness-of-fit; (4) differences in the acceptance of LMS; and (5) moderating effect assessment.
- *Chapter 7 Discussion:* This chapter presents an in-depth discussion of the study findings obtained in Chapters 5 and 6. The results are connected with the literature regarding LMS acceptance and use.
- *Chapter 8 Conclusion:* This conclusion is based on the results obtained in this research. A summary of the research objectives and findings, their contribution to theory and domain, and recommendations and implications are presented. Finally, future research directions are suggested based on the limitations of this study.

CHAPTER 2: RESEARCH BACKGROUND

2.1 Introduction

The aim of this chapter is to provide an overview of the published literature on the three areas that underpin this study; LMS, usability, and technology-acceptance theories and models. This will help those who are not familiar with the topic to recognise and understand the basic parts of this research. The chapter investigates what LMS are, describes the features and functions of LMS, compares commercial and open-source LMS, and summarises the advantages and disadvantages of LMS. Furthermore, the chapter introduces more literature about the usability of LMS with usability definitions, effectiveness of usability in student use of LMS, and heuristics used for LMS. This will help the researcher, in the next chapter, to select the appropriate usability attributes to assess student acceptance of LMS. Finally, the aim of the study is to explore the use of new LMS technology in Saudi universities, and, therefore, technology adoption theories are introduced to locate an appropriate theoretical perspective for the research.

2.2 Learning Management Systems

Learning management systems were introduced in 1990s (Coates, James, & Baldwin, 2005). Learning management systems have been widely adopted in many academic institutions (Hussein, 2011; Dahlstrom, Brooks, & Bichsel, 2014) and are the primary system utilised by higher-educational institutions worldwide (Persico, Manca, & Pozzi, 2014; Alturki & Aldraiweesh, 2016; Alshammari, 2015). More explanation about LMS, including LMS definition, features, advantages, and disadvantages, is provided in the next subsections.

2.2.1 Definition of Learning Management Systems

The field of education has been influenced by the development of information and communication technologies, which has given rise to the emergence of new terminology in educational technology, such as e-learning systems, LMS, virtual learning environments (VLE), and computer-based training systems (CBT). Based on a mixed-method analysis, it was found (Moore, Dickson-Deane, & Galyen, 2011) that the use of terminology for various educational technologies is inconsistent among researchers. This highlights the importance of clarifying the differences between the emerged terms in e-learning.

Starting with the broadest term, e-learning systems refers to technological systems that provide individuals with access to education through the utilisation of the Internet (Islam, 2013). Accordingly, the term e-learning systems is very broad and, therefore, it may include any systems that deliver education to learners via the Internet, such as LMS and VLE (Martín-Blas & Serrano-Fernández, 2009). On the other hand, an LMS is a web-based learning system that is composed of multiple features, allowing educators to develop course content and learning activities and learners to fulfil learning assignments (Chaubey & Bhattacharya, 2015). This definition indicates that LMS is a type of e-learning system and more toward managing the delivery of e-learning courses. Learning management systems consist of various tools that helps in managing courses, such as user registration, announcements, email, forums, assignment submission, quizzes, course materials, and calendars (Kabassi, et al., 2016). Blackboard, Moodle, and Sakai are examples of LMS. Moore et al. (2011) reviewed previous literature on learning environments and revealed that most researchers consider the terms LMS and VLE as synonyms. The term LMS is widely used in North America, while the synonymous term VLE is widely used in Europe and Asia (Martindale & Dowdy, 2010). However, some researchers perceive the two terms differently. It was stated (Lin & Chen, 2013) that although LMS and VLE are related terms, each of the two systems emphasises different aspects. Pinner (2014) argued that VLE is more constructivist and aims to provide an online environment to collaborate and extend discussions between the educator and learners, while the other term (LMS) aims to track learning objects. Therefore, defining the two terms is dependent on how institutions use the two systems. Finally, CBT refers to a software package employed for delivering training courses via computers and involves interactions between trainees and personal or networked computers for accessing training programs (Gorecky, Khamis, & Mura, 2017). Therefore, CBT is considered as an interactive educational process with less involvement from educators. Unlike LMS and VLE, CBT is more often used by companies and organisations to provide training courses for their employees than educational institutions (Tao, 2011).

Learning management systems have been defined differently among researchers based on the functions integrated into the system. It was stated (Ghazal, Aldowah, & Umar, 2018) that LMS are information systems utilised by teachers to effectively create, amend, and maintain course materials online. Hussein (2011) described LMS as software intended to manage educational processes and activities. Learning management systems are web-based systems that allow teachers to develop course content, deliver knowledge, and assess student progress (Venter, van Rensburg, & Davis, 2012). An LMS is an application developed with the particular goal of assisting teachers in meeting their learning objectives of delivering knowledge to students (Machado & Tao, 2007). In the view of Chaubey and Bhattacharya (2015), LMS can be described as web-based or cloud-based applications that aim to provide the effective delivery of education. Moreover, an LMS is a platform for managing content, materials delivery, and users who may include students, administrators, teachers, and designers (Abdul Rahman, Ghazali, & Ismail, 2010). In the view of Medina-Flores and Morales-Gamboa (2015), LMS are applications that are mainly used for delivering education through ICT. Learning management systems are aimed to encourage course management and collaboration between teachers and students through the utilisation of ICT (Medina-Flores & Morales-Gamboa, 2015). Dube and Scott (2014) consider the use of an LMS as supporting a flexible teaching style facilitated by the web to help alleviate problems of limited resources and increased student numbers.

The system is composed of many well-integrated features to help teachers and students meet their teaching and learning objectives (Althobaiti & Mayhew, 2016). Basic versions of LMS are used as a storage space for educational materials, where advanced versions offer different features and functions (Chu, et al., 2010). Learning management systems provide educational institutions with the capability to share, store, and manage the learning materials and content. Learning management systems enable academics to utilise various instructional methods, technologies, and resources to enhance traditional learning (Kabassi, et al., 2016). In common use, LMS can encompass the provision of course registration, upload and download of learning materials, synchronous and asynchronous communication between students and teachers, assignment submission, exams, and student performance assessment.

Even though these features are different from one LMS to another (Alharbi & Drew, 2014), Kabassi et al. (2016) reported that LMS are basically composed of three tools: communication tools, content tools, and assessment tools. The communication tools aim to enhance the academic interaction between students and teachers (Swart, 2016). While Kasim and Khalid (2016) declared that discussion boards and announcements are the most popular communication tools in LMS, Kabassi et al. (2016) categorised the communication tools into synchronous and asynchronous tools. Synchronous communication (real-time) includes discussion board and chat; however, asynchronous communication (not real-time) includes email and announcements (Alshammari, 2015). Moreover, LMS offer methods for one-to-one communication (e.g. email) and many-to-many communication (e.g. forum) (Naveh, Tubin, & Pliskin, 2012). Hariri (2013) argued that the existence of more than one tool enables each student to choose the appropriate tool for communication; for example, shy students might prefer to use email rather than a forum. Such tools enhance student performance in exams (Elmahadi & Osman, 2013), encourage students to engage with learning (Hariri, 2013), and enable interactive learning (Amin, Afrin Azhar, & Akter, 2016) and online communities with immediate feedback (Naveh, Tubin, & Pliskin, 2012).

Another feature of LMS is content management tools (Kabassi, et al., 2016; Kasim & Khalid, 2016). One of the LMS capabilities is managing, modifying, and storing learning content for authorised users (Freire, Arezes, & Campos, 2012). Learning management systems enrich course content by providing teachers with the capabilities of managing, designing, and introducing courses as desired (Kabassi, et al., 2016). Content tools are used for developing and delivering course materials such as links to other sources, uploaded files, and learning objects. The content of learning materials usually includes texts, videos, or images (Alshammari, 2015).

The third feature reported by Kabassi et al. (2016) is assessment tools. Learning management systems offer great assessment features to save the time of faculties and provide secured exams (Alghamdi & Bayaga, 2016). Assessment tools facilitate the job of faculties by integrating different functions such as questions database and marking schema (Kasim & Khalid, 2016). Formative and summative assessment tools are provided including tests, surreys, quizzes, assignments submission, exams, and grading (Kabassi, et al., 2016). Such tools provide students with immediate feedback regarding their performance, and students therefore can increase their efforts to overcome the weaknesses in their performance (Hariri, 2013). All these features enhance the pedagogical level of education to be compatible with the era of ICT development (Alghamdi & Bayaga, 2016).

2.2.2 Types of Learning Management Systems

Nowadays, there is a number of LMS used by academic institutions and other organisations for education and training purposes. Learning management systems are not all the same (Dalsgaard, 2006), and features are different from one LMS to another (Alharbi & Drew, 2014). Therefore, LMS might be categorised based on different aspects such as cost and locality.

One of the important aspects that an organisation has to consider when choosing an LMS is the financial cost associated with the system. To avoid the high cost of LMS, some organisations tend to either utilise an open-source platform or develop their own LMS (Aydin & Tirkes, 2010). The users of open-source LMS benefit from the low-cost service because of the availability of the source code. Open-source LMS provide users with the right to use and make changes to the system (Chaubey & Bhattacharya, 2015), and the platform therefore can be tailored to the preferences of organisations (Kasim & Khalid, 2016). However, open-source LMS entail extensive efforts in customising them (Ivanović, et al., 2013). Since open-source LMS are usually more complicated than commercial LMS, they require skilled users for even minor customisation (Machado & Tao, 2007). Organisations should not expect that open-source systems are free of financial costs since they need to hire technical experts or obtain support as a paid service (Carvalho, Areal, & Silva, 2011). Moodle and Sakai, which are characterised with ease of use and flexibility, are the most popular examples in this category (Dube & Scott, 2014).

Proprietary LMS (commercial), on the other hand, are more expensive than open-source LMS (Carvalho, Areal, & Silva, 2011). Even though proprietary LMS provide better technical support than open-source LMS (Raman, Don, Khalid, & Rizuan, 2014), proprietary LMS require financial commitments from organisations using them (Carvalho, Areal, & Silva, 2011). Kasim and Khalid (2016) compared proprietary and open-source LMS and reported that proprietary LMS require the purchase of a license for each user annually along with support and maintenance fees. Furthermore, proprietary platforms usually cannot be tailored based on the preferences of organisations since they are developed based on a set of standards (Kasim & Khalid, 2016). Many popular LMS come under this category such as Blackboard, Desire2Learn, and SuccessFactors.

From a different perspective, LMS are typically provided in different forms. Learning management systems can be provided as a local system. In this form, LMS are installed locally on the premises and servers of organisations. Usually, the technical support of local LMS is the responsibility of organisations. Therefore, local LMS might be the best choice for organisations that already have an IT team in place.

On the other hand, LMS can be also provided as software as a service (SaaS) or cloud based. In this category, LMS are hosted on the servers of vendors, and users need the Internet to connect remotely to LMS (Masud & Huang, 2012). With SaaS LMS, all support, maintenance, and upgrades are provided by vendors rather than organisations (Chaubey & Bhattacharya, 2015). Therefore, SaaS/cloud LMS might be the best choice for organisations that do not have an IT team in place. Organisations that use this type of LMS might benefit from the low start-up costs, improved security, and enhanced accessibility (Masud & Huang, 2012). This might justify why 87% of organisations use this type of LMS, while 13% use local LMS (Medved, 2015). Many popular LMS come under this category such as Docebo, Litmos LMS, and Jusur (Saudi LMS).

2.2.3 Advantages of Learning Management Systems

One of the most important advantages is that the system enhances student control and flexibility by enabling them to learn at anytime and anywhere (Chaubey & Bhattacharya, 2015; Chu, et al., 2010; Althobaiti & Mayhew, 2016). In traditional classrooms, students must attend the class at a specific time in the same geographical location for a certain period of time. Learning management systems provide students with a convenient way to overcome the physical and time obstacles of traditional learning (Chu, et al., 2010). Swart (2016) reported that LMS have the abilities of building, supporting, conveying, and encouraging learning without the limitations of time and place. This advantage is the most important characteristic of LMS (Chaubey & Bhattacharya, 2015), especially for students who have jobs and work for long hours (Chu, et al., 2010). Therefore, such systems provide individuals with equal opportunities to learn from anywhere and at any time (Hassanzadeh, Kanaani, & Elahi, 2012).

Empirically, a study (Uziak, Oladiran, Lorencowicz, & Becker, 2018) investigated the perspective of 275 university students in Botswana on the use of Blackboard. Students agreed that Blackboard improves the learning quality (81%), makes best use of time

(65%), makes students organised (84%), helps in achieving assignments more quickly and efficiently (84%), helps in presenting the content in an organised way (81%), helps in understanding the materials (81%), and improves the student-teacher interaction (83%). From a teacher standpoint, an American study (Dahlstrom, Brooks, & Bichsel, 2014) found that 74% of teachers reported the usefulness of LMS, 71% agreed that LMS enhance student learning, and 60% reported that LMS are crucial for teaching activities.

Besides the aforementioned advantages, studies (Chaubey & Bhattacharya, 2015; Kabassi, et al., 2016; Chu, et al., 2010; Alghamdi & Bayaga, 2016; Srichanyachon, 2014) addressed various advantages of LMS:

- Learning management systems provide a centralised learning where all materials are available in one place.
- Well-designed LMS support pedagogical and instructional strategies such as a student-centred approach.
- Learning management systems enable teachers to design courses and material as desired through the use of well-integrated tools.
- Learning management systems provide a cost-effective way for delivering education to a large audience worldwide.
- Learning management systems are a great solution to accommodate large numbers of students in different places in the world.
- Learning management systems are beneficial in storing, archiving, and retrieving materials.
- Learning management systems are not static, and materials therefore can be easily reusable and modified in different modules.
- Learning management systems help in assessing students, tracking the performance of each student, and comparing a student’s performance with other students.

- Learning management systems encourage interactive and collaborative learning by providing great mediums between teacher and student, between teacher and multiple students, and between groups of students.

2.2.4 Disadvantages of Learning Management Systems

Despite the foregoing advantages of LMS, some scholars view LMS from a different angle. Current LMS are not free of problems (Althobaiti & Mayhew, 2016). Studies (Nokelainen, 2006; Zaharias, 2009; Althobaiti & Mayhew, 2016; Orfanou, Tselios, & Katsanos, 2015) confirmed that such a system experiences usability problems related to the users of the system. Consequently, unusable LMS distract student concentration, require more effort and time, increase student frustration, and force students to focus on how to use the system rather than the content because of the low level of the system learnability (Sorenson, 2016). In addition, the adopting of LMS entails the continuous training of teachers, students, and administrators to enhance their technical skills (Al-Adwan, Al- Adwan, & Smedley, 2013). Further studies (Chu, et al., 2010; Arkorful & Abaidoo, 2015) added the following:

- Learning management systems might conflict with the student-centred approach and entail the organisation concentrating on improving the technology itself rather than students.
- The adoption of LMS requires hiring technical experts and extra costs.
- Learning management systems require support, a help feature, and training for users.
- Since LMS can be accessed from computers and mobiles, security issues are usually involved. For example, hackers may exploit the system vulnerabilities to steal login credentials or hack the system. Therefore, it is imperative for LMS vendors to ensure that the system is secure by implementing latest security standards and protocols to protect the system from security threats.
- Some users perceive traditional face-to-face education as more effective.

- As LMS entail self-motivation, students with low self-motivation or bad studying behaviours might be affected negatively.
- In terms of improving the communication skills of students, LMS might affect social skills negatively. Despite that students may obtain a great academic knowledge by using LMS, they might not have the required skills to deliver their obtained knowledge to other people. As LMS are web-based e-learning systems, they may minimise socialisation skills and limit the importance of face-to-face skills.
- Learning management systems might not be the optimal solution for all disciplines. For example, scientific majors that need hands-on practical experiences (e.g. medicine and engineering) might be more complex to be studied via LMS as they require developing practical skills. However, LMS might be more appropriate to be used in social science and humanities.

As discussed in this section, an unusable LMS might be costly to introduce in terms of licences and training, while not necessarily realising the educational benefits. As such, how the LMS is designed and implemented affects the effectiveness as an educational tool, and, therefore, the usability of LMS is presented in the next section.

2.3 Usability

Usability is one of the important quality characteristics of an LMS that attracts students to use the system (Dobozy & Reynolds, 2010). System usability has been researched for over 50 years (Zaharias, 2009) and the usability of systems ranging from simple websites to complex control systems has been the subject of many studies. To consider the usability of LMS this section presents more details about the definition of usability, key usability concepts, heuristics, attributes, and related work.

2.3.1 Definition of Usability

The definition of usability has been proposed by many scholars and organisations, and they have never agreed on a single definition (Green & Pearson, 2011; Aziz & Kamaludin, 2014). Usability has been widely defined as the degree to which individuals can use products to achieve certain tasks with effectiveness, efficiency, and satisfaction within a certain environment (ISO 9241, 1998). Shackel (2009) defined usability as a technology used effectively and easily by specific users to accomplish specific tasks within a specific environment. In the view of Medina-Flores and Morales-Gamboa (2015), usability coordinates different parts of systems and assists in identifying the quality attributes from user point of view. Usability can be defined as the quality of systems (Casare, Silva, Martins, & Moraes, 2016); user experience with systems (Al-Khalifa, 2010); an important component of any user interface, that helps in assessing the easiness of user interfaces (Nielsen, 1993); user satisfaction when performing tasks on systems (Abdul Rahman, Ghazali, & Ismail, 2010); how easy is a system to learn and use (Thowfeeka & Abdul Salam, 2014); the ability of a product to be used (Bevan, Carter, & Harker, 2015); and elements that allow users to avoid mistakes, perform tasks easily, and remember how to use the system in the future (Benaida, 2014). Usability enables users to measure the acceptance of systems for delivering the expected objectives (Alturki & Aldraiweesh, 2016). Simply, usability can be described as the easiness of using systems (Oztekin, Kong, & Uysal, 2010). Those definitions indicate the meaning of usability in terms of the design goals of systems.

Some scholars, on the other hand, tend to define usability in terms of the attributes or heuristics associated with usability. Usability may refer to separate quality attributes (e.g. learnability, performance, and satisfaction) or all of them as a whole (Seffah & Metzker, 2004). Usability is more than a single attribute (Althobaiti & Mayhew, 2016) and cannot be perceived as only ease of use (Shackel, 2009). Nielsen (1993) indicated that a usable system has to achieve learnability, efficiency, memorability, lack of errors, and satisfaction. Similarly, Palmer (2002) defined usability in terms of five characteristics, namely download delay, navigability, content, interactivity, and response time. In the view of Shackel (2009), usability refers to effectiveness, learnability, flexibility, and attitude. The diversity in the term usability makes the process of measuring system usability very difficult and open to interpretation (Green & Pearson, 2011).

One of the most internationally accepted definitions of usability across fields is the definition provided by the International Organisation for Standardisation (ISO) (Bevan, Carter, & Harker, 2015; Quiñones & Rusu, 2017). Usability refers to the degree to which a particular individual can utilise a particular product to accomplish certain goals with effectiveness, efficiency, and satisfaction in a certain context (ISO 9241, 1998). The definition of ISO 9241 indicated that the usability of systems relies on four elements: type of user, specified products, desired results, and the context of use (Hasan, 2009; Aziz & Kamaludin, 2014). Furthermore, the ISO 9241 definition addressed three primary usability attributes that can be used to measure the usability of systems. These attributes are effectiveness, efficiency (the two are relevant to the performance of the system), and user satisfaction (see Table 2.1). The ISO 9241 definition intersects with the definition of Nielsen's (1993) and Shackel's (2009) into the three attributes (efficiency, effectiveness, and satisfaction).

Table 2.1 The Primary Attributes of Usability

Attributes	**Definition**
Effectiveness	The degree to which goals are accomplished in relation to accuracy and completeness.
Efficiency	Resources used to accomplish goals.
Satisfaction	How users are comfortable and satisfied with the features of systems.

Source: (ISO 9241, 1998)

Human-computer interaction (HCI) and usability are currently integral components of the processes of system development that aim to improve system facilities and ensure that the needs of users are satisfied (Al Mahdi, Naidu, & Kurian, 2019). For system designers, HCI can help in identifying the needs that can include text style, graphics, colours, and fonts (Nielsen, 1994). Usability in relation to HCI is a concept that helps to confirm if the process of development produced a system that is effective, efficient, safe, utility, and most critically, easy to learn, remember, use, and evaluate (Nielsen & Molich, 1990). Researchers, such as Issa and Isaias (2015), also add the need for practical visibility and pinpoint the need for the system to provide job satisfaction to users in a firm. The integration of HCI and usability entail user productivity; wastage of time and having to struggle with complicated instructions (Nielsen, 2012). HCI has been developed to be an area of study that is critical to ensure enhanced and improved usability of products. According to Nielsen (1994), HCI should involve users when building and implementing new systems and require considering cognitive and other relevant behavioural factors that affect how computer users interact with the system (Harte, et al., 2017; Nielsen, 1994). In short, all user interfaces that humans use can be considered as a form of HCI, and how easy or difficult the interaction between users and interfaces can be considered as usability measures.

According to Nielsen (1993), Nielsen (1994), Nielsen (2012), and Nielsen and Molich (1990), the success of usability design results from considering different aspects of HCI. Observing these aspects will help in designing HCI that supports flawless usability. Firstly, HCI that supports good usability has a simple and natural dialogue. The system should ensure irrelevant information is left out. Nielsen (1993) highlighted that every piece of the extraneous information is competing with a piece of relevant information, diminishing the visibility of what the user has to see. Besides, systems should display and communicate the language of users (Nielsen, 1994). The aspects of HCI designed for high usability experience emphasise the language that the user understands (Sherman & Craig, 2019). Therefore, using languages that are only understood by the developer should be avoided to improve user experience.

Furthermore, the memory load of the user should be minimised to promote usability in HCI (Nielsen, 1993). Users should not be required to remember information from one section of dialogue to another. If the system cannot automate this, the user should be availed with help from the points they can retrieve easily from the system. Another aspect that Nielsen and Molich (1990) stated to be supportive of usability in HCI is consistency. Actions, commands, and word situations should always mean the same thing, regardless where they occur in the system. It is also essential for the system to provide users with feedback, and, therefore, they are able to understand what is happening in the system in a timely way.

In addition, Nielsen and Molich (1990) recognised the need for clearly marked exits, noting that errors are common with users, and whenever that happens, there should be a quick emergency exit. The user does not have to go through an extended dialogue to undo their function. Shortcuts are also crucial to usability because they help expert users to speed up their interaction with systems. However, novice users require experience. Nielsen (1993) highlighted that error messages should be expressed in plain and understandable languages. This enables the user to understand the problem and propose or recommend a solution. More importantly, a careful design of systems, which considers the aspects of HCI, minimises errors because a lot of mistakes with the system can affect perceived usability (Nielsen, 2012). Finally, Nielsen (1994) emphasised that the documentation of a system is an important key to usability, proposing the need for documentation. However, this should be easy to handle and focused on the tasks of users.

2.3.2 Usability Heuristics

The terms usability heuristics, parameters, and attributes have been used interchangeably by scholars. Usability heuristics can be defined as a set of very well-known usability design guidelines used to address usability issues (Jimenez, Lozada, & Rosas, 2016). One of the most distinguished heuristics is the ten Nielsen's (1994) usability heuristics (Quiñones & Rusu, 2017) that have been used as the basis for designing new heuristics (Jimenez, Lozada, & Rosas, 2016). Nielsen (1994) produced a list of general heuristics that covers the majority of usability problems in user interface design, which are described in Table 2.2.

Table 2.2 Nielsen’s Usability Heuristics

Usability Heuristics	Definition
Visibility of system status	Users should be always notified about the state of the system through feedback.
Match between system and the real world	Systems should use well-known words rather than technical words, and information should be displayed in a logical order.
User control and freedom	When selecting a function by mistake, users should be able to undo this mistake easily.
Consistency and standards	The used terms and expressions should maintain the same meaning across the systems.
Error prevention	Systems should prevent a problem from happening by a careful and well-done design.
Recognition rather than recall	To reduce user memory load, objects should be visible, and users do not have to remember information from one screen to another.
Flexibility and efficiency of use	Systems should be appropriate for both experience and less-experienced users.
Aesthetic and minimalistic design	Screens should not be loaded with too many items and should include only relevant objects.
Help users recognise, diagnose, and recover from errors	Error messages have to be communicated in user language with no technical terms or codes. Error messages should display the problem and suggest how it can be solved.
Help and documentation	Help documents should not be too large and should be easy to use.

Source: (Nielsen, 1994)

However, general usability heuristics, such as Nielsen’s (1994), seek to evaluate traditional problems of user interfaces and might not be adequate to evaluate features related to a particular product (Jimenez, Lozada, & Rosas, 2016). Furthermore, usability scholars believe that general usability heuristics are not fixed and should be modified based on the field of the system under evaluation (Koulocheri, Soumplis, Kostaras, & Xenos, 2011). Even though studies (Thowfeeka & Abdul Salam, 2014; Alturki & Aldraiweesh, 2016; Medina-Flores & Morales-Gamboa, 2015; Orfanou, Tselios, & Katsanos, 2015) used only general usability heuristics to evaluate LMS, Zaharias and Koutsabasis (2012) reported that there is a consensus between e-learning evaluators to extend general usability heuristics when evaluating the usability of LMS. Mtebe and Kissaka (2015) added that there are small amount of general usability heuristics and they are not appropriate for evaluating the usability of LMS. Therefore, new sets of usability heuristics were developed to evaluate certain products and domains based on existing heuristics, literature reviews, theories, guidelines, and usability problems (Quiñones & Rusu, 2017).

Several studies developed usability heuristics for the domain of e-learning. Table 2.3 represents some, but not all, studies conducted on e-learning usability heuristics. These domain-specific heuristics identify the more relevant usability problems (Sorenson, 2016). Most of these studies integrated Nielsen's heuristics (Nielsen, 1994) with guidelines and principles relevant to the field of education (Mtebe & Kissaka, 2015). Table 2.3 displays usability heuristics developed specifically for the domain of e-learning.

Table 2.3 e-Learning Usability Heuristics

Study	System	Methodology	Heuristics	Validation
(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	Using five experts in Africa
(Koulocheri, Soumplis, Kostaras, & Xenos, 2011)	Learning activity management system	Existing heuristics and usability evaluation studies	10 Nielsen's heuristics Customisation of content Navigation Interactivity Tools and multimedia integration Role management	Using four experts Greece
(Oztekin, Kong, & Uysal, 2010)	e-Learning system	Existing heuristics in usability and quality	Error prevention Visibility Flexibility Course management Interactivity, feedback and help Accessibility Consistency Assessment Memorability Completeness Aesthetics Reduce redundancy	Learner-based questionnaires and Structural Equational Modelling in 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	Using four experts and user testing in Kuwait

Study	System	Methodology	Heuristics	Validation
			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 & Poylymenakou, 2009)	e-learning application	Literature review	Content Learning support Visual design Navigation Accessibility Interactivity Self-assessment and learnability Motivation to learn	Learner-based questionnaires and factor analysis in corporate settings
(Ssemugabi & De Villiers, 2007)	Web-based learning application	Existing heuristics 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
(Nokelainen, 2006)	LMS	Existing heuristics	Learner control Learner activity Collaborative learning Goal orientation Applicability Added value Motivation Valuation of previous Knowledge Flexibility	Student-based questionnaires in Finland

Study	System	Methodology	Heuristics	Validation
			Feedback	
(Reeves, et al., 2002)	e-Learning application	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 USA

Other studies of LMS usability e.g. (Medina-Flores & Morales-Gamboa, 2015; Al-Khalifa, 2010) proposed their own set of usability heuristics, and this might be attributed to the generality of traditional usability heuristics (Jimenez, Lozada, & Rosas, 2016).

2.3.3 Importance of Usability in Learning Management Systems

Usability is one of the essential concepts in the field of HCI (Green & Pearson, 2011) and is considered a crucial attribute in developing systems with high quality (Benaida, 2014; Aziz & Kamaludin, 2014). As usability is a factor that determines the use of systems (Madan & Dubey, 2012), Melis, Weber, and Andrès (2003) declared that it is not adequate to develop only useful systems but important to make them usable by implementing appropriate techniques from the field of human-computer interaction. Therefore, it is perceived that usability is one of the important characteristics of systems that produces various benefits (Dobozy & Reynolds, 2010).

Usability is considered as an important characteristic in terms of quality. It is perceived as a quality requirement for all systems, and LMS are no exception (Casare, Silva, Martins, & Moraes, 2016; Oztekin, Kong, & Uysal, 2010). The success of systems is more than just functionality; however, it also depends on their quality (Hayat, Lock, & Murray, 2015). Oztekin et al. (2010) argued that usability and quality are correlated. In other words, when the usability of a system increases, its quality will increase and vice versa. In fact, the need for usability has been perceived as an important quality requirement that influences user satisfaction with LMS (Costabile, De Marsico, Lanzilotti, Plantamura, & Roselli, 2005). Therefore, the importance of usability was realised by experts because of the effect of usability on the quality of systems (Hayat, Lock, & Murray, 2015).

Furthermore, usability helps in avoiding many problems relevant to the users of LMS. Studies (Nokelainen, 2006; Zaharias, 2009; Orfanou, Tselios, & Katsanos, 2015; Althobaiti & Mayhew, 2016) demonstrated that LMS experience many usability problems. Albion (1999) and Sorenson (2016) reported that unusable systems distract student concentration, increase student frustration, and force students to focus on how to use the system rather than the content, in which case the LMS would be considered as a barrier rather than a supportive tool. Unusable systems encourage users to abandon using them and look for alternatives instead (Benaida, 2014). Consequently, these problems contribute to the system's disqualification and student dissatisfaction. Enhancing the usability might help in solving many of the aforementioned problems (Albion, 1999). Therefore, LMS have to be usable in order to avoid problems relevant to LMS users such as frustration and dissatisfaction (Althobaiti & Mayhew, 2016; Sales Júnior, Ramos, Pinho, & Santa Rosa, 2016).

In addition, usability is necessary to ensure student satisfaction and use of LMS. Studies (Green, Inan, & Denton, 2012; Chiu, Hsu, Sun, Lin, & Sun, 2005; Wu, Tennyson, & Hsia, 2010) empirically revealed that the students' satisfaction, which leads to better educational experience, is influenced by the usability of LMS. Hall (2006) asserted that the effective adoption of VLE does not only depend on the training provided to students, but on the students' satisfaction with the adopted LMS. Furthermore, students who do not face design problems when using LMS tend to be satisfied and interested to use the system again and again (Dağhan & Akkoyunlu, 2016; Sales Júnior, Ramos, Pinho, & Santa Rosa, 2016). In Taiwan, it was concluded (Chiu, Hsu, Sun, Lin, & Sun, 2005) that perceived usability affects the students' satisfaction influencing the continuous use of e-learning systems. In the same direction, it was confirmed (Dağhan & Akkoyunlu, 2016) that students with high perceived usability are more likely to continue using VLE. Consequently, an unusable LMS causes students to avoid using the system, which, in turn, contributes to the failure of the system objectives (Blecken, Bruggemann, & Marx, 2010).

Finally, unusable LMS might cause serious educational problems. At the point when neglecting the usability of LMS, students may exert a lot of time and energy attempting to understand the system itself, instead of focusing on the learning content (Mtebe & Kissaka, 2015). One of the serious issues in e-learning systems is the continuously high dropout rates. It was reported (Liyanagunawardena, Adams, & Williams, 2013) that around 10% of students completed their online course. A recent study (Reich & Ruipérez-Valiente, 2019) found that out of 5.63 million students who had been registered at online courses offered by Massachusetts Institute of Technology and Harvard University, less than 10% completed their courses over six years. This high withdrawal rate might indicate that systems experience problems and students were dissatisfied with e-learning systems. Past studies (Sales Júnior, Ramos, Pinho, & Santa Rosa, 2016; Zaharias, 2009) attributed the dropout rate of e-learning courses to the usability problems faced by students. Thus, the usability of LMS might affect the high dropout rates in e-learning.

2.3.4 Cultural Usability

Barber and Badre (1998) were first to introduce the term culturability (the integration of the terms culture and usability) and claimed that culture and usability cannot be separated. Cultural usability implies that usability attributes and user interface design standards are not equally appreciated across cultures because a user's cultural background influences the perceived usability (Wallace, Reid, Clinciu, & Kang, 2013;

Hertzum, et al., 2007). The emergence of cultural usability has affected the definition of usability. Instead of restricting the definition to the original usability attributes, the usability definition has to be expanded to include the target culture. Hsieh (2011) asserted that the culture is one of the usability attributes beside efficiency, satisfaction, and effectiveness. Supporting culturability, previous research (Alamri, Cristea, & Al-Zaidi, 2014; Wallace, Reid, Clinciu, & Kang, 2013; Al-Wabil & Al-Khalifa, 2009; Clemmensen, Hertzum, Hornbæk, Shi, & Yammiyavar, 2009; Hsieh, 2011; Zaharias, 2008; Frandsen-Thorlacius, Hornbæk, Hertzum, & Clemmensen, 2009) concluded that a user's cultural background strongly impacts the perceived usability, meaning that users rate a system's usability differently based on their cultural background.

On the other hand, the integration of the culture into usability has brought problems (Frandsen-Thorlacius, Hornbæk, Hertzum, & Clemmensen, 2009). Because of the small amount of research on usability in the context of Eastern cultures, the majority of the introduced usability attributes and questionnaires are specifically designed for Western cultures (Hsieh, 2011). Al-Wabil and Al-Khalifa (2009) argued that it is improper to use the attributes identified for Westerners to evaluate the usability for Easterners because usability is perceived differently between Western and Eastern cultures. Furthermore, it was asserted that websites are unfairly designed for Western cultures, and the same bias might be claimed for LMS (Zaharias, 2008). Such problems can arise because of the small amount of published literature on cultural usability (Frandsen-Thorlacius, Hornbæk, Hertzum, & Clemmensen, 2009) and the unavailability of usability attributes and user interface design standards that are clearly defined for the target culture (Al-Wabil & Al-Khalifa, 2009).

Although the majority of usability studies have disregarded the concept of cultural usability (Clemmensen, Hertzum, Hornbæk, Shi, & Yammiyavar, 2009), other studies have questioned that. To demonstrate that usability is understood differently between Westerners and Easterners, Frandsen-Thorlacius et al. (2009) compared perceived usability within the context of Chinese and Danish cultures. The authors used a questionnaire with 154 Chinese and 258 Danish participants to prioritise seven usability attributes based on the importance. Frandsen-Thorlacius et al. (2009) concluded that perceived usability is influenced by cultural aspects. Moreover, effectiveness and non-frustration were more related to Danish users, whereas visual appearance, satisfaction, and fun were more related to Chinese users. Wallace et al. (2013) utilised the USE (usefulness, satisfaction, and ease of use) survey (Lund, 2001) to examine the importance of usability attributes across four countries, USA, New Zealand, Philippines, and Taiwan. The authors concluded that Taiwanese and American users rated efficiency and effectiveness more importantly than satisfaction, New Zealander users rated efficiency more importantly than satisfaction, and Filipino users rated effectiveness more importantly than efficiency. Another evidence from the study of Zaharias (2008) who investigated the influence of culture on the perceived usability of e-learning courses in different international contexts: Greece, Romania, Bulgaria, and Turkey. The study of 131 trainees revealed that the four nationalities rated the usability attributes differently.

Having discussed the usability of LMS, the next section highlights the most popular technology-acceptance theories and models in the field of information systems.

2.4 Technology-Acceptance Theories

The acceptance and usage of technologies have been investigated via various theories and models, such as the theory of reasoned action (Fishbein & Ajzen, 1975), theory of planned behaviour (Ajzen, 1985), and the TAM (Davis, Bagozzi, & Warshaw, 1989). This section provides more details about the most widely-used models related to the acceptance and usage in information systems.

2.4.1 Theory of Reasoned Action

Theory of reasoned action (TRA) is one popular model that has been successfully demonstrated in explaining and predicting user behaviour in a large number of fields (Davis, Bagozzi, & Warshaw, 1989). Theory of reasoned action was founded in 1967 by Martin Fishbein and further developed by Martin Fishbein and Icek Ajzen in 1975. Theory of reasoned action primarily provides insights about an individual's behaviour by defining the relationships between intention, attitude, and subjective norms (Fishbein & Ajzen, 1975; Ajzen & Fishbein, 1980).

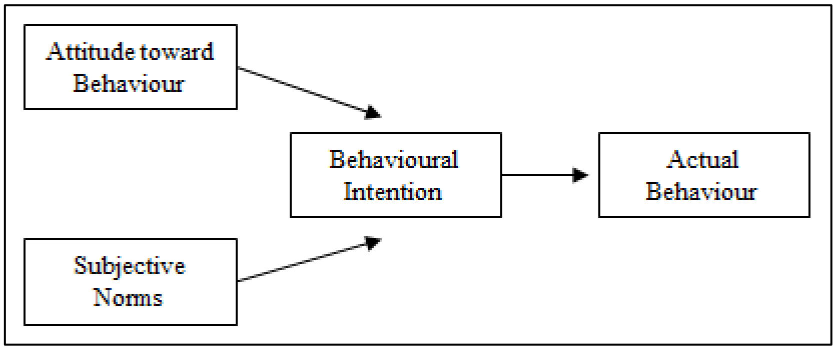

Figure 2.1 Theory of Reasoned Action
Source: (Fishbein & Ajzen, 1975)

Figure 2.1 and Table 2.4 show that TRA comprises three determinants: behavioural intention, attitude toward behaviour, and subjective norms. According to TRA, the key predictor of an individual's actual behaviour is his or her behavioural intention (Fishbein & Ajzen, 1975). For better understanding of behavioural intention, TRA suggests an investigation of attitude toward behaviour and subjective norms has to be carried out. Attitude toward behaviour is influenced by previous beliefs, evaluations, and outcomes. Thus, the better consequences an individual expects from performing a certain behaviour, the more positive attitude the person has and vice versa (Ajzen & Fishbein, 1980). Subjective norms are positively associated with normative beliefs and the individual's motivation to meet the normative beliefs. In other words, the more motivation to meet the normative beliefs an individual has, the more positive subjective norms he or she obtains and vice versa. Therefore, TRA can be explained by defining behavioural intention, determined by attitude and subjective norms.

Table 2.4 The Determinants of TRA

Constructs	Definitions
Behavioural intention	An individual's aim or plan to behave in a certain way with no guarantee to do so.

Constructs	Definitions
Attitude toward behaviour	The degree to which an individual believes that performing the behaviour is positive or negative.
Subjective norms	The degree to which an individual feels that people think he or she should perform the behaviour (Kocaleva, Stojanovic, & Zdravev, 2015).

Source: (Fishbein & Ajzen, 1975)

As is the case with other theories, TRA is not free from limitations. One of the serious limitations in TRA is the assumption that behaviours are under the volitional control of individuals (Glanz, Rimer, & Viswanath, 2008; Ajzen, 1991). However, this is not always the case. An individual has control when there are no constraints to perform a specific behaviour, and the individual does not have control when there are constraints to perform the behaviour. In fact, constraints such as time, cost, and ability limit the freedom to perform the behaviour (Samaradiwakara & Gunawardena, 2014). Davis et al. (1989) asserted that TRA is unable to predict a specific behaviour in certain situations such as an individual with a low-level control. Another limitation is that TRA does not identify beliefs that are associated with a specific behaviour (Davis, Bagozzi, & Warshaw, 1989; Davis, 1986). Consequently, TRA necessitates researchers to identify the beliefs that are operative with the investigated behaviour.

2.4.2 Theory of Planned Behaviour

As mentioned previously, TRA has failed to predict participant behaviour in situations in which participants have a low-level of volitional control (Davis, Bagozzi, & Warshaw, 1989). To succeed in dealing with this limitation, TRA was extended by Icek Ajzen to include a third contributor towards behavioural intention, so-called perceived behavioural control, and renamed to theory of planned behaviour (TPB) (Ajzen, 1985). Theory of planned behaviour is depicted in Figure 2.2. Unlike TRA, TPB considers that it is not always the case that an individual has a complete control over whether to perform a specific behaviour. Perceived behavioural control refers to whether an individual perceives performing a behaviour will be either easy or difficult (Ajzen, 1991). Thus, behavioural intention will not be strong when perceived behavioural control is not high even if an individual has a positive attitude toward behaviour and subjective norms.

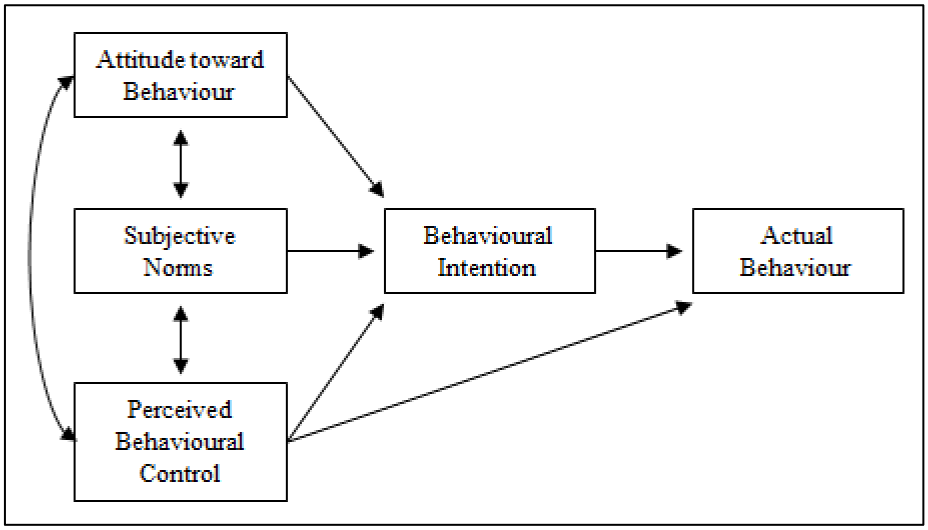

Figure 2.2 Theory of Planned Behaviour
Source: (Ajzen, 1991)

Theory of planned behaviour has been criticised throughout the years. In particular studies have shown that determinants of TPB (attitude toward behaviour, subjective norms, and perceived behavioural control) are insufficient in predicting an individual's behavioural intention (Ajzen & Fishbein, 2005). Ajzen (1991) pointed out that TPB is open for additional determinants to explain the variance in the intention or behaviour. Another limitation stems from the study conducted by Taylor and Todd (1995b), who criticised the utilisation of only one variable, perceived behavioural control, to present all non-controllable variables that affect individual behaviour.

2.4.3 Technology Acceptance Model

The technology acceptance model was initially created by Davis (1986) and further developed by Davis et al. (1989) with the aim of producing a model for computer technology acceptance based on TRA but excluding subjective norms. Davis (1986) justified the elimination of subjective norms as there is not enough information available to participants about the social influence during the stage of acceptance testing. Figure 2.3 depicts the TAM, which assumes that when someone is introduced to a new technology, his or her decision to use it will be influenced by a number of factors. The extended technology acceptance model (Venkatesh & Davis, 2000) and the unified theory of acceptance and use of technology (Venkatesh, Morris, Davis, & Davis, 2003) were developed as an extension of the TAM.

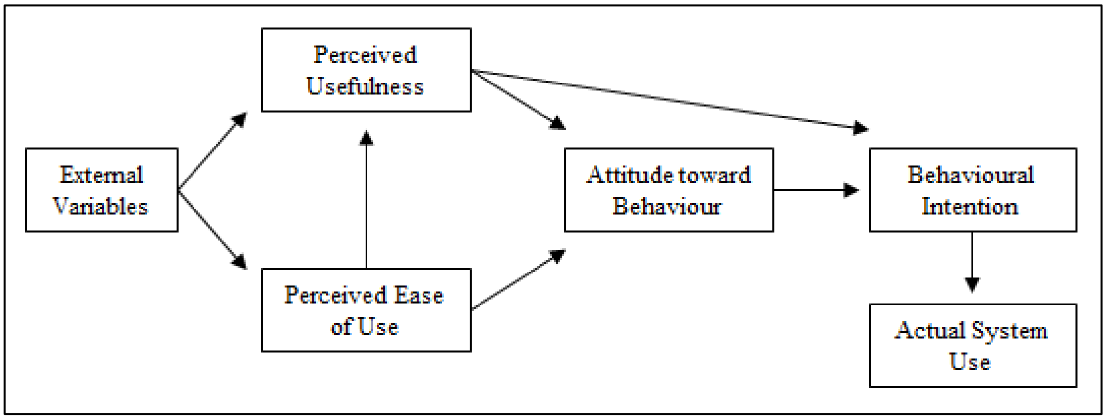

Figure 2.3 The Technology Acceptance Model
Source: (Davis, Bagozzi, & Warshaw, 1989)

Primarily, the TAM is composed of five constructs (see Table 2.5): perceived ease of use, perceived usefulness, attitude towards behaviour, behavioural intention, and actual system use. Figure 2.3 shows that the actual system use is directly influenced by behavioural intention, which is affected by both attitude towards behaviour and perceived usefulness. Attitude towards behaviour is directly influenced by perceived ease of use and perceived usefulness alike. The TAM primarily depends on two variables, perceived ease of use and perceived usefulness, to examine an individual's beliefs and attitude toward computer technology acceptance (Davis, Bagozzi, & Warshaw, 1989). Perceived ease of use affects perceived usefulness directly, and both perceived ease of use and perceived usefulness are influenced by external variables.

Table 2.5 The Determinants of the TAM

Constructs	Definitions
Behavioural intention	An individual's aim or plan to behave in a certain way with no guarantee to do so (Fishbein & Ajzen, 1975).
Attitude toward behaviour	The degree to which an individual believes that performing the behaviour is positive or negative (Fishbein & Ajzen, 1975).

Perceived usefulness	The degree to which an individual believes that utilising the technology under investigation would improve his or her performance (Davis, 1986).
Perceived ease of use	The extent to which an individual believes that utilising the technology under investigation would not require significant effort (Davis, 1986).

In their final model, Davis et al. (1989) eliminated the construct of attitude toward behaviour because of its weak mediation of the effect between perceived usefulness and behavioural intention. Furthermore, the direct influence of perceived usefulness on intention was strong. On the other hand, attitude was not successful in medicating the relationship between perceived ease of use and intention. Figure 2.4 depicts the revised version of the original TAM.

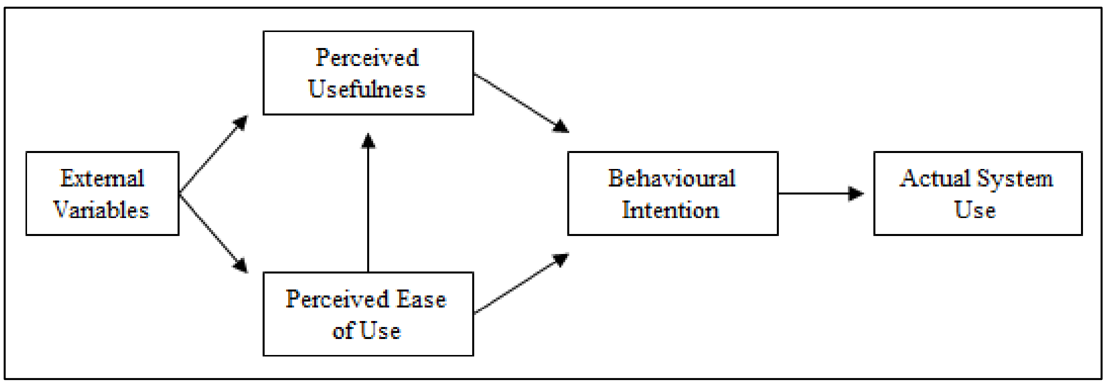

Figure 2.4 Revised Technology Acceptance Model
Source: (Davis, Bagozzi, & Warshaw, 1989)

Despite the wide adoption, the TAM is not problem-free. First, the TAM has failed to explain the reasons for which an individual would perceive the investigated technology useful (Venkatesh & Davis, 2000) and easy to use (Venkatesh, 2000). Another limitation is that the TAM explained around 40% of variance in behavioural intention, which was deemed low (Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Davis, 2000; Venkatesh & Morris, 2000). Thus, extending the TAM with external variables might improve its explanatory power. Finally, previous research has revealed results that are contradicted by the original TAM. For example, Shroff, Deneen, and Ng (2011) concluded that perceived usefulness does not influence the students' attitude toward using e-portfolios and attitude does not affect behavioural intention.

Furthermore, Muniasamy et al. (2014) found that the students' behavioural intention to use LMS is not affected by their attitude.

2.4.4 Technology Acceptance Model 2

In response to the limitations of the TAM, Venkatesh and Davis (2000) extended the TAM to explain the key determinants of perceived usefulness. The extended model, known as the TAM2, includes social influence processing factors (subjective norms, image, and voluntariness) and cognitive instrumental processing factors (job relevance, output quality, result demonstrability, and perceived ease of use). Figure 2.5 and Table 2.6 show the adopted determinants of perceived usefulness.

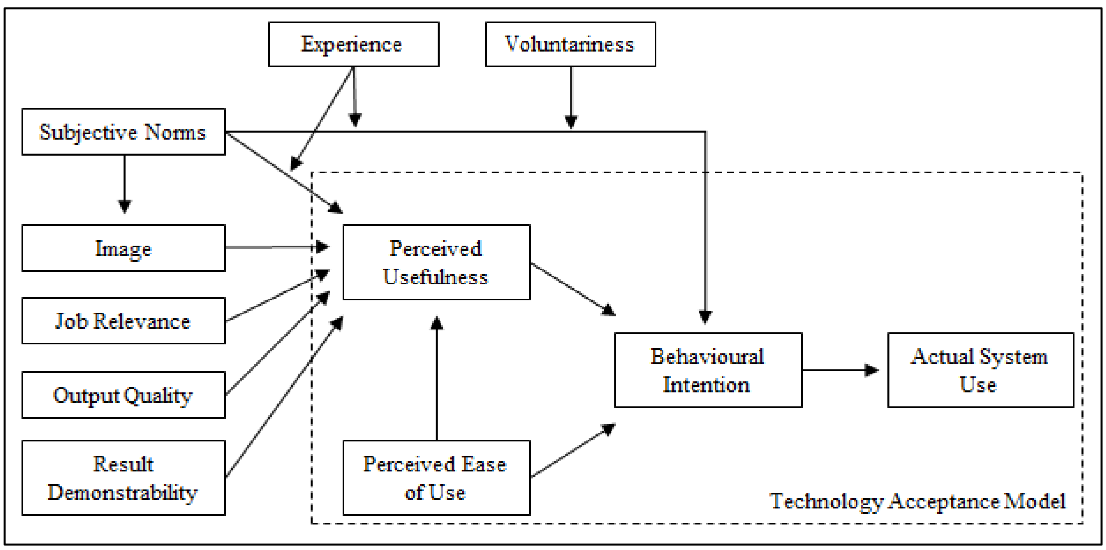

Figure 2.5 Technology Acceptance Model 2
Source: (Venkatesh & Davis, 2000)

Venkatesh and Davis (2000) conducted a longitudinal study to investigate the proposed model on 156 workers in four organisations who use four systems, where the use of two systems were voluntary and the use of the other two systems were mandatory. The results demonstrated the success of the proposed model in both voluntary and mandatory use, where subjective norms have no influence in voluntary settings. Furthermore, the influence of subjective norms on perceived usefulness and behavioural intention tends to be decreased when experience is increased. Based on statistical regression analysis, the proposed model explains 40-60% of the variance in perceived usefulness and 34-52% of the variance in behavioural intention.

Table 2.6 The Determinants of Perceived Usefulness in the TAM2

Constructs	Definitions
Subjective norms	The degree to which an individual feels that people think he or she should perform the behaviour (Kocaleva, Stojanovic, & Zdravev, 2015).
Image	The degree to which the use of the system improves an individual's status within society (Venkatesh & Davis, 2000).
Job relevance	The degree to which the technology is related to the job of someone (Venkatesh & Davis, 2000).
Output quality	The quality of the system in performing the job (Venkatesh & Davis, 2000).
Results demonstrability	The results of using the system will be tangible (Moore & Benbasat, 1991).

2.4.5 Technology Acceptance Model 3

The most recent revision of the TAM resulted in a new model, referred to as the TAM3. The key contribution of the TAM3 is in addressing the determinants of perceived ease of use and perceived usefulness (Venkatesh & Bala, 2008); therefore, the TAM3 was born from the incorporation of the TAM2 (Venkatesh & Davis, 2000) and the model of perceived ease of use determinants (Venkatesh, 2000). Figure 2.6 depicts the determinants of the TAM3.

Venkatesh and Davis (2000) hypothesised that perceived usefulness is influenced by subjective norms, image, job relevance, output quality, results demonstrability, and perceived ease of use. The determinants of perceived usefulness were explained in Section 2.4.4 and Table 2.6. Output quality, experience, and voluntariness are considered as moderators.

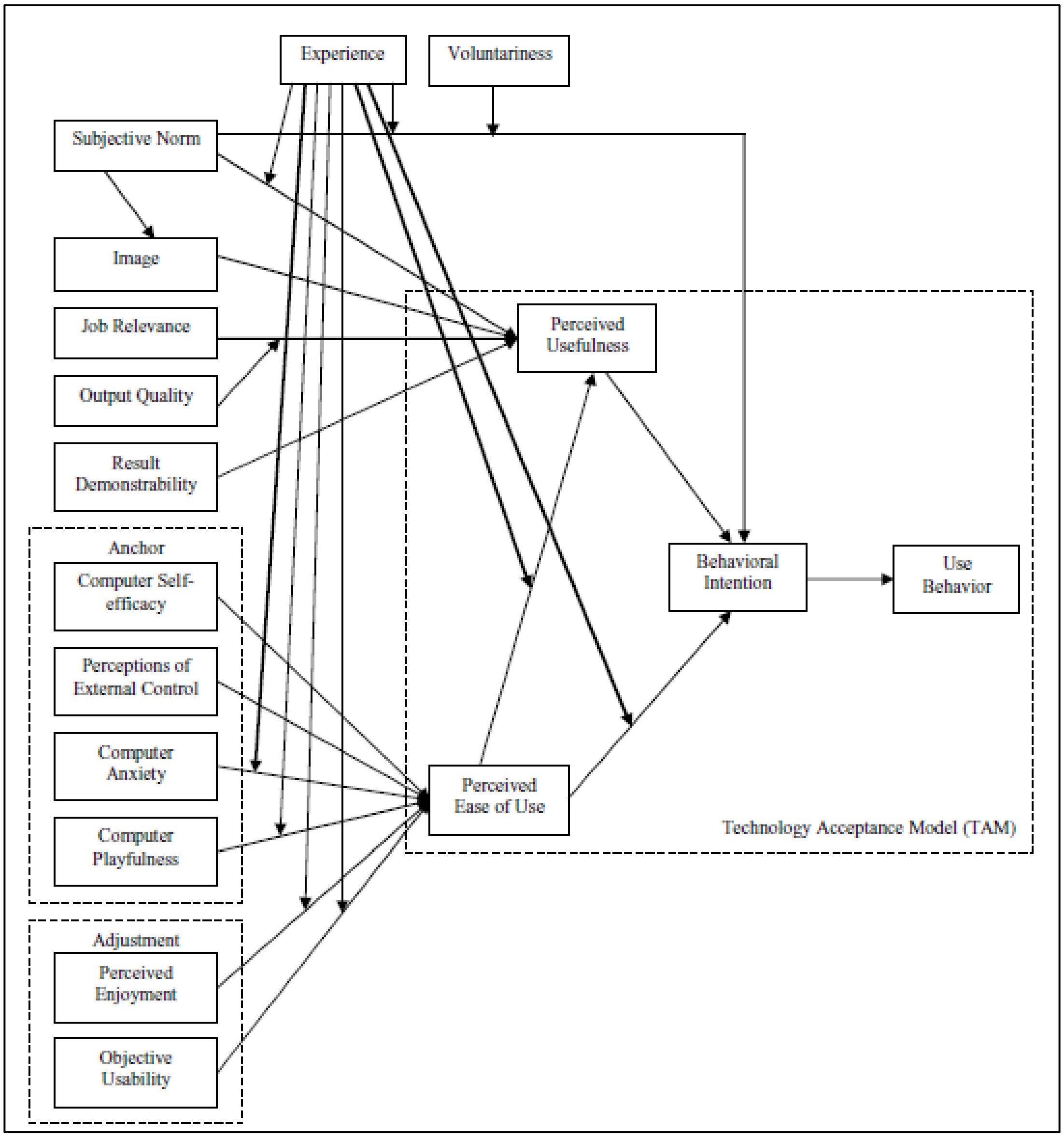

Figure 2.6 Technology Acceptance Model 3
Source: (Venkatesh & Bala, 2008)

On the other side of the model, Venkatesh and Bala (2008) hypothesised that perceived ease of use is influenced by what they call anchors and adjustments. Table 2.7 includes the definitions of the determinants of perceived ease of use. These parameters were called ‘anchors’ because when the facts about the system’s ease of use are absent, individuals tend to depend on general information (anchor) to perceive the system’s ease of use. Venkatesh (2000) theorised that the anchors, related to computers and their use, drive an individual's preliminary perception about the system's ease of use. The four anchors that affect perceived ease of use are computer self-efficacy, perceptions of external control, computer anxiety, and computer playfulness (Venkatesh & Bala, 2008; Venkatesh, 2000). The influence of computer anxiety and computer playfulness on perceived ease of use tends to be decreased when experience is increased; in contrast, the effect of computer self-efficacy and perceptions of external control on perceived ease of use tends to be increased when experience is increased (Venkatesh & Bala, 2008; Venkatesh, 2000). However, the individual's perception will be adjusted after gaining experience with the system but still depend on the initial anchors. Furthermore, Venkatesh (2000) theorised that the effect of the adjustments, perceived enjoyment and objective usability, on perceived ease of use will be stronger when more experience has been gained.

Table 2.7 The Determinants of Perceived Ease of Use in the TAM3

Constructs	Definitions
Computer self-efficacy	The degree to which an individual thinks that he or she has the ability to perform a certain task on the computer (Compeau & Higgins, 1995).
Perceptions of external control	The degree to which an individual thinks that organisational resources are available to facilitate the system use (Venkatesh, Morris, Davis, & Davis, 2003).
Computer anxiety	The degree to which an individual is afraid to use the system (Venkatesh, 2000).
Computer playfulness	The essential motivation to interact with the new system (Venkatesh & Bala, 2008).
Perceived enjoyment	The degree to which an individual perceives that the system is enjoyable regardless of the outcomes (Venkatesh, 2000).
Objective usability	Comparing technologies based on the actual, as opposed to user perception, effort that is required to accomplish certain tasks (Venkatesh, 2000).

2.4.6 Unified Theory of Acceptance and Use of Technology

Venkatesh et al. (2003) developed the unified theory of acceptance and use of technology (UTAUT) based on a wide review and evaluation of eight technology-acceptance theories and models: TRA, TPB, the TAM, the motivation model (Davis, Bagozzi, & Warshaw, 1992), the augmented TAM (A-TAM) (Taylor & Todd, 1995a), the model of PC utilisation (Thompson, Higgins, & Howell, 1991), innovation diffusion theory (Moore & Benbasat, 1996), and social cognitive theory (Bandura, 1986). Figure 2.7 shows the framework of the UTAUT.

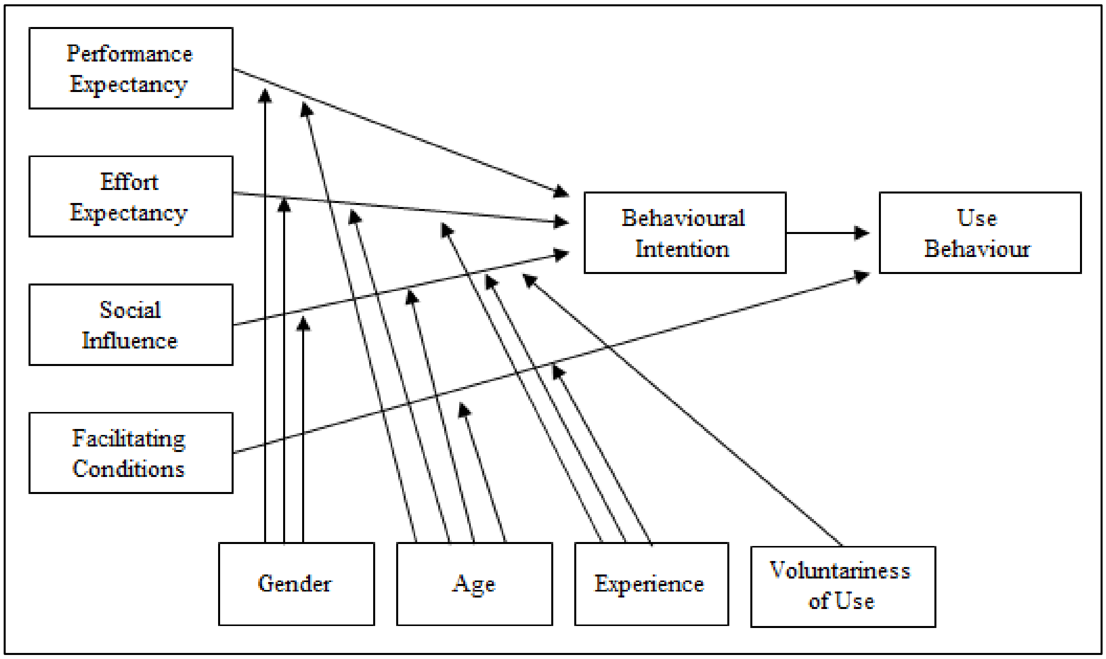

Figure 2.7 Unified Theory of Acceptance and Use of Technology
Source: (Venkatesh, Morris, Davis, & Davis, 2003)

Venkatesh et al. (2003) theorise that the acceptance of new technologies is measured by four determinants, which are performance expectancy, effort expectancy, social influence, and facilitating conditions, that influence user intention and actual behaviour. Table 2.8 has the definitions of UTAUT determinants. The unified theory posits that performance expectancy, effort expectancy, and social influence affect behavioural intention, whereas facilitating conditions and intention directly affect use behaviour.

Table 2.8 The Determinants of the UTAUT

Constructs	**Definitions**
Performance Expectancy	The degree to which an individual expects that his or her performance will be enhanced when performing a certain behaviour.
Effort Expectancy	The degree to which an individual expects that performing a certain behaviour will be not require significant effort.
Social Influence	The degree to which an individual believes that people think he or she should perform a certain behaviour.

Constructs	Definitions
Facilitating Conditions	The degree to which an individual thinks that organisational resources are available to facilitate performing a certain behaviour.

Source: (Venkatesh, Morris, Davis, & Davis, 2003)

The unified theory assumes that four moderating variables, which are gender, age, experience, and voluntariness of use, influence the relationships between the key determinants and intention and use behaviour (Venkatesh, Morris, Davis, & Davis, 2003). The influence of performance expectancy on behavioural intention is moderated by gender and age, so that it is more important for male and younger users. Furthermore, gender, age, and experience moderate the effect of effort expectancy on intention, so that it is more important for female, older, and less-experienced users. The impact of social influence on behavioural intention is moderated by all the four moderators, so that it is more important for female, older, less-experienced, and mandatory users. Finally, age and experience moderate the influence of facilitating conditions on use behaviour, so that it is more important for older and more-experienced users.

To validate the UTAUT empirically, Venkatesh et al. (2003) conducted a longitudinal study on 215 workers in four organisations who use four systems, where two systems were voluntary use and two systems were mandatory. The results demonstrated the success of the proposed model in the four organisations on both voluntary and mandatory systems. Although the eight models explained between 17% and 53% of variance in behavioural intention, the UTAUT explained 70% of variance in the behavioural intention. Therefore, the UTAUT was credited with a large explanatory power (Tarhini, Arachchilage, Masa'deh, & Abbasi, 2015). However, the UTAUT was criticised that it was developed to investigate the technology acceptance in employees' context, and it is, therefore, unknown how to use the UTAUT in other contexts, such as consumer acceptance (Venkatesh, Thong, & Xu, 2012).

2.4.7 Extended Unified Theory of Acceptance and Use of Technology

The extended unified theory of acceptance and use of technology is one of the most recent theories and models in the domain of information systems. Venkatesh et al. (2012) extended the UTAUT to examine the technology acceptance in the context of consumer behaviour (see Figure 2.8). Besides the four determinants of the UTAUT, Venkatesh et al. (2012) adapted three additional factors, namely hedonic motivation, price value, and habit. The definitions of those determinants are presented in Table 2.9. The extended model, referred to as the UTAUT2, posits that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit affect behavioural intention, whereas facilitating conditions, habit, and intention directly affect user behaviour.

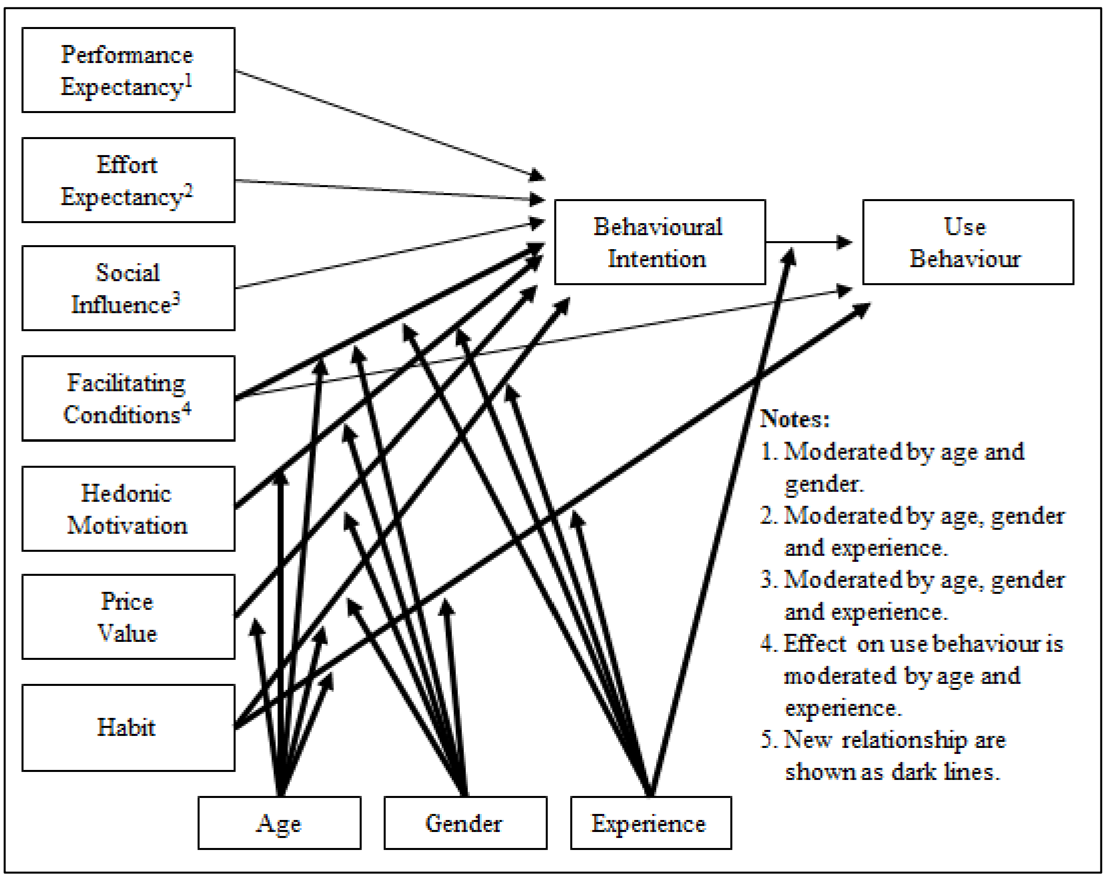

Figure 2.8 Unified Theory of Acceptance and Use of Technology 2
Source: (Venkatesh, Thong, & Xu, 2012)

In addition to the moderating effect proposed in the UTAUT, the UTAUT2 theorises that personal characteristics, age, gender, and experience, influence the relationships between the key determinants and intention and use behaviour (Venkatesh, Morris, Davis, & Davis, 2003). The influence of facilitating conditions on behavioural intention is moderated by age, gender, and experience, so that it is more important for older, female, and less-experienced users. Furthermore, age, gender, and experience moderate the effect of hedonic motivation on intention, so that it is more important for younger, male, and less-experienced users. The impact of price value on behavioural intention is moderated by age and gender, so that it is more important for younger and female users. The influence of habit on behavioural intention and use behaviour is moderated by the three moderators, so that it is more important for older, male, and more-experienced users. Finally, experience moderates the effect of intention on use behaviour, so that it is stronger for less-experienced users.

Table 2.9 The Determinants of the UTAUT2

Constructs	Definitions
Hedonic motivation	It refers, also known as perceived enjoyment, to the degree to which an individual believes that using a specific technology would be fun.
Price value	An individual's trade-off between the advantages of a specific technology and the monetary cost of using the technology.
Habit	The degree to which a user believes the behaviour to be automatic.

Source: (Venkatesh, Thong, & Xu, 2012)

Venkatesh et al. (2012) validated the UTAUT2 empirically with 1,512 users of internet mobile technology in Hong Kong. The results demonstrated the success of the proposed model on voluntary settings. The model explained 74% of variance in behavioural intention and 52% in use behaviour. However, the UTAUT and the UTAUT2 were criticised that they produce biased results across cultures (see for example (El-Masri & Tarhini, 2017)).

2.4.8 Comparison of Technology-Acceptance Theories

Many models and frameworks have been used to assess the acceptance and use of technology in the field of information systems, such as TRA, TPB, the TAM, the

TAM2, the TAM3, the UTAUT, and the UTAUT2. Although the diversity in such theories adds more flexibility to the assessment, the existence of various frameworks makes the selection decision even harder (Tarhini, Arachchilage, Masa'deh, & Abbasi, 2015). Therefore, this section highlights some positives and negatives of the discussed theories, which may impact the decision of selecting an appropriate model.

To solve the limitations of TRA, TPB was extended. The two theories posit that user intention is influenced by attitude toward behaviour and subjective norms. However, Ajzen (1985) added the input factor of perceived behavioural control in TPB, which affects user intention and actual behaviour. Theory of planned behaviour was developed to overcome TRA's limitations in predicting user behaviours in situations in which participants have a low level of control (Davis, Bagozzi, & Warshaw, 1989). Therefore, the extension of TRA is considered as a necessity from the perspective of researchers (Ajzen, 1985; Ajzen, 1991). Neither TRA nor TPB take into consideration the environmental or economic factors (LaMorte, 2018) and personal or demographic variables that might influence user intention. Finally, both theories are context-specific and were developed in social psychology (Ajzen, 1991; Ajzen & Fishbein, 2005).

Another extension of TRA produced the TAM. The two theories posit that the attitude toward behaviour directly affects behavioural intention. However, the subjective norms construct is the main difference between TRA and the TAM (Tarhini, Arachchilage, Masa'deh, & Abbasi, 2015). Unlike the TAM, many models, including TRA, consider subjective norms as a key determinant of behavioural intention. Davis et al. (1989) argued that subjective norms might not influence behavioural intention, especially when an individual uses the technology in voluntary settings. Further, there is not enough information available to participants about the social influence during the stage of acceptance testing (Davis, 1986). While TRA was developed in social psychology and has been used across various domains (Davis, 1986), the TAM was developed in the domain of technology, and, therefore, it is more related to the acceptance of computer-based technology (Davis, Bagozzi, & Warshaw, 1989).

Finally, the TAM has surpassed TRA by the wide use in technology acceptance, simplicity, and robustness (Tarhini, Arachchilage, Masa'deh, & Abbasi, 2015).

The extended technology acceptance model was developed as an extension of the TAM. The two models posit that behavioural intention directly influences actual system use. However, it is noteworthy that the TAM2 has excluded the construct of attitude toward behaviour. The extended technology acceptance model was developed to overcome the limitations of the TAM in explaining the reasons for which an individual would perceive the investigated technology useful (Venkatesh & Davis, 2000). Therefore, the perceived usefulness construct in the TAM2 was extended to include social influence processing factors (subjective norms, image, and voluntariness) and cognitive instrumental processing factors (job relevance, output quality, result demonstrability, and perceived ease of use). Unlike the TAM, the TAM2 has two moderators, experience and voluntariness, that influence the relationships between subjective norms and behavioural intention from one side and subjective norms and perceived usefulness from the other side. Although TAM2 succeeds in revising the external variables that influence perceived usefulness, both models have failed to identify the external variables that influence perceived ease of use. The explained variance in user intention is 40% by the TAM (Davis, Bagozzi, & Warshaw, 1989) and around 52% by the TAM2 (Venkatesh & Davis, 2000). This might suggest the extension of the TAM with external factors to identify the drivers of perceived ease of use and perceived usefulness and to improve the explanatory power of the TAM.

The most recent revision of the TAM is the TAM3, considered as a combination of the TAM2 (Venkatesh & Davis, 2000) and the model of perceived ease of use determinants (Venkatesh, 2000). Both the TAM3 and the TAM2 have adopted the determinants of perceived usefulness. However, the TAM3 and the model of perceived ease of use determinants have adopted the factors of perceived ease of use. Unlike the TAM, the TAM2, and the model of perceived ease of use determinants, the TAM3 identifies the determinants of both perceived ease of use and perceived usefulness. The explained variance in user intention is 40% by the TAM, 52% by the TAM2, and 53%

by the TAM3. Although the TAM3 includes many constructs and relationships, the model did not achieve much in relation to the explained variance in user intention compare to the TAM2.

The model of the UTAUT was primarily developed based on reviewing and evaluating eight technology acceptance theories, of which TAM is only one. The unified theory proposes four independent variables (performance expectancy, effort expectancy, social influence, and facilitating conditions), four moderating variables (gender, age, experience, and voluntariness of use), and two dependent variables (behavioural intention and use behaviour) (Venkatesh, Morris, Davis, & Davis, 2003). This model shares four constructs with the TAM, performance expectancy (like perceived usefulness), effort expectancy (like perceived ease of use), behavioural intention, and use behaviour. In contrast with the UTAUT, the TAM does not include moderating variables, for which the TAM has been criticised (Al-Gahtani, 2008; Venkatesh & Morris, 2000; Venkatesh, Morris, Davis, & Davis, 2003). Further, the UTAUT assumes that behavioural intention is directly affected by performance expectancy, effort expectancy, and social influence. However, perceived ease of use and perceived usefulness influence behavioural intention in the TAM. Finally, the explained variance in user intention is 40% by the TAM and 70% by the UTAUT.

The extended unified theory of acceptance and use of technology was developed based on the UTAUT and assumes seven independent variables (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit), three moderating variables (gender, age, and experience), and two dependent variables (behavioural intention and use behaviour) (Venkatesh, Thong, & Xu, 2012). Similar to the UTAUT, the UTAUT2 intersects with the TAM in the four constructs. In contrast with the TAM, the UTAUT2 proposes three moderating variables. While the two main constructs (perceived ease of use and perceived usefulness) influence behavioural intention in the TAM, the UTAUT2 assumes that behavioural intention is directly affected by the seven independent variables. This might justify the high percentage of the variance explained by the UTAUT2 in user intention, 74%.

The aforementioned comparisons have revealed that each model has its own positives and negatives. Models are either complicated with high explanatory power (e.g. the UTAUT2) or simple with reasonable explanatory power (e.g. the TAM) (Tarhini, Arachchilage, Masa'deh, & Abbasi, 2015). The integration of seven independent variables and three moderating variables in addition to the two dependent variables makes the UTAUT2 a complex model compared to the flexibility and simplicity of the TAM. Given this complexity, the extension of the UTAUT2 with additional eight usability factors requires a lot of effort and resources not reasonably available in this study. Moreover, the main objective of this study is to investigate the effect of usability attributes on student use of LMS. Consequently, the selection of the UTAUT2 as the base of this work may not be appropriate as more than half of its independent variables are irrelevant to perceived usability (e.g. social influence, hedonic motivation, price value, and habit). In addition, compared to the more recent model (the UTAUT2), the TAM has been widely used to examine user acceptance in the domain of information systems (Nabavi, Taghavi-Fard, Hanafizadeh, & Taghva, 2016) and student acceptance of e-learning (Šumak, HeričKo, & PušNik, 2011; Baki, Birgoren, & Aktepe, 2018). For instance, the TAM (Davis, 1989) has been adopted more than 44,000 times, according to Google Scholar (as of July 04, 2019). This popularity may indicate the reliability and validity of the TAM when examining student acceptance of LMS. Besides, previous literature indicates that there is a dearth of studies in relation to the integration of usability attributes into the TAM, especially within the context of Saudi higher education (see Section 3.5). Finally, the TAM has been criticised by researchers (Abbasi, Tarhini, Elyas, & Shah, 2015; Claar, Dias, & Shields, 2014; Holden & Rada, 2011; Tarhini, Hone, & Liu, 2014a) for having multiple limitations, such as producing inconsistent results when used in non-Western cultures, the lack of moderating variables, and the low explanatory power. Therefore, this study aims to overcome these limitations by extending and examining the TAM with moderating variables in a non-Western culture, Saudi Arabia. More details about the justification for the selection of the TAM are provided in the next chapter (Section 3.3).

2.5 Conclusion

This chapter presented and discussed previous literature on the three areas that support this research. The chapter showed that LMS are web-based educational systems that are used to support learning activities and enhance student academic achievements. However, student use and satisfaction with those systems rely, to a large degree, on perceived usability of LMS. While the previous literature recommended the utilisation of domain-specific usability attributes, little research has been conducted to understand usability heuristics and attributes that are appropriate for student use of LMS. Furthermore, the majority of the introduced usability attributes are specifically designed for developed countries. As usability understood differently across cultures (cultural usability), it is improper to use those attributes to evaluate perceived usability in developing countries and Eastern cultures, such as Saudi Arabia. Addressing this gap necessitates the validation of those usability attributes in Eastern cultures. Based on technology-acceptance theories reviewed in Section 2.4, the next chapter explains and justifies the proposed research model to examine the effect of usability attributes on student use of LMS in higher education in Saudi Arabia.

CHAPTER 3: CONCEPTUAL FRAMEWORK

3.1 Introduction

The previous chapter reviewed several theories and models regarding technology acceptance and use that can be employed to develop the proposed model of this research. The primary objective of this chapter is to explain and justify the development of the conceptual framework based on the gaps in the existing literature and the current state of knowledge. This objective is achieved in stages. The first stage is to analyse critically the current state of knowledge regarding LMS adoption. Previous studies regarding technology acceptance and the use of LMS from the perspective of students in Saudi Arabia are reviewed. In the second stage, the adaption and extension of the TAM in this research, in addition to the other theories presented in the previous chapter, are justified. Furthermore, this study aims to understand the effect of usability attributes, and, therefore, discusses previous literature regarding the utilisation of perceived usability in technology-acceptance theories and models (third stage). This discussion helps to determine further gaps in knowledge and justifies the selected usability attributes. In the fourth stage, the variables and moderators adopted in the proposed model are explained in detail, and relevant literature regarding each hypothesis is provided to justify the research hypotheses.

3.2 Learning Management Systems Acceptance in Saudi Arabia

Technology-acceptance theories have been employed to investigate the acceptance and usage of LMS from the perspective of students. Table 3.1 provides a summary of those studies conducted in the context of Saudi higher education, including the theory used, additional factors, moderating variables, sample size, data collection method and data analysis method.

Based on this review, several interesting points and research gaps need to be addressed. First, a common limitation in the reviewed studies is that they targeted students registered at specific institutions with a small sample size. Therefore, the generalisability of their results to all students in Saudi higher education is questionable. Additionally, most of these studies used a quantitative research approach through the utilisation of surveys for data collection and statistical techniques for data analysis. Thus, this current research considers these points and targets all students registered at Saudi public universities. A quantitative approach is employed in common with all but one of the studies previously conducted; therefore, to obtain the necessary broad geographical spread, the data were collected via an online survey in this study also.

In addition, reviewing the previous literature revealed that little research (only those studies listed in Table 3.1) has been conducted to understand student acceptance and use of LMS in Saudi universities. This lack is consistent with the findings of Alharbi and Drew (2014). Consequently, student acceptance of LMS in Saudi Arabia remains uncertain (Almarashdeh & Alsmadi, 2016), and, thus, there is a demand for more studies to understand the factors that affect student use of LMS (Alshammari, Ali, & Rosli, 2016)

The TAM is the one of the most popular frameworks for assessing user acceptance and usage of new technologies in the field of information systems (Nabavi, Taghavi-Fard, Hanafizadeh, & Taghva, 2016). Table 3.1 reveals that the overwhelming majority of the studies used the TAM. This finding indicates the importance and robustness of the TAM for understanding student use of LMS in Saudi Arabia, which justifies the utilisation of the TAM in this current research. However, some of the studies in Table 3.1 did not extend the original models using external factors. This result is in accordance with Bousbahi and Alrazgan (2015), who found that a large number of TAM studies did not investigate the influence of external variables regarding the student use of LMS. Adopting external variables contributes to the understanding of factors affecting technology use and explaining greater variance in dependent variables (Davis, 1989). Tang and Chen (2011) conducted a systematic review of TAMs and recommended the adoption of new external variables from other theories and fields. This current study, therefore, adopts that recommendation and adds eight external factors to the proposed model.

Finally, the review of the studies regarding Saudi students' acceptance of LMS demonstrated that several factors have been examined, such as satisfaction, social influence, computer self-efficacy, perceived enjoyment, and lab practice. The importance of perceived usability on user behaviour is confirmed in the literature regarding information systems (Aziz & Kamaludin, 2014; Booi & Ditsa, 2013; Gül, 2017; Lacka & Chong, 2016; Scholtz, Mandela, Mahmud, & Ramayah, 2016). However, the investigation of the effect of perceived usability on student use of LMS is completely absent regarding Saudi higher education. Furthermore, although researchers (Claar, Dias, & Shields, 2014; Ong & Lai, 2006; Al-Gahtani, 2016; Tarhini, Elyas, Akour, & Al-Salti, 2016; Ilie, Slyke, Green, & Hao, 2005; Tarhini, 2013) emphasise the importance of moderating variables in the domain of e-learning systems, most studies listed in Table 3.1 did not investigate the effect of moderators on the student use of LMS in Saudi Arabia. Moderating variables help to understand the differences between groups and enhance the explanatory power of models. Thus, eight usability factors and four demographic characteristics were adopted for the proposed model as independent variables and moderators, respectively.

Table 3.1 Summary of LMS Acceptance Studies in Saudi Arabia

Study	Theory	Additional Factors	Moderators	Target Population	Sample Size	Data Collection	Data Analysis Method
(Abdel-Maksoud, 2018)	TAM	Satisfaction	N/A	Students at a single university	75 students	Online survey	Regression analysis
(Alotaibi, 2017)	UTAUT	Lab practice	N/A	Students at a single university	51 ICT students	Focus groups	Thematic analysis
(Almarashdeh & Alsmadi, 2016)	TAM	N/A	N/A	Students at a single university	216 students	Paper-based survey	Regression analysis
(Al-Gahtani, 2016)	TAM3	N/A	Experience Voluntariness	Students at a single university	286 students	Paper-based survey	PLS-SEM using SmartPLS
(Muniasamy, Eljailani, & Anandhavalli, 2014)	TAM	N/A	N/A	Students at a single university	160 female diploma students	Paper-based survey	Regression analysis
(Al-Aulamie, 2013)	TAM	Information quality Functionality Accessibility User interface design Computer playfulness Enjoyment Learning goal orientation	Gender	Students at three universities	766 undergraduate students	Online survey	CB-SEM using AMOS
(Al-Mushasha, 2013)	TAM	University support Computer self-efficacy	N/A	Students at three universities	224 Students	Paper-based survey	Regression analysis
(Alenezi, 2012)	TAM	System performance System functionality System response System interactivity	N/A	Students at five universities	408 undergraduate students	Paper-based survey	Regression analysis
(Al-Harbi, 2011)	TAM + TRA	University support Computer self-efficacy Accessibility	N/A	Students at a single university	531 students	Paper-based survey	Regression analysis

Study	Theory	Additional Factors	Moderators	Target Population	Sample Size	Data Collection	Data Analysis Method
(Alenezi, Abdul Karim, & Veloo, 2011)	TAM	Training Technical support Facilitating conditions	N/A	Students at five universities	408 undergraduate students	Paper-based survey	Regression analysis
(Alenezi, Abdul Karim, & Veloo, 2010)	TAM	Perceived enjoyment Computer self-efficacy Computer anxiety Internet experience	N/A	Students at five universities	408 undergraduate students	Paper-based survey	Regression analysis

3.3 Reasons for Selecting the Technology Acceptance Model

The proposed model for this research is based on the TAM (Davis, Bagozzi, & Warshaw, 1989) and derived from the published literature concerning usability within the context of educational technologies. The adoption of the TAM stems from the following considerations:

- *Popularity in information systems:* The TAM is a well-recognised theory for understanding the acceptance and use of technologies (Alharbi & Drew, 2014; Tarhini, Hone, & Liu, 2014b; Tang & Chen, 2011; Aljeeran, 2016; Al-Busaidi & Al-Shihi, 2010). The TAM has been used to investigate the acceptance of different technologies (e.g. LMS, computer applications, mobiles, email, and Internet) under different situations (e.g. culture and time) with different moderators (e.g. age, organisations, experience, and educational level) and different users (e.g. teachers, students, and professionals) (Al-Gahtani, 2008). Supporting the popularity of the TAM, Davis (1989) has been cited more than 43,000 times, and the work of Davis et al. (1989) has been employed more than 22,300 times, according to Google Scholar (as of January 27, 2019). In a statistical meta-analysis, King and He (2006) reviewed 88 published studies and reported the validity and robustness of the TAM. Furthermore, Nabavi et al. (2016) reviewed 191 research papers regarding technology continuance intention and found that the TAM is the second most popular model after the information system continuous model (Bhattacherjee, 2001). Therefore, the robustness and effectiveness of the TAM are well established in the field of information systems (Amin, Afrin Azhar, & Akter, 2016).
- *Popularity in e-learning systems:* The literature review presented in Section 3.2 provides evidence of the popularity of the TAM when studying student acceptance and use of LMS. In addition to Saudi Arabia, many studies (Al-Adwan, Al- Adwan, & Smedley, 2013; Tarhini, Hone, Liu, & Tarhini, 2017;

Almarashdeh & Alsmadi, 2016; Hwa, Hwei, & Peck, 2015; Majdalawi, Almarabeh, & Mohammad, 2014; Mohammadi, 2015) have achieved successful outcomes by using the TAM to understand student utilisation of LMS. Furthermore, meta-analysis studies (Šumak, HeričKo, & PušNik, 2011; Baki, Birgoren, & Aktepe, 2018) have revealed that the TAM is dominant and robust for understanding the acceptance and use of e-learning systems. For example, Baki et al. (2018) reviewed previous literature concerning technology acceptance and demonstrated that 203 papers used the TAM to assess e-learning systems. Šumak et al. (2011) found that 86% of their reviewed studies (42 papers) used the TAM and concluded that it is a good model for measuring the acceptance of e-learning. Abdullah and Ward (2016) conducted a quantitative meta-analysis of 107 studies of e-learning adoption and confirmed the popularity of the TAM. This popularity indicates the effectiveness of the TAM when examining student acceptance and uncovering factors that might influence their use of LMS.

- *Flexibility:* The TAM has the flexibility to add more variables to the original model and to examine the influence of those external variables on the acceptance and use of technologies in a straightforward manner (Yoon, 2016; Revythi & Tselios, 2019; Aljeeran, 2016). As the objective of this study is to investigate the effect of usability attributes on student use of LMS, this feature enables the researcher to integrate easily the desired usability attributes into the proposed model.
- *Overcoming TAM's limitations:* The TAM has been criticised for having some limitations. First, the TAM produces inconsistent results when used in non-Western cultures (Sun & Zhang, 2006; Tarhini, Hone, & Liu, 2014b). This issue illustrates the importance of testing the model in non-US cultures to ensure its applicability and reliability (it was originally developed in the US) (Sun & Zhang, 2006). The unique cultural aspects of Saudi Arabia, such as gender segregation and religion (see Section 1.7), necessitate the examination of the TAM within this new context. Second, the TAM explains around 40%

of variance in user intention, which is deemed to be low (Abbasi, Tarhini, Elyas, & Shah, 2015; Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Davis, 2000; Venkatesh & Morris, 2000; Claar, Dias, & Shields, 2014; Holden & Rada, 2011). As the constructs of perceived ease of use and perceived usefulness explain only a small amount of variance in user behaviour (Al-Aulamie, 2013; Waehama, McGrath, Korthaus, & Fong, 2014), this current study extends the TAM with eight usability factors to improve its explanatory power. Another limitation is that the TAM does not include moderating variables (Al-Gahtani, 2008; Venkatesh & Morris, 2000; Venkatesh, Morris, Davis, & Davis, 2003), and previous literature on the Saudi e-learning acceptance has disregarded the moderating effect (Abdel-Maksoud, 2018; Al-Harbi, 2011; Al-Mushasha, 2013; Alenezi, 2012; Almarashdeh & Alsmadi, 2016; Alotaibi, 2017; Muniasamy, Eljailani, & Anandhavalli, 2014). Moderators help to understand the effects of personal characteristics on user acceptance, to explain the inconsistency in the results across cultures (Sun & Zhang, 2006) and improve the model's explanatory power (Venkatesh, Morris, Davis, & Davis, 2003). Thus, this study overcomes these limitations by extending the TAM with four personal moderators and eight usability factors, and by testing the model in a non-Western culture, Saudi Arabia.

3.4 External Variables of the Technology Acceptance Model

The TAM provides a theoretical framework for assessing how external variables explain the perceptions that are provided by previous theories (Yang, Zhou, Hou, & Xiang, 2014). Perceived ease of use and perceived usefulness are the two main constructs in the TAM and are influenced by external variables that are related to a particular technology (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989). These external variables may vary from one technology to another, from one culture to another and from one user to another (Al-Busaidi & Al-Shihi, 2010). Through the mediation of perceived ease of use and perceived usefulness, the external variables influence individuals' behavioural intention and actual use (Davis, Bagozzi, & Warshaw, 1989). Meta-analysis studies (Šumak, HeričKo, & PušNik, 2011; Abdullah & Ward, 2016; Baki, Birgoren, & Aktepe, 2018) provided evidence that perceived ease of use and perceived usefulness are the two main variables that can affect user perception toward using e-learning systems. Tang and Chen (2011) conducted a systematic review of TAMs and recommended the extension of TAM constructs and the adoption of new external variables from other theories and fields, for example, usability and content quality.

There is a number of reasons why extending the TAM with external variables is important. First and foremost, such an extension is significant for identifying the key determinants of perceived ease of use and perceived usefulness to predict acceptance and understand the use of technologies (Abdullah & Ward, 2016; Holden & Rada, 2011). While the TAM has been successful in predicting user acceptance of technology, it does not explain acceptance nor identify the system characteristics that affect perceived ease of use and perceived usefulness (Venkatesh & Davis, 1996). The model does not provide system-designers with enough information regarding how to develop an accepted system (Venkatesh, 2000). Due to the flexibility of the TAM (Yoon, 2016) and the inefficiency of perceived ease of use and perceived usefulness constructs (Waehama, McGrath, Korthaus, & Fong, 2014; Al-Aulamie, 2013), this current research extends the TAM by using eight usability attributes to understand student use of LMS.

In addition, using the TAM with external variables usually improves the explained variance of constructs (Davis, 1989). Although previous research (Almarashdeh & Alsmadi, 2016; Muniasamy, Eljailani, & Anandhavalli, 2014) has favoured the explanatory power of the original TAM and applied it to the field of LMS, the TAM has been criticised for its low explanatory power (Abbasi, Tarhini, Elyas, & Shah, 2015; Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Davis, 2000; Venkatesh & Morris, 2000; Claar, Dias, & Shields, 2014; Holden & Rada, 2011). Abdullah and Ward (2016) found that e-learning studies that extended the TAM enhanced the total variance from 52% to 70%. Therefore, the TAM has been extended using external factors to better understand the use of technology and increase the explanatory power (Nikou & Economides, 2017). The proposed model of this research supports scholarly opinion that the TAM alone is insufficient to examine actual behaviour (Tarhini, Hone, Liu, & Tarhini, 2017); therefore, eight usability attributes were added to the original TAM.

Reviewing the literature revealed that e-learning researchers have extended the TAM and examined the effect of various psychological, personal, demographic, and technical factors regarding perceived ease of use and perceived usefulness. Abdullah and Ward (2016) reviewed 107 e-learning studies and found that self-efficacy, subjective norm, enjoyment, computer anxiety, and experience are the most widely used external factors for the TAM regarding e-learning systems. Baki et al. (2018) reviewed 203 TAM studies of e-learning systems and identified 129 external factors. They demonstrated that self-efficacy, subjective norm, interaction, enjoyment, anxiety, and compatibility are the variables most validated for use with the TAM. Although scholars have been extending the TAM for many years, the influence of perceived usability on the utilisation of LMS has been relatively overlooked (Holden & Rada, 2011). This lack is evident in the TAM review studies (Abdullah & Ward, 2016; Baki, Birgoren, & Aktepe, 2018; King & He, 2006; Nabavi, Taghavi-Fard, Hanafizadeh, & Taghva, 2016; Šumak, HeričKo, & PušNik, 2011) and usability studies in the following section.

3.5 Perceived Usability and Technology Acceptance

Past research highlights the importance of perceived usability on technology acceptance and use (see Table 3.2). In Greece, Revythi and Tselios (2017) examined the influence of accessibility on student use of LMS and demonstrated the influence of system accessibility on TAM constructs (perceived ease of use, perceived usefulness, attitude, and behavioural intention). Using pharmacy and physical education students at Helwan University in Egypt, Khedr, Hana, and Shollar (2012) concluded that interface design and content impact student perceived ease of use and perceived usefulness of LMS. Similarly, Theng and Sin (2012) demonstrated the effect of four usability attributes, namely interaction, navigation, user interface, and personalisation, on student perceived ease of use and perceived usefulness of LMS. Booi and Ditsa (2013) adopted four usability attributes into the TAM and revealed that the perceived usability of a university web-portal was positively correlated with student acceptance in South African universities. Lee and Kozar (2012) reviewed literature regarding the usability of e-commerce websites and proposed a model that incorporates ten usability attributes. Based on factor analysis, they found that the usability attributes positively impact customer intention to use a website, which, in turn, leads to their use. Scholtz et al. (2016) and Gül (2017) extended the TAM with three usability attributes (presentation, navigation, and learnability) and concluded that perceived usability influences employee use of enterprise resource planning (ERP) systems. Using the TAM, scholars found that the utilisation of technologies is influenced by different usability attributes, including, but not limited to, efficiency (Aziz & Kamaludin, 2014; Lacka & Chong, 2016); interaction (Jung & Yim, 2017); presentation and interface (Scholtz, Mandela, Mahmud, & Ramayah, 2016; Nikou & Economides, 2017; Khedr, Hana, & Shollar, 2012; Gül, 2017); ease of access (Aziz & Kamaludin, 2014); learnability (Scholtz, Mandela, Mahmud, & Ramayah, 2016; Aziz & Kamaludin, 2014; Lacka & Chong, 2016; Lin, 2013; Gül, 2017); and navigation (Scholtz, Mandela, Mahmud, & Ramayah, 2016; Gül, 2017). Several studies that utilised the TAM to understand the influence of usability attributes on LMS acceptance are briefly introduced in Table 3.2.

Table 3.2 Studies of the TAM with Usability Attributes

Study	System	Usability Attributes	Country	Target Population	Sample	Data Collection Method	Data Analysis Method
(Revythi & Tselios, 2019)	LMS	Accessibility	Greece	Education students at University of Patras	345 students	Paper-based survey	PLS-SEM
(Al-Aulamie, 2013)	LMS	Information quality Functionality Accessibility User interface design	Saudi Arabia	Students at three universities	766 undergraduate students	Online survey	CB-SEM using AMOS
(Khedr, Hana, & Shollar, 2012)	LMS	Interface design Content quality	Egypt	Pharmacy and physical education students at Helwan University	253 students	Paper-based survey	CB-SEM using AMOS
(Theng & Sin, 2012)	LMS	Interaction Navigation structure User interface Personalisation	Singapore	Students at a local university	451 students	Paper-based survey	PLS-SEM

Reviewing previous literature regarding perceived usability and technology acceptance revealed important points and research gaps. First, the importance of perceived usability on technology acceptance and use has been demonstrated. Nevertheless, Table 3.1 and Table 3.2 reveal that little research has been conducted regarding the influence of usability attributes on LMS acceptance and use. This observation is also reported by researchers (Naqvi, Chandio, Abbasi, Burdi, & Naqvi, 2016; Scholtz, Mandela, Mahmud, & Ramayah, 2016; Theng & Sin, 2012) and TAM review studies (Abdullah & Ward, 2016; Baki, Birgoren, & Aktepe, 2018; King & He, 2006; Nabavi, Taghavi-Fard, Hanafizadeh, & Taghva, 2016; Šumak, HeričKo, & PušNik, 2011). Holden and Rada (2011) reported that the influence of usability on the utilisation of educational technologies has not received enough attention. Moreover, the review indicates that no studies have investigated the importance of perceived usability on LMS acceptance and use with Saudi students from various educational levels (undergraduate and postgraduate). In addition, there are several limitations in the studies that do examine the influence of usability on student use of LMS (Khedr, Hana, & Shollar, 2012; Revythi & Tselios, 2019; Theng & Sin, 2012). For example, these studies targeted students at a single institution; thus, researchers should be cautious with the generalisability of the findings. Furthermore, each study covered a maximum of four web or general usability attributes and neglected other important usability factors related to LMS, such as instructional assessment. Finally, the TAM has been criticised for its lack of technical characteristics, such as usability attributes, of the system under investigation (Venkatesh & Davis, 1996). As the TAM was introduced prior to the growing request for system usability, the model does not include the parameter of usability (Holden & Rada, 2011). Such a limitation indicates a need to extend the TAM with usability attributes that are related to the investigated technology. This extension assists in understanding the full picture of technology acceptance and use (Holden & Rada, 2011). Addressing these limitations, this study incorporates usability attributes related to LMS into the TAM to better understand the acceptance and use of LMS from the perspectives of students in Saudi higher education.

For this study, the following eight usability attributes identified by Zaharias and Poylymenakou (2009) are integrated into the proposed conceptual model: content quality (CQ), learning support (LS), visual design (VD), system navigation (SN), ease of access (EOA), system interactivity (SI), instructional assessment (IA), and system learnability (SL). These usability attributes were selected for the following reasons:

- *Rational origination:* Based on a profound review of many studies in the domains of usability, e-learning, and educational technologies, Zaharias (2005) carefully proposed 12 usability attributes that might affect student motivation to learn. The 12 attributes are learnability, accessibility, consistency, navigation, VD, interactivity, content and resources, instructional feedback, IA, learner guidance and support, media use, and learning strategies design. In the study conducted by Zaharias and Poylymenakou (2009), the 12 usability attributes were reviewed by 15 experts from academic settings. Based upon a factor analysis of 113 questionnaires from employees in four organisations from four countries (Greece, Romania, Bulgaria, and Turkey), Zaharias and Poylymenakou (2009) conclude that eight of the usability attributes are associated with student motivation to learn.
- *New context:* Zaharias and Poylymenakou (2009) used factor analysis, a first-generation multivariate analysis technique, to evaluate the reliability and validity of the attributes. They recommend that future researchers refine the proposed attributes, use them with different users, systems, and contexts, and validate them using second-generation multivariate analysis techniques, such as the SEM technique. Accordingly, in this present study, the eight usability attributes have been adopted into the TAM to understand student use of LMS in the context of Saudi higher education and analysed using the PLS-SEM technique, which has never previously been done. This approach adds novelty and originality to the current study.

- *Usability problem detection:* The robustness and ability of the eight attributes to detect usability problems have been examined in previous studies (Althobaiti & Mayhew, 2016; Junus, Santoso, Isal, & Utomo, 2015). To evaluate the usability of the Saudi LMS (Jusur), Althobaiti and Mayhew (2016) used the attributes to conduct an empirical study to evaluate subjective usability from the students' perspective. At the University of Indonesia, Junus et al. (2015) evaluated the teachers' perceived usability of LMS using the eight usability attributes.

Having justified the selection of TAM and usability attributes, the next section introduces the proposed research model.

3.6 The Research Conceptual Model

A conceptual model is a diagram that shows the research independent and dependent variables, relationships between them and hypotheses that will be tested (Hair, Celsi, Money, Samouel, & Page, 2016). The conceptual model of this study is depicted in Figure 3.1 and includes three main parts. The first part consists of the usability attributes that might influence student use of LMS. According to Davis et al. (1989), those variables are the external variables of the TAM, which precede the perceived ease of use and perceived usefulness constructs. For this study, the eight usability attributes proposed by Zaharias and Poylymenakou (2009) were integrated into the model: CQ, LS, VD, SN, EOA, SI, IA, and SL. The second part of the model comprises the four constructs of the TAM: perceived ease of use (PEOU), perceived usefulness (PU), behavioural intention to use LMS (BI), and actual use (AU). The last part is composed of four personal characteristics, namely gender, age, level of education, and LMS experience, that might moderate the relationships between the model's variables. The moderation effect occurs when one variable (e.g. gender) affects the strength or direction of a relationship between two constructs or variables (Hair, Hult, Ringle, & Sarstedt, 2017).

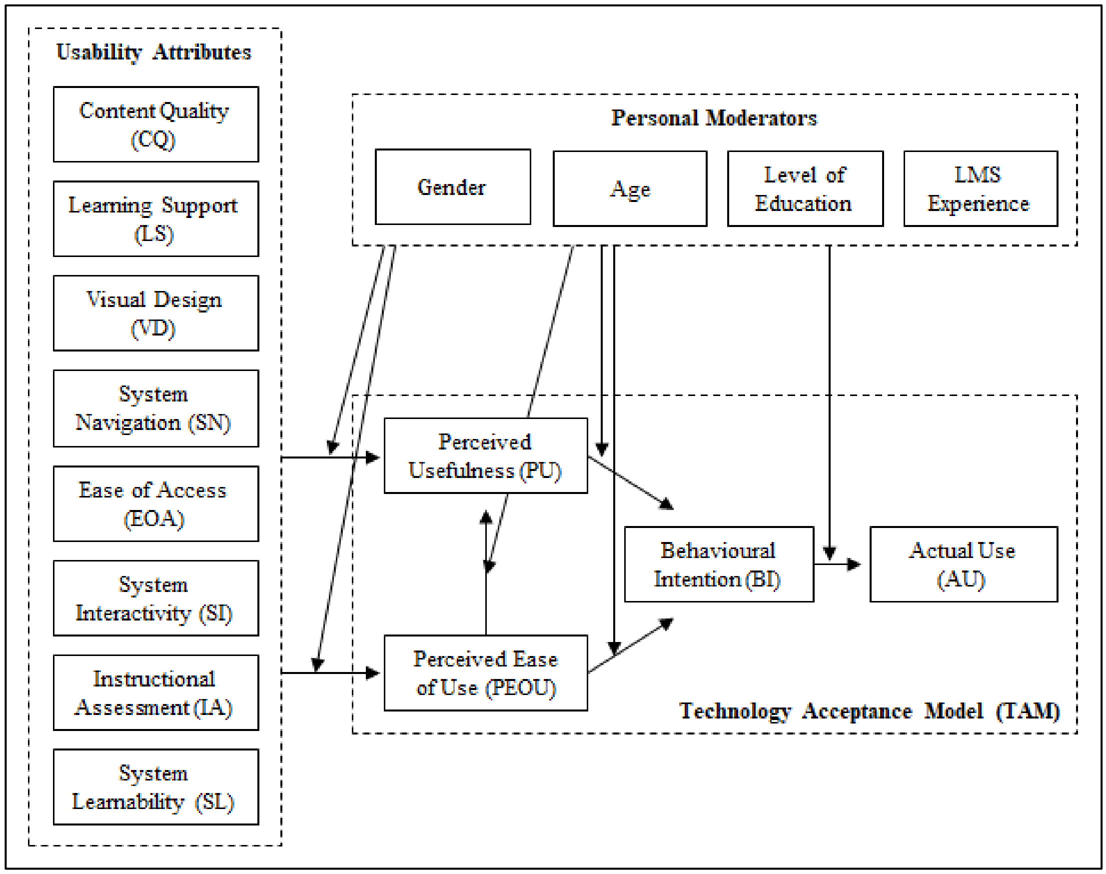

Figure 3.1 The Proposed Conceptual Model

Reviewing previous literature revealed that the proposed conceptual model has some similarities with previously proposed models. For example, Al-Aulamie (2013) has proposed a conceptual model to investigate the acceptance of LMS by undergraduate students at King Faisal University, Dammam University, and King Fahd University of Petroleum and Minerals in Eastern Region, Saudi Arabia. Al-Aulamie (2013) adopted four usability factors into the TAM, information quality, functionality, accessibility, and user interface design. It was assumed that PEOU is affected by accessibility and user interface design and PU is affected by the four usability factors. Further, Al-Aulamie (2013) postulated that gender moderates the proposed relationships in the model. In another Saudi study (Alenezi, 2012), it was proposed that system performance, system functionality, system response, and system interactivity influence undergraduate student behavioural intention to use LMS. Khedr et al. (2012) examined the acceptance of LMS by pharmacy and physical education students at

Helwan University in Egypt. Using the TAM, Khedr et al. (2012) assumed that two usability factors, namely learner interface design and content quality, have an effect on PEOU and PU. In Singapore, Theng and Sin (2012) proposed that PEOU and PU are influenced by system interaction, system navigation, user interface, and personalisation. Therefore, there are four common relationships between this current study and the model of Theng and Sin (2012).

After introducing the research conceptual model, the importance of the variables included in the model are explained in the next sections. Furthermore, the direct relationships between the independent and dependent variables are hypothesised and justified by reviewing previous studies that proposed similar hypotheses in the domain of acceptance of e-learning systems by students in higher education. This is common in a deductive approach, which enables the researcher to propose hypotheses at first and then test them (Bryman, 2016).

3.7 Usability Attributes

3.7.1 Content Quality

The terms ‘course content’, ‘content quality’, and ‘information quality’ have been used interchangeably throughout studies. Zaharias (2009) stated that CQ refers to the individual’s perception about the quality of information that is written, spoken or presented in e-learning systems. This factor, as a usability attribute, includes the accuracy of used terms (Junus, Santoso, Isal, & Utomo, 2015), sufficiency of materials to support the course objectives (Al-Ammari & Hamad, 2008), and relevance of information (Junus, Santoso, Isal, & Utomo, 2015). Furthermore, the content of e-learning systems should be organised in an appropriate sequence and provide adequate resources (Zaharias & Poylymenakou, 2009). As some content problems are associated with the way information is displayed to the users of e-learning systems, this might generate usability problems too (Freire, Arezes, & Campos, 2012). E-learning systems with high-quality content can maximise the chance of system acceptance and vice versa (Al-Aulamie, 2013). DeLone and McLean (1992) asserted the significance of information quality in their information systems success model and postulated that information quality influence user satisfaction and intention. Using the model of DeLone and McLean (1992), it was concluded (Mohammadi, 2015; Yakubu & Dasuki, 2018; Kurt, 2018; Ohliati & Abbas, 2019) that the content quality of e-learning systems affects student satisfaction and intention, which, in turn, impact student use. Naveh et al. (2012) examined the success factors of LMS in an Israeli university and concluded that content completeness and currency are positively associated with student use and satisfaction of LMS. The direct influence of content quality on student use of LMS has been empirically demonstrated (Cidral, Oliveira, Felice, & Aparicio, 2017; Saba, 2012). Furthermore, Tran (2016) provided evidence that when the content quality of LMS is high, students tend to perceive the system as useful. In Emirates, it was concluded (Salloum, Al-Emran, Shaalan, & Tarhini, 2018) that CQ directly impacts student acceptance of e-learning systems. Therefore, content quality is an important characteristic for evaluating e-learning systems (Zaharias & Poylymenakou, 2009).

It has been found that there is no common consensus regarding the relationship between the content of LMS and perceived ease of use. A study (Ghazal, Aldowah, & Umar, 2018) revealed that the course content of LMS does not have a positive effect on the students' perceived ease of use in the Faculty of Open Education in Yemen. Similarly, it was empirically demonstrated (Kang & Shin, 2015) that South Korean students' perceived ease of use of e-learning systems is not influenced by system content. By contrast, it was empirically found (Lee, Hsiao, & Purnomo, 2014; Alkandari, 2015; Bhatiasevi, 2011; Salloum, 2018) that the content quality of LMS is a determinant of students' perceived ease of use in Indonesia, Kuwait, Thailand, and Emirates, respectively. In Pakistan (Shah, Bhatti, Iftikhar, Qureshi, & Zaman, 2013) and Malaysia (Lau & Woods, 2009), students demonstrated the presence of the influence of CQ on PEOU in e-learning environment. Therefore, the following hypothesis is proposed to examine the effect of content quality on students' perceived ease of use of LMS in Saudi higher education.

H1: *CQ has a direct positive influence on students' PEOU of LMS.*

On the other hand, the impact of content quality of LMS on students' perceived usefulness has been demonstrated. Many studies (Al-Aulamie, 2013; Al-Rahmi, et al., 2018; Alkandari, 2015; Bhatiasevi, 2011; Ghazal, Aldowah, & Umar, 2018; Khedr, Hana, & Shollar, 2012; Lee, Hsiao, & Purnomo, 2014; Salloum, 2018) revealed that the content quality of LMS has a positive influence on students' perceived usefulness. In Saudi Arabia, Al-Aulamie (2013) has proposed a conceptual model based on the TAM to investigate the acceptance of LMS by students at three universities in Eastern Region. Based on 766 online questionnaires received from undergraduate students, Al-Aulamie (2013) confirmed that information quality is significant for Saudi students to perceive the system to be useful. More accurately, information quality was the second strongest determinant of PU among the independent variables. Damnjanovic, Jednak, and Mijatovic (2015) and Lwoga (2014) found that when students perceive that LMS have high-quality information, they are more likely to perceive the system to be useful. Previous research (Poelmans, Wessa, Milis, Bloemen, & Doom, 2008; Zhang, Liu, Yan, & Zhang, 2017) demonstrated the existence of a direct effect between information quality of e-learning systems and students' perceived usefulness. Shah et al. (2013) provided evidence that content quality impacts students' perceived usefulness in a Pakistani e-learning environment. Even though the majority of studies supported the relationship between content quality and perceived usefulness, it was concluded (Kang & Shin, 2015) that the content quality of LMS does not influence the perceived usefulness of students in South Korea. Therefore, the relationship between the content quality of LMS and perceived usefulness is, to some extent, established. To examine this relationship, the following hypothesis is proposed.

H2: *CQ has a direct positive influence on students' PU of LMS.*

3.7.2 Learning Support

It is important to provide students with the required LS in any educational environment as it impacts their motivation for learning (Zaharias, 2009). It was reported (Uribe, 2014) that researchers expressed their concerns regarding the implementation of computer-based learning systems without learning support. Since LMS are educational systems, the required support is far from purely technical. In the view of Zaharias and Poylymenakou (2009), LS refers to the ability of e-learning systems to provide users with tools and features needed to support learning activities. Furthermore, those e-learning systems should support students using help documents. Zaharias (2009) found that students were unable to achieve difficult learning tasks using e-learning systems without help. The help documents of e-learning systems should be written in a clear language for students (Zaharias, 2009), rich with the information that students need (Oztekin, Kong, & Uysal, 2010), and available for students whenever necessary (Ssemugabi & De Villiers, 2007). In addition, a good e-learning system should provide high-quality tools that support individual and group-based learning activities (Junus, Santoso, Isal, & Utomo, 2015), such as discussion boards and communication tools.

Reviewing past literature related to e-learning, it was found that studies investigating the effect of learning support on student use are scarce. The majority of research adopted technical support rather than learning support. Nonetheless, one study (Wang, 2018) was conducted in China and concluded that perceived learning support influences behavioural intention to use e-learning. Following this, the researcher expects that when students perceive LMS have good learning support, they are most likely to perceive LMS easy to use and useful. To examine the influence of learning support on student use of LMS in Saudi higher education, the following hypotheses are proposed.

H3: *LS has a direct positive influence on students' PEOU of LMS.*
H4: *LS has a direct positive influence on students' PU of LMS.*

3.7.3 Visual Design

Visual design is one of the crucial elements in web design (Zaharias, 2009) and software development (Liu, Chen, Sun, Wible, & Kuo, 2010). This factor refers to how the interface layout and menus are appropriate and attractive (Scholtz, Mandela, Mahmud, & Ramayah, 2016). The user interface has become more and more complicated (Jung & Yim, 2017), and students usually make their judgments regarding e-learning systems based on the interface design (Khedr, Hana, & Shollar, 2012). E-learning systems should be attractive enough in order to encourage users to use the system (Koulocheri, Soumplis, Kostaras, & Xenos, 2011). Nevertheless, visual design is an important factor that is usually disregarded in e-learning (Reyna, 2013). In e-learning systems, good visual design enables users to easily understand the interface elements, such as fonts, graphics, and layout (Junus, Santoso, Isal, & Utomo, 2015). Systems with good visual design place important information in an area to which students will be attracted (Zaharias & Poylymenakou, 2009). A good visual design helps students to understand the content and reduces their cognitive load (Liu, Chen, Sun, Wible, & Kuo, 2010; Zaharias, 2009). However, systems with poor visual design make it difficult to understand the information presented in the system (Scholtz, Mandela, Mahmud, & Ramayah, 2016). Therefore, visual design has become an important driver for students' satisfaction (Sánchez-Franco, Villarejo-Ramos, Peral-Peral, Buitrago-Esquinas, & Roldán, 2013) and their positive attitude (Ayub, Tarmizi, Jaafar, Ali, & Luan, 2010) in online learning systems

Previous research in e-learning acceptance disclosed that the effect of VD on the two main constructs of the TAM is still not well-established. It has been found (Al-Aulamie, 2013; Khedr, Hana, & Shollar, 2012; Theng & Sin, 2012; Liu, Chen, Sun, Wible, & Kuo, 2010; Cho, Cheng, & Lai, 2009) that when students perceive that e-learning systems have good visual design are more likely to perceive the system as easy to use. Using the TAM, Al-Aulamie (2013) proposed a direct relationship between VD and PEOU to investigate the acceptance of LMS by undergraduate students at three universities in Eastern Region, Saudi Arabia. Al-Aulamie (2013) used a multivariate analysis technique and confirmed that user interface design is the second strongest determinant of PEOU among the independent variables in his model. Two studies (Thong, Hong, & Tam, 2002; Jeong, 2011) demonstrated the effect of VD of an e-library on PEOU using students from Hong Kong and Korea, respectively. However, the relationship between visual design and perceived usefulness in e-learning is still not well understood. Cho et al. (2009) and Khedr et al. (2012) found that interface design of e-learning systems affects students' perceived usefulness. By way of contrast, Al-Aulamie (2013) revealed that user interface design of LMS does not influence the perceived usefulness of 766 undergraduate students in Saudi Arabia. By way of contrast, Al-Aulamie (2013) tested a direct relationship between VD and PU to understand factors that impact the acceptance of LMS by Saudi students. Al-Aulamie (2013) revealed that the influence of user interface design on PU is not significant. Likewise, it was empirically demonstrated (Parsazadeh, Zainuddin, Ali, & Rezaei, 2017) that VD of Moodle LMS does not affect the Malaysian students' perceived usefulness. Similarly, Jeong (2011) found that VD of an e-library does not affect the students' PU. Therefore, the following hypotheses are proposed to examine the influence of visual design on both PEOU and PU.

H5: *VD has a direct positive influence on students' PEOU of LMS.*
H6: *VD has a direct positive influence on students' PU of LMS.*

3.7.4 System Navigation

System navigation has been an important element in designing e-learning systems (Zaharias & Poylymenakou, 2009) that has a direct influence on perceived usability (Gilani, et al., 2016). Many studies (Koulocheri, Soumplis, Kostaras, & Xenos, 2011; Medina-Flores & Morales-Gamboa, 2015; Ssemugabi & De Villiers, 2007) have used SN as a usability attribute to evaluate e-learning systems. The navigation of LMS refers to the degree to which the organisation of LMS is understandable and appropriate for students (Naveh, Tubin, & Pliskin, 2012). Even though links are of considerable importance in systems, the navigation of e-learning systems is more than hyperlinks (Gilani, et al., 2016). System navigation is 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. The navigation of e-learning systems should allow students to leave when they desire and then easily return to the system (Zaharias & Poylymenakou, 2009). In addition, the desired information in LMS should be reached easily and efficiently (Naveh, Tubin, & Pliskin, 2012). With a system that has good navigation, users are informed where they are (Gilani, et al., 2016) and where they can go within the system (Koulocheri, Soumplis, Kostaras, & Xenos, 2011). Therefore, good navigation is an important factor for the success of systems (Gilani, et al., 2016).

Studies have demonstrated the effect of SN on both PEOU and PU. In e-learning systems, Theng and Sin (2012) found that the navigation of LMS has a positive influence on students' perceived ease of use in Singapore. Naveh et al. (2012) examined the success factors of LMS and concluded that SN is an important factor for student use of LMS. The 40 students expressed the significance of reaching the desired information easily and efficiently. Apart from LMS, Naqvi et al. (2016) proposed a theoretical framework for the acceptance of web-based transaction systems and hypothesised that SN affects PEOU. In respect to digital libraries, Pakistani students said that SN has a positive impact on their perceived ease of use and perceived usefulness (Khan & Qutab, 2016). Likewise, students in Hong Kong demonstrated the effect of SN on PEOU of an e-library (Thong, Hong, & Tam, 2002). In e-commerce, Green and Pearson (2011) found the effect of navigation on the perceived usefulness of online shopping websites using 344 undergraduate students. Accordingly, it is expected that when students perceive that LMS have good navigation, they are more likely to perceive the system to be useful and easy to use. To examine the influence of SN on student use of LMS, the following hypotheses are proposed.

H7: *SN has a direct positive influence on students' PEOU of LMS.*
H8: *SN has a direct positive influence on students' PU of LMS.*

3.7.5 Ease of Access

Ease of access of LMS refers to the degree to which users can access the system without difficulty from the login process to the course content (Naveh, Tubin, & Pliskin, 2012; Park, 2009). Junus et al. (2015) described EOA as the ability of e-learning systems to provide users with an easy access to features and functions. In terms of this research, EOA means the perceived ability of LMS to provide students with flexible access to all features and course materials (Tran, 2016). Ease of access includes, but is not limited to, the support of different platforms (Alsumait & Al-Osaimi, 2009), smooth login, response time, quick download, appropriate use of materials (Zaharias, 2009), and freedom from technical issues (Zaharias & Poylymenakou, 2009). The poor accessibility of LMS, such as a long login process and slow download of elements, causes students frustration (Naveh, Tubin, & Pliskin, 2012). Multimedia files and graphics usually require more time to load, and this delay can make users disappointed (Aziz & Kamaludin, 2014). Furthermore, the slow response of systems may force students to reduce their learning because of waiting and time limitations (Zaharias, 2009). However, EOA affects students' attitude toward e-learning systems (Lee, 2008). Al-Harbi (2011) combined TRA and the TAM and found that EOA plays an important role in the students' intention to use e-learning systems in a single university in Saudi Arabia. Furthermore, a study of 306 students in a Saudi higher-educational institution confirmed that EOA is a critical success factor for e-learning systems (Alhabeeb & Rowley, 2018). This might show the importance of EOA in student acceptance of LMS.

In previous research, the effect of EOA on PEOU has been demonstrated. Studies (Ariffin, Alias, Abd Rahman, & Sardi, 2014; Naveh, Tubin, & Pliskin, 2012; Ayub, Tarmizi, Jaafar, Ali, & Luan, 2010) examined the success factors of LMS and concluded that EOA is a critical element for student use of LMS. Previous literature (Al-Aulamie, 2013; Lee, Hsiao, & Purnomo, 2014; Kang & Shin, 2015; Park, 2009; Tran, 2016; Salloum, 2018) provided evidence that students tend to perceive LMS easy to use when they are highly accessible. In Saudi Arabia, Al-Aulamie (2013) hypothesised a positive effect between accessibility and PEOU based on the TAM in the context of LMS acceptance. Al-Aulamie (2013) stated that the inconsistency between accessibility and the two main variables of the TAM (PEOU and PU) necessitates the examination of the relationships between them. Based on 766 online questionnaires received from undergraduate students, the results showed that accessibility is the strongest determinant of PEOU among the independent variables. Aziz and Kamaludin (2014) revealed that the accessibility of a Malaysian university website positively influenced the perceived ease of use of 82 users. Apart from LMS, Naqvi et al. (2016) hypothesised that the EOA of web-based transaction systems affects PEOU. Furthermore, students in Hong Kong demonstrated the effect of EOA of an e-library on PEOU (Thong, Hong, & Tam, 2002). However, this relationship was not found to be significant with Pakistani students (Kanwal & Rehman, 2017). To examine the relationship between EOA and PEOU, the following hypothesis is proposed.

H9: *EOA has a direct positive influence on students' PEOU of LMS.*

On the other hand, scholars have yet to agree on the relationship between EOA and PU. Aziz and Kamaludin (2014) concluded that the accessibility of a Malaysian university website does not influence perceived usefulness. Similarly, it was revealed (Kang & Shin, 2015; Park, 2009; Lee, 2008) that EOA does not affect the students' perceived usefulness of e-learning systems. Students in Hong Kong proved that EOA of e-library does not affect PU (Thong, Hong, & Tam, 2002). By contrast, Al-Aulamie (2013) proposed and confirmed the effect of LMS accessibility on PU in the context of Saudi higher education. However, the statistical analysis revealed that accessibility is the weakest determinant of PU among the independent variables. Likewise, it was demonstrated (Moreno, Cavazotte, & Alves, 2017; Parsazadeh, Zainuddin, Ali, & Rezaei, 2017; Salloum, 2018) that EOA of LMS positively affects the students' perceived usefulness in Brazil, Malaysia, and UAE, respectively. To examine the relationship between EOA and PU, the following hypothesis is proposed.

H10: *EOA has a direct positive influence on students' PU of LMS.*

3.7.6 System Interactivity

System interactivity is a key factor in learning activities (Premchaiswadi, Porouhan, & Premchaiswadi, 2012) that represents how students are engaged with e-learning systems during their education (Zaharias, 2009). In the view of Theng and Sin (2012), it refers to how students learn by interacting with other students, teachers, and objects using LMS. Junus et al. (2015) defined SI as including all sorts of communications accessed via e-learning systems during the learning experience. This communication can be (1) between students and teachers, (2) between students themselves, and (3) between students and the LMS. System interactivity, as a usability factor, was proposed and examined by various studies to evaluate the usability of e-learning systems (Althobaiti & Mayhew, 2016; Junus, Santoso, Isal, & Utomo, 2015; Koulocheri, Soumplis, Kostaras, & Xenos, 2011; Zaharias & Poylymenakou, 2009; Alsumait & Al-Osaimi, 2009; Oztekin, Kong, & Uysal, 2010). This demonstrates the significance of students' interactivity with LMS from a usability perspective. Considering LMS acceptance, it was shown that SI affects students' intention to use LMS (Premchaiswadi, Porouhan, & Premchaiswadi, 2012; Alenezi, 2012; Agudo-Peregrina, Hernández-García, & Pascual-Miguel, 2014) and their perceived learning success (Janson, Söllner, & Leimeister, 2017). Therefore, e-learning systems should promote the interaction between users for the sake of knowledge sharing and ideas exchange (Koulocheri, Soumplis, Kostaras, & Xenos, 2011).

The relationship between SI and PEOU is still ambiguous. Alkandari (2015), Lin, Persada, and Nadlifatin (2014), and Tran (2016) provided evidence that when LMS have good interactivity, students tend to perceive the system as easy to use. Furthermore, the interactivity of e-learning systems was empirically found to affect students' PEOU in Malaysia, Taiwan, Brazil, and China, respectively (Baharin, Lateh , Nathan, & Nawawi, 2015; Huang & Liaw, 2018; Freitas, Ferreira, Garcia, & Kurtz, 2017; Li, Duan, Fu, & Alford, 2012). However, other studies (Pituch & Lee, 2006;

Baleghi-Zadeh, Ayub, Mahmud, & Daud, 2017) in the students' acceptance of e-learning systems contradict these findings. To clarify the ambiguity of the relationship between SI and PEOU, the following hypothesis is proposed.

H11: *SI has a direct positive influence on students' PEOU of LMS.*

It has been found that there is a consensus between researchers about the relationship between the perceived interactivity of LMS and perceived usefulness. Studies investigated and agreed upon the effect of LMS interactivity on university students' perceptions of usefulness in Saudi Arabia (Alenezi, 2012; Al-Harbi, 2011), Kuwait (Alkandari, 2015), Singapore (Theng & Sin, 2012), Taiwan (Liaw, 2008; Lin, Persada, & Nadlifatin, 2014; Pituch & Lee, 2006), and Malaysia (Parsazadeh, Zainuddin, Ali, & Rezaei, 2017; Baleghi-Zadeh, Ayub, Mahmud, & Daud, 2017). Moreover, the interactivity of other e-learning systems empirically affected PU for Malaysian and Taiwanese students, respectively (Baharin, Lateh , Nathan, & Nawawi, 2015; Huang & Liaw, 2018). Conversely, Li et al. (2012) concluded that the relationship between SI and PU is insignificant in the students' acceptance of e-learning systems. Following most studies, it is expected that when LMS have good interactivity, students are more likely to perceive the system useful. Therefore, the following hypothesis is proposed.

H12: *SI has a direct positive influence on students' PU of LMS.*

3.7.7 Instructional Assessment

Instructional assessment, also known as individual self-assessment or formative assessment, is a crucial element in designing e-learning systems (Zaharias, 2009) as it is a good way to assess students' learning (Terzis & Economides, 2011). Researchers (Zaharias, 2009; Zaharias & Poylymenakou, 2009; Uribe, 2014; Kayler & Weller, 2007) have stressed the importance of IA when implementing educational technologies. Instructional assessment can give feedback about the students' accomplishments in relation to course objectives (Kayler & Weller, 2007), enable students to learn more by answering questions (Wang, 2014), and enhance students' academic achievement (Uribe, 2014). As IA should be designed into online learning systems (Kayler & Weller, 2007), learning management systems usually provide a variety of assessment tools including surveys, quizzes, and tests. These should be good self-assessment tools to help students in understanding the content of courses. Therefore, it is expected that when students perceive that LMS have good IA, they are more likely to have a positive attitude and use the system. To the best of the researcher's knowledge, this variable has never been adopted into the TAM. To examine the influence of self-assessment on both PEOU and PU, the following hypotheses are proposed.

H13: *IA has a direct positive influence on students' PEOU of LMS.*
H14: *IA has a direct positive influence on students' PU of LMS.*

3.7.8 System Learnability

System learnability might be the most essential usability attribute, since users need first to learn how to use the system (Nielsen, 1993). Aziz and Kamaludin (2014) reported that learning how to use the system is a requirement to accomplish the efficiency and effectiveness of the used system. Shackel (2009) and Nielsen (1993) indicated that a usable system has to achieve various usability attributes and SL is one of them. According to Nielsen (1993), SL refers to the degree to which users can learn how to use the system without difficulty. In e-learning, Junus et al. (2015) described SL as the capability of e-learning systems to help users learn how to use the system easily. It is very important, especially for novice users, to be able to successfully interact with the system within a short time (Blecken, Bruggemann, & Marx, 2010). With a highly learnable system, users believe that they can start using the system with a minimum of training, help, and orientation (Jabar, Usman, & Awal, 2013). Systems with poor learnability can lead to more user training, technical support, and maintenance cost. In an ideal world, e-learning systems should not have a significant learning curve; therefore, students would learn how to use the system from the first attempt (Zaharias, 2009). Therefore, learnability is crucial for the usability of e-learning systems (Kakasevski, Mihajlov, Arsenovski, & Chungurski, 2008).

The impact of SL of e-learning systems on students' PEOU and PU has not yet received much attention from researchers. Scholars (Gül, 2017; Scholtz, Mandela, Mahmud, & Ramayah, 2016) empirically concluded that interface usability including SL has a positive influence on both PEOU and PU of ERP systems. In the same line, Aziz and Kamaludin (2014) revealed that the SL of a Malaysian university website positively influenced PEOU and PU of 82 users. However, it was found (Lin, 2013) that there is no significant correlation between the SL of e-learning systems and students' PEOU. Following these studies, the researcher believes that SL has a positive influence on the students' PEOU and PU. To examine the influence of SL, the following hypotheses are proposed.

H15: *SL has a direct positive influence on students' PEOU of LMS.*
H16: *SL has a direct positive influence on students' PU of LMS.*

3.8 Variables of the Technology Acceptance Model

3.8.1 Perceived Ease of Use

Perceived ease of use is a key construct in the TAM (Davis, 1989). The significance of PEOU was suggested by various technology-acceptance theories, such as the TAM (Davis, Bagozzi, & Warshaw, 1989); the A-TAM (Taylor & Todd, 1995a); the TAM2 (Venkatesh & Davis, 2000); determinants of PEOU (Venkatesh, 2000); and the TAM3 (Venkatesh & Bala, 2008). Perceived ease of use can be defined as the extent to which an individual believes that utilising the technology under investigation would not require significant effort (Davis, 1986). In the context of this research, PEOU refers to the extent to which students in Saudi higher education think that using LMS would be easy. In line with the TAM (Davis, 1989), students perceiving LMS as easy to use, they are more likely to use the system. Furthermore, PEOU was postulated to be an antecedent to PU and BI in various technology models, such as the TAM, the TAM2, the model of PEOU determinants, and the TAM3. Compared to other constructs, the meaning of PEOU is similar to the effort expectancy construct in the UTAUT (Venkatesh, Morris, Davis, & Davis, 2003) and the UTAUT2 (Venkatesh, Thong, & Xu, 2012).

The influence of PEOU on PU was suggested by various studies. Using the TAM3, Al-Gahtani (2016) asserted a positive relationship between PEOU and PU at King Khalid University in Saudi Arabia. With the same model, a study (Almazroi, Shen, Teoh, & Babar, 2016) revealed that the Saudi students' perceived usefulness of cloud e-learning systems is positively influenced by PEOU. Al-Aulamie (2013) proposed a direct relationship between PEOU and PU to investigate the acceptance of LMS by undergraduate students at three universities in Eastern Region, Saudi Arabia. Al-Aulamie (2013) used a multivariate analysis technique and confirmed that PEOU is an important determinant of PU. Based on the TAM, studies (Almarashdeh & Alsmadi, 2016; Alenezi, 2012; Alenezi, Abdul Karim, & Veloo, 2011; Alenezi, Abdul Karim, & Veloo, 2010; Al-Mushasha, 2013; Muniasamy, Eljailani, & Anandhavalli, 2014) demonstrated a positive effect of the students' PEOU on PU of e-learning systems in Saudi Arabia. Outside Saudi Arabia, studies (Hwa, Hwei, & Peck, 2015; Majdalawi, Almarabeh, & Mohammad, 2014; Al-Adwan, Al- Adwan, & Smedley, 2013; Park, 2009; Mohammadi, 2015; Baharin, Lateh , Nathan, & Nawawi, 2015; Abdullah & Toycan, 2017; Lee, Hsiao, & Purnomo, 2014; Hsu & Chang, 2013; Tanduklangi, 2017) concluded that the students' perceived ease of use has a positive influence on their perceived usefulness of LMS. In an e-learning environment, 400 students showed the presence of this influence (Shah, Bhatti, Iftikhar, Qureshi, & Zaman, 2013). In library mobile applications, Yoon (2016) revealed that the students' perceived ease of use has a positive influence on perceived usefulness in South Korea. With regard to e-portfolios, a study (Abdullah, Ward, & Ahmed, 2016) demonstrated that the students' perceived usefulness is positively influenced by perceived ease of use in the United Kingdom. Based on the previous literature and technology-acceptance theories, this research predicts that when students perceive LMS easy to use, they are more likely to perceive LMS useful. To examine the influence of PEOU on PU, the following hypothesis is proposed.

H17: *PEOU has a direct positive influence on students' PU of LMS.*

On the other hand, researchers in e-learning systems acceptance have investigated the impact of PEOU on BI, and the findings were inconsistent. Using the TAM3, Al-Gahtani (2016) asserted a positive relationship between PEOU and BI at King Khalid University in Saudi Arabia. With the same model, Almazroi et al. (2016) revealed that the Saudi students' intention to use cloud e-learning systems is positively influenced by PEOU. In Saudi Arabia, Al-Aulamie (2013) has proposed a conceptual model based on the TAM to investigate the acceptance of LMS by students at three universities in Eastern Region. Based on 766 online questionnaires received from undergraduate students, Al-Aulamie (2013) confirmed that PEOU is significant for Saudi students to intent to use LMS. Using the TAM, a positive influence of PEOU on the students' intention to use e-learning systems was demonstrated in five Saudi universities (Alenezi, Abdul Karim, & Veloo, 2011), Indonesia (Lee, Hsiao, & Purnomo, 2014; Tanduklangi, 2017), Pakistan (Shah, Bhatti, Iftikhar, Qureshi, & Zaman, 2013), Lebanon (Tarhini, Hone, Liu, & Tarhini, 2017), UK (Tarhini, Hone, & Liu, 2014a), Malaysia (Hwa, Hwei, & Peck, 2015), and Iraq (Abdullah & Toycan, 2017; Al-Azawei, Parslow, & Lundqvist, 2017). Sharma and Chandel (2013) revealed a strong relationship between PEOU and BI when students use websites for learning. Concerning e-portfolios, a study (Abdullah, Ward, & Ahmed, 2016) demonstrated that the students' behavioural intention is positively influenced by PEOU in the United Kingdom. Moreover, studies in the context of e-learning systems concluded an indirect effect of PEOU on BI through PU (Tarhini, Elyas, Akour, & Al-Salti, 2016; Baharin, Lateh , Nathan, & Nawawi, 2015). By contrast, Amin et al. (2016) concluded that PEOU does not have a positive influence on the students' intention to use LMS in Bangladesh. The same result was reached by Park (2009) with South Korean students, Baharin et al. (2015) with Malaysian students, and Mohammadi (2015) with Iranian students. In library mobile applications, Yoon (2016) revealed that the students' perceived ease of use does not have a positive influence on their behavioural intention in South Korea. Following most studies and theories, this research expects that when students perceive LMS easy to use, they are most likely to intend to use the LMS. To examine the influence of PEOU on BI, the following hypothesis is proposed.

H18: *PEOU has a direct positive influence on students' BI to use LMS.*

3.8.2 Perceived Usefulness

Perceived usefulness is a key construct in the TAM (Davis, 1989). The significance of PU was suggested by various technology models, such as the TAM (Davis, Bagozzi, & Warshaw, 1989); the A-TAM (Taylor & Todd, 1995a); the TAM2 (Venkatesh & Davis, 2000); the model of PEOU determinants (Venkatesh, 2000); and the TAM3 (Venkatesh & Bala, 2008). Perceived usefulness can be defined as the degree to which an individual believes that utilising the technology under investigation would improve his or her performance (Davis, 1986). For the purpose of this study, PU refers to the extent to which students in Saudi universities think that using LMS would improve their performance. According to the TAM (Davis, 1989), students perceiving LMS as useful are more likely to use the system. Compared to other constructs, the meaning of PU is similar to the performance expectancy construct in the UTAUT (Venkatesh, Morris, Davis, & Davis, 2003) and the UTAUT2 (Venkatesh, Thong, & Xu, 2012). Perceived usefulness was assumed to be a direct antecedent to BI in various models, such as the TAM, the A-TAM, the TAM2, the model of PEOU determinants, and the TAM3. Furthermore, it was found (Davis, 1993) that PU is a direct determinant of AU. In comparison to PEOU, PU has stronger influence on user intention and behaviour (Davis, 1989). Many studies in the acceptance of e-learning systems (Al-Gahtani, 2016; Tarhini, Hone, Liu, & Tarhini, 2017; Almazroi, Shen, Teoh, & Babar, 2016; Ramírez Anormaliza, Sabate, & Audet Llinàs, 2016; Ma, Chao, & Cheng, 2013) supported the same result.

Many studies highlighted the significance of PU in predicting individuals' intention to use e-learning systems. Using the TAM3, Al-Gahtani (2016) asserted a positive relationship between PU and BI at King Khalid University in Saudi Arabia. With the same model, Almazroi et al. (2016) revealed that the Saudi students' intention to use cloud e-learning systems is positively influenced by PU. Al-Aulamie (2013) proposed and confirmed the effect of PU on BI in the context of Saudi higher education. More importantly, the statistical analysis revealed that PU is the strongest determinant of BI among the proposed variables. Using the TAM, studies (Alenezi, Abdul Karim, & Veloo, 2010; Alenezi, Abdul Karim, & Veloo, 2011; Al-Mushasha, 2013; Muniasamy, Eljailani, & Anandhavalli, 2014) demonstrated a positive relationship between PU and BI of e-learning systems in Saudi Arabia. Apart from Saudi Arabia, studies (Abdullah & Toycan, 2017; Tanduklangi, 2017; Al-Azawei, Parslow, & Lundqvist, 2017; Tarhini, Hone, Liu, & Tarhini, 2017; Amin, Afrin Azhar, & Akter, 2016; Hwa, Hwei, & Peck, 2015; Mohammadi, 2015; Baharin, Lateh , Nathan, & Nawawi, 2015; Lee, Hsiao, & Purnomo, 2014; Majdalawi, Almarabeh, & Mohammad, 2014; Tarhini, Hone, & Liu, 2014a; Al-Adwan, Al- Adwan, & Smedley, 2013) concluded that the students' perceived usefulness has a positive influence on their intention to use LMS. The same result was supported with students in an e-learning environment (Shah, Bhatti, Iftikhar, Qureshi, & Zaman, 2013), websites for learning (Sharma & Chandel, 2013), library mobile applications (Yoon, 2016), and e-portfolios (Abdullah, Ward, & Ahmed, 2016). In contrast, Park (2009) found that PU does not have a positive influence on the students' intention to use LMS in South Korea. In line with the previous literature with regard to technology acceptance, this research postulates that perceiving LMS useful leads to the students' intention to use the system. To examine the influence of PU on BI, the following hypothesis is proposed.

H19: *PU has a direct positive influence on students' BI to use LMS.*

3.8.3 Behavioural Intention

The significance of BI arises from various theories and models, such as TRA (Fishbein & Ajzen, 1975); TPB (Ajzen, 1985); the TAM (Davis, Bagozzi, & Warshaw, 1989); A-TAM (Taylor & Todd, 1995a); the TAM2 (Venkatesh & Davis, 2000); the model of PEOU determinants (Venkatesh, 2000); and the TAM3 (Venkatesh & Bala, 2008). Behavioural intention can be defined as an individual's aim or plan to perform the behaviour (Fishbein & Ajzen, 1975). In the context of this study, BI refers to the students' aim or plan to use LMS in Saudi higher education. According to technology-acceptance theories, including TRA, TPB, the TAM, the TAM2, the TAM3, and the model of PEOU determinants, BI is the only predictor of AU and provides evidence of the persons' willingness to use the technology. In the TAM (Davis, Bagozzi, & Warshaw, 1989), the actual use of a technology is influenced by a persons' intention to use this technology, which is predicted by PEOU and PU. In the context of LMS, Jong (2009) found that the relationship between BI and AU is the strongest of the relationships in his model.

Past literature in e-learning systems indicated that the relationship between BI and AU is well-established. Based on the TAM, studies (Alenezi, 2012; Alenezi, Abdul Karim, & Veloo, 2011) demonstrated a positive effect of the Saudi students' intention to use LMS on AU. Studies (Mohammadi, 2015; Baleghi-Zadeh, Ayub, Mahmud, & Daud, 2017; Tarhini, 2013) revealed that the students' actual use of LMS is positively influenced by BI. Furthermore, Al-Gahtani (2008) and Al-Gahtani, Hubona, and Wang (2007) when examining the acceptance of computer technology using 722 employees in Saudi Arabia concluded that the relationship between BI and AU is the strongest. Consistent with the previous studies and theories, this research expects that the students' intention to use LMS contributes to their actual use of the system. To examine the influence of BI on AU, the following hypothesis is proposed.

H20: *BI has a direct positive influence on students' AU of LMS.*

3.9 Personal Moderators

Considering demographic characteristics is important when evaluating e-learning systems (Islam, Abdul Rahim, Liang, & Momtaz, 2011). Several studies (Claar, Dias, & Shields, 2014; Ong & Lai, 2006; Alenezi, 2011; Al-Gahtani, 2016; Tarhini, Elyas, Akour, & Al-Salti, 2016; Ilie, Slyke, Green, & Hao, 2005; Tarhini, 2013) demonstrated the effect of demographic characteristics on the students' acceptance of e-learning systems. Furthermore, understanding the effect of demographic characteristics on technology acceptance may help, in turn, to spread technologies (Al-Gahtani, 2008). The moderation effect occurs when one variable (e.g. gender) affects the strength or direction of a relationship between two variables (Hair, Hult, Ringle, & Sarstedt, 2017). Nevertheless, the moderating effect of the personal characteristics on technology acceptance and use has previously been widely disregarded (Morris, Venkatesh, & Ackerman, 2005; Sun & Zhang, 2006), and precisely the TAM has been barely investigated with moderators (Al-Gahtani, 2008; Venkatesh, Morris, Davis, & Davis, 2003).

Sun and Zhang (2006) suggested that moderating variables could mitigate the problem of low explanatory power of technology-acceptance models and the inconsistency in the results across cultures. Venkatesh et al. (2003) examined eight models and demonstrated that the explanatory power of six out of the eight models increased after extending the models with moderators. For example, they concluded that after the inclusion of voluntariness, gender, and age as moderators into TPB, the explanatory power was raised to 36%, 46%, and 47%, respectively. The TAM, in particular, was criticised for the lack of moderating variables (Venkatesh & Morris, 2000; Venkatesh, Morris, Davis, & Davis, 2003; Al-Gahtani, 2008). Venkatesh et al. (2003) found that the explanatory power was raised to 52% after the inclusion of a gender moderating effect into the TAM.

From a methodological standpoint, investigators usually assume that data were collected from identical participants and analyse the full set of data. However, this assumption is not always correct (Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Sarstedt, Ringle, & Gudergan, 2018; Sarstedt, Henseler, & Ringle, 2011). The collected data, in most cases, incorporate a number of varied personal characteristics of users, such as gender, age, educational level, and previous experience. Not considering those differences between users may contribute to incorrect interpretations of the results (Hair, Sarstedt, Ringle, & Mena, 2012). For example, when the relationship between two constructs is negatively significant for more-experienced participants and positively significant for less-experienced participants, the analysis of the full set of data might not find any significance. This highlights the importance of investigating the personal differences between the participants.

The present study aims to extend the TAM to investigate the effect of the students' demographic characteristics that may work as moderators, namely gender, age, educational level, and experience, on the relationships between the proposed model's variables. Therefore, the variables moderating the relationships between the independent and dependent variables are explained next.

3.9.1 Gender

Technology-acceptance models, such as the UTAUT (Venkatesh, Morris, Davis, & Davis, 2003) and the UTAUT2 (Venkatesh, Thong, & Xu, 2012), have considered gender moderating effect as there is a difference in the process of making decisions between men and women (Venkatesh & Morris, 2000). Gender is one of the demographic characteristics that has an influence on individual perception, attitude, and behaviour (Nosek, Banaji, & Greenwald, 2002). Past studies (Venkatesh, Thong, & Xu, 2012; Sun & Zhang, 2006; Morris, Venkatesh, & Ackerman, 2005; Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh & Morris, 2000; Venkatesh, Morris, & Ackerman, 2000) consider that gender plays an important role in explaining user behaviour in information systems.

In terms of e-learning, review studies on gender (Goswami & Dutta, 2016; Shaouf & Altaqqi, 2018) found that gender is an important variable in e-learning. Research has uncovered differences between male and female students in perception (Al-Youssef, 2015), patterns of use (Ng & Tan, 2017), and acceptance of LMS (Tarhini, Hone, & Liu, 2014a). Understanding the differences between male and female students toward computer technologies enables teachers to choose the appropriate learning processes for each gender (Ong & Lai, 2006) and contributes to the advancements of technologies (Goswami & Dutta, 2016). Specially in Saudi Arabia, it is expected that gender differences would influence student use of LMS as the Saudi educational system implements gender segregation in all academic stages (Alenezi, 2011). For example, Al-Aulamie (2013) found that gender moderates the relationships between seven independent variables (information quality, functionality, accessibility, user interface design, computer playfulness, enjoyment, and learning goal orientation) and the original constructs of the TAM in the context of LMS acceptance by undergraduate students in Saudi Arabia. Nevertheless, it has been stated (Tarhini, Hone, & Liu, 2014a; Ramírez-Correa, Arenas-Gaitán, & Rondán-Cataluña, 2015; Brinson, 2016) that the scarcity in research related to the gender moderating effect in e-learning systems acceptance is very evident, especially in the Arab world (Smeda, 2017; Tarhini, 2013). On the other hand, studies in e-learning systems (Arenas-Gaitán, Rondan-Cataluña, & Ramirez-Correa, 2010; Dečman, 2015; Khechine, Lakhal, Pascot, & Bytha, 2014; Raman, Don, Khalid, & Rizuan, 2014; Ramírez-Correa, Arenas-Gaitán, & Rondán-Cataluña, 2015; Wong, Teo, & Russo, 2012) have concluded that gender does not moderate the use of e-learning systems. To investigate gender moderating effect on student use of LMS, the following hypotheses are proposed.

H21(a,b,c,d,e,f,g,h): *Gender moderates the effect of usability variables (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PEOU of LMS.*
H22(a,b,c,d,e,f,g,h): *Gender moderates the effect of usability variables (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PU of LMS.*
H23: *Gender moderates the effect of students' PEOU on PU of LMS.*
H24: *Gender moderates the effect of students' PEOU on BI to use LMS.*

H25: *Gender moderates the effect of students' PU on BI to use LMS.*
H26: *Gender moderates the effect of students' BI on AU of LMS.*

3.9.2 Age

Age is one of the demographic characteristics that has an influence on an individual perception, attitude, and behaviour (Nosek, Banaji, & Greenwald, 2002). Past studies (Venkatesh, Thong, & Xu, 2012; Sun & Zhang, 2006; Morris, Venkatesh, & Ackerman, 2005; Venkatesh, Morris, Davis, & Davis, 2003; Morris & Venkatesh, 2000; Porter & Donthu, 2006) consider that age plays an important role in explaining user behaviour in information systems. Venkatesh et al. (2003) concluded that after the inclusion of age as a moderator, the explanatory power of TPB was raised to 47%. In spite of this, it was reported that age as a moderating factor in technology acceptance and adoption has not sufficiently given consideration (Seuwou, Banissi, & Ubakanma, 2017; Tarhini, Hone, & Liu, 2014a).

In the UTAUT, Venkatesh et al. (2003) demonstrated that age moderates the relationship between effort expectancy (same as PEOU) and BI, where the relationship is stronger for older than younger users. They argued that prior research (Morris & Venkatesh, 2000) supports their finding that older users are more motivated by effort expectancy. They also found that age moderates the relationship between performance expectancy (same as PU) and BI, where the relationship is stronger for younger users. They reported that their findings were compatible with previous literature in attitude that confirms that younger users are more motivated by extrinsic rewards, which, they maintain, is directly associated with usefulness.

Considering e-learning systems, prior studies have failed to provide consistent results regarding the moderating effect of age. Tarhini et al. (2014a) studied the moderating effect of students' age at a single university in England. They concluded that age moderates the relationships between PEOU, PU, and self-efficacy and BI. Khechine et al. (2014) investigated the moderating effect of age on the students' acceptance of a webinar system in a Canadian university. They found that age moderates the effect of performance expectancy and facilitating conditions on BI. Considering developing countries, Tarhini et al. (2014b) showed that the age of Lebanese students moderates the influence of PEOU, subjective norms, and quality of work life on BI in e-learning systems. On the contrary, Altawallbeh, Thiam, Alshourah, and Fong (2015) demonstrated that age does not moderate the students' acceptance and use in Jordanian universities. Abbasi (2011) investigated the acceptance of e-learning systems in Pakistan and found that age does not influence user behaviour. Similar results were revealed by Rahman, Jamaludin, and Mahmud (2011) who examined the Malaysian postgraduate students' use of an e-library. Therefore, the following hypotheses are proposed to investigate the influence of age in the context of Saudi e-learning systems.

H27(a,b,c,d,e,f,g,h): *Age moderates the effect of usability variables (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PEOU of LMS.*
H28(a,b,c,d,e,f,g,h): *Age moderates the effect of usability variables (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PU of LMS.*
H29: *Age moderates the effect of students' PEOU on PU of LMS.*
H30: *Age moderates the effect of students' PEOU on BI to use LMS.*
H31: *Age moderates the effect of students' PU on BI to use LMS.*
H32: *Age moderates the effect of students' BI on AU of LMS.*

3.9.3 Level of Education

Level of education in the context of this study indicates the students' level in higher education whether undergraduate or postgraduate. Past studies (Burton-Jones & Hubona, 2006; Abu-Shanab, 2011; Sun & Zhang, 2006; Mahmood, Hall, & Swanberg, 2001; Agarwal & Prasad, 1999; Claar, Dias, & Shields, 2014; Lymperopoulos & Chaniotakis, 2005) consider that there is a positive relationship between educational level and user behaviour in technology. As the other demographic characteristics, level of education was examined as an external variable that affects PEOU and PU (Burton-Jones & Hubona, 2006; Porter & Donthu, 2006; Agarwal & Prasad, 1999; Claar, Dias, & Shields, 2014; Lymperopoulos & Chaniotakis, 2005) and as a moderator that influences the relationships between the proposed variables (Abu-Shanab, 2011; Sun & Zhang, 2006; Tarhini, 2013; Tarhini, Hone, & Liu, 2014b).

Reviewing previous literature revealed that little research has been conducted to understand the moderating effect of educational level on students use of e-learning systems. For example, Tarhini (2013) compared the students' acceptance of e-learning systems in Lebanon and the UK and found that education moderated most of the proposed relationships in both countries. Furthermore, Tarhini et al. (2014b) showed that the educational level of Lebanese students moderates the influence of PEOU and subjective norms on BI in e-learning systems, where the relationship is stronger for less educated students. To examine the moderation effect of students' educational level on the relationships between the examined variables, the following hypotheses are proposed.

H33(a,b,c,d,e,f,g,h): *Level of education moderates the effect of usability variables (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PEOU of LMS.*
H34(a,b,c,d,e,f,g,h): *Level of education moderates the effect of usability variables (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PU of LMS.*
H35: *Level of education moderates the effect of students' PEOU on PU of LMS.*
H36: *Level of education moderates the effect of students' PEOU on BI to use LMS.*
H37: *Level of education moderates the effect of students' PU on BI to use LMS.*
H38: *Level of education moderates the effect of students' BI on AU of LMS.*

3.9.4 Experience

Experience is one of the demographic characteristics that refers to someone's involvement with the investigated technology over a period of time (Sun & Zhang, 2006). In accordance with Venkatesh and Morris (2000), experience in the context of this study indicates the number of years students have of using LMS. Venkatesh (2000) argued that users make their beliefs about the target system based on their experience with it, and they will be able to assess particular variables (e.g. usability and enjoyment) when gaining more experience. During the last two decades, a variety of technology-acceptance models, including the A-TAM (Taylor & Todd, 1995a); the model of PEOU determinants (Venkatesh, 2000); the TAM2 (Venkatesh & Davis, 2000); the TAM3 (Venkatesh & Bala, 2008); the UTAUT (Venkatesh, Morris, Davis, & Davis, 2003); and the UTAUT2 (Venkatesh, Thong, & Xu, 2012), considered that experience as a moderator plays an important role in explaining user behaviour in information systems. This might be attributed to knowledge obtained from previous behaviours affecting user intention (Fishbein & Ajzen, 1975; Taylor & Todd, 1995a). It was stated (Venkatesh, 2000) that experience is the most used moderator in technology-acceptance studies. Šumak et al. (2011) conducted a meta-analysis of e-learning systems acceptance and concluded that studies usually tend to investigate the difference in relationships between more-experienced and less-experienced users. Furthermore, it was reported (Abdullah, Ward, & Ahmed, 2016) that experience is an important variable in e-learning acceptance by students.

Venkatesh et al. (2003) proposed the UTAUT and demonstrated that experience moderates the relationship between effort expectancy (same as PEOU) and BI, where the relationship is stronger for users with limited experience. Supporting this argument, the relationship between PEOU and BI in past research is more relevant for less-experienced users (Venkatesh & Morris, 2000). Venkatesh et al. (2003) justified their findings that users with prior experience and knowledge have a better foundation to learn new technologies, and PEOU, therefore, is not that crucial for them. Venkatesh et al. (2003) demonstrated that experience does not moderate the relationship between performance expectancy (same as PU) and BI. In the TAM3, Venkatesh and Bala (2008) posited that experience has a moderating effect on the determinants of PEOU and PU. Taylor and Todd (1995a) proposed the A-TAM based on TPB and the TAM and found that PEOU → Attitude, PU → BI, and BI → AU are significantly different between more-experienced and less-experienced students in using a computing resource centre.

Prior experience is an important moderating variable in student use of e-learning systems. Using the TAM3, Al-Gahtani (2016) examined the students' acceptance of e-learning systems in Saudi Arabia and demonstrated that experience moderates the relationships between the key determinants and the two main constructs (PEOU and PU). Tarhini (2013) investigated the moderating effect of experience on the students' acceptance of e-learning systems in Lebanon and the UK, and the findings were different between the two countries. For example, students' experience moderated the relationship PU → BI in the UK, but not in Lebanon. Moreover, Tarhini et al. (2014b) showed that the experience of Lebanese students moderates the influence of PEOU, PU, and subjective norms on BI in e-learning systems. However, it was concluded (Zhang, Liu, Yan, & Zhang, 2017) that students' experience moderates the impact of PU, information satisfaction, and interaction satisfaction on continuous intention to use VLE in China. To investigate the moderating effect of experience on student use of LMS, the following hypotheses are proposed.

H39(a,b,c,d,e,f,g,h): *Experience moderates the effect of usability variables (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PEOU of LMS.*
H40(a,b,c,d,e,f,g,h): *Experience moderates the effect of usability variables (CQ, LS, VD, SN, EOA, SI, IA, SL) on students' PU of LMS.*
H41: *Experience moderates the effect of students' PEOU on PU of LMS.*
H42: *Experience moderates the effect of students' PEOU on BI to use LMS.*
H43: *Experience moderates the effect of students' PU on BI to use LMS.*
H44: *Experience moderates the effect of students' BI on AU of LMS.*

3.10 Summary

In this chapter, the proposed theoretical framework that may be useful in explaining and understanding the effect of usability attributes and demographic characteristics on student use of LMS within the context of higher education was described. The proposed model was developed based on the most popular technology model in the domain of information systems, the TAM, and the published literature regarding usability factors within the context of educational technologies. The research conceptual model is composed of three parts, usability, TAM variables, and moderating variables. These variables are: content quality, learning support, visual design, system navigation, ease of access, system interactivity, assessment, system learnability, perceived ease of use, perceived usefulness, behavioural intention, actual use, gender, age, level of education, and experience.

Consequently, the research model proposed 44 hypotheses for the relationships between the model constructs. Among those hypotheses, 16 hypotheses (H1 – H16) were proposed between the usability attributes and TAM variables. Regarding the second part, four hypotheses (H17 – H20) were proposed between TAM variables (PEOU, PU, and BI). Finally, 24 hypotheses (H21 – H44) were proposed for the moderating effect of the demographic characteristics (gender, age, level of education, and experience) on the direct relationships in the proposed model. The researcher advocates that the TAM alone is insufficient to model student behaviour and extending the TAM using usability attributes and demographic characteristics would better explain the constructs of PEOU and PU. The researcher also believes that it is worthwhile to investigate the influence of usability attributes and demographic characteristics on student use of LMS in the settings of Saudi higher-educational institutions. Hence, the next chapter explains the research methodology used to empirically examine the model proposed in this chapter.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 Introduction

This chapter discusses the selection of the methodological approaches used for data collection and analysis to examine the proposed model and hypotheses. More information about the methodology used in this study is provided, including the research paradigm, the research approach, the research method, the research design, the population and sampling, the instrument development, the data-collection procedures, and the data analysis technique.

4.2 Research Paradigm

A paradigm, also known as a worldview, refers to a set of assumptions and beliefs that constitute how one perceives the world (Kivunja & Kuyini, 2017). A paradigm determines what topic should be studied in a discipline, how a study should be conducted, and how findings should be interpreted (Bryman, 2016). There are four schools of thought that are widely discussed in the literature: positivism, constructivism, critical theory, and pragmatism (Creswell, 2014; Kivunja & Kuyini, 2017; Sekaran & Bougie, 2016). The characteristics, definitions, and methodology of the four paradigms are briefly introduced in Table 4.1.

Table 4.1 Research Paradigms

Paradigm	Characteristics	Definition	Methodology
Positivism	Objective Cause-effect Empirical measures Theory verification	Positivism, also known as scientific method, considers objectivity to be fundamental for competent inquiry.	Experimental Quantitative Deductive Hypothesis testing
Constructivism	Understanding Multiple views Historical and cultural considerations Theory generation	Constructivism, also known as interpretivism, believes that people develop subjective meanings toward things, and those meanings are different based on the historical and cultural background.	Qualitative Inductive Open-ended questions

Paradigm	Characteristics	Definition	Methodology
Critical theory	Political Justice Collaborative Change-orientated	Critical theory, also known as the transformative paradigm, focuses on the history or needs of a marginalised group in society. The approach links political, economic, and social actions.	Uses either qualitative or quantitative approach
Pragmatism	Problem-centred Consequences Pluralistic	Pragmatism focuses on the research problem and then employs mixed methods to derive knowledge about the problem.	Mixed methods (qualitative and quantitative approaches)

Source: (Creswell, 2014; Sekaran & Bougie, 2016)

After considering the differences between the four schools of thought, the positivism research paradigm was chosen for the present study based on the following reasons:

- *Quantitative measures:* A positivist perspective employs quantitative measures to collect empirical data from the desired sample and explain human behaviour (Kivunja & Kuyini, 2017). Furthermore, scientists in information systems (e.g. Myers, 2013) assert that a study is considered positivist if the researcher uses quantifiable measures and hypothesis testing. To investigate the research problem in this study, quantitative data were collected from students to support the proposed model and test the hypotheses formulated. Therefore, the selection of the positivist research paradigm was justified from a methodological viewpoint.
- *Deductive reasoning:* Researchers (Creswell, 2014; Kivunja & Kuyini, 2017; Sekaran & Bougie, 2016) emphasise that the positivist paradigm is linked with deductive theory, the dominant approach for the relationship between theory and research (Bryman & Bell, 2015). In a deductive study, the researcher defines a specific theory, develops hypotheses, determines measures, and reaches findings (Bryman, 2016). Thus, the present work used the TAM as the basis to produce the proposed research model and postulate the research hypotheses.
- *Cause-effect approach:* From a positivist perspective, the problem under investigation is caused by several factors; therefore, researchers should

examine the causes of the dependent variable (Sekaran & Bougie, 2016). In this present study, the research problem of student use of LMS is caused by other independent variables; thus, the factors that impact the students' use of LMS are empirically assessed.

- *Statistics:* Finally, a positivist researcher usually employs sophisticated statistical techniques to analyse the collected quantitative data (Cohen, Manion, & Morrison, 2013; Sekaran & Bougie, 2016). In this present study, the PLS-SEM statistical technique (see Section 4.7.1) was selected to examine the proposed model and test the hypotheses (see Chapter 3).

Following this justification of the 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) and a roadmap with directions to carry out the research (Hair, Celsi, Money, Samouel, & Page, 2016). Therefore, the research design is important to ensure the delivery of the study and balance the time constraints and budget limitations (Sue & Ritter, 2012). This study uses a quantitative approach, a survey tool, and a cross-sectional design. The following subsections illustrate the selected research design and justify its selection.

4.3.1 Quantitative Approach

The selected research approach usually falls under one of three categories: quantitative, qualitative, or mixed methods. Quantitative methods aim to collect numerical data from participants and involve the use of statistical techniques (Bryman, 2016). Quantitative research seeks to test the proposed hypotheses and examines the relationships between independent and dependent variables (Creswell, 2014). Furthermore, quantitative methods employ a deductive approach, which is related to the positivist philosophy (Bryman & Bell, 2015). In contrast, qualitative methods are more related to texts rather than numerical data (Bryman, 2016). Qualitative research seeks to understand subjective meanings expressed by the participants toward social or human problems (Creswell, 2014). Moreover, qualitative methods employ an inductive approach, which is related to the constructivist philosophy (Bryman & Bell, 2015). Table 4.2 describes the characteristics of the two approaches.

Table 4.2 Quantitative and Qualitative Approaches

Characteristics	Quantitative Research	Qualitative Research
Paradigm	Positivism	Constructivism or critical theory
Theory	Deductive: theory testing	Inductive: theory generation
Design	Survey or experiments	Ground theory, case study, narrative …
Data type	Numerical data	Texts and images
Instrument	Closed questions	Open-ended questions
Analysis	Statistical analysis	Thematic analysis

Source: (Bryman & Bell, 2015; Creswell, 2014)

The motivation for selecting a quantitative approach in the current study is derived from several dimensions:

- *Quantitative theory:* The TAM (Davis, 1989), which is the core of the proposed model, is quantitative in nature, and most studies in e-learning acceptance (e.g. Abdullah, Ward, & Ahmed, 2016; Baleghi-Zadeh, Ayub, Mahmud, & Daud, 2017; Gül, 2017; Huang & Liaw, 2018; Kanwal & Rehman, 2017) have used a quantitative approach.
- *Positivist paradigm:* From a philosophical perspective, the positivist research paradigm, which was chosen for this research, is more appropriate with quantitative methods (Bryman & Bell, 2015; Creswell, 2014). This investigation, which attempts to observe the world in an objective manner without the investigator's influence on the research problem, requires the testing of hypotheses regarding human behaviour toward the acceptance of LMS.
- *Research aim:* Researchers (Creswell, 2014; Kivunja & Kuyini, 2017) agree that a quantitative approach is best when the research aims to identify factors

that impact an outcome. This present work aims to identify the usability factors that influence student use of LMS in Saudi public universities.

- *Deductive reasoning:* Regarding the research design, this present study utilised the TAM as its starting point to produce the research model and postulate the research hypotheses. Therefore, this study benefits from deductive reasoning, which is linked with quantitative research (Bryman, 2016; Sekaran & Bougie, 2016).

4.3.2 Survey Research Method

The researcher not only selects the research approach (quantitative, qualitative, or mixed methods), but also decides upon the research method used in the selected approach. To collect quantitative or qualitative data, researchers have employed various research techniques, such as surveys, experiments, grounded theory, and case studies. The process of selecting the most appropriate research method is subject to several considerations, including the research paradigm, the design and approach, the research problem and questions, the target population, and the researcher's experience (Creswell, 2014).

One of the most commonly used methods for gathering data is the survey research method. Fink (2017) defines surveys as a method for collecting data about individuals' feelings, beliefs, knowledge, and behaviour. In survey research, these aspects are described quantitively (Creswell, 2014). Survey data can be collected via different forms, including mail, telephone, fax, the Internet, and personal interviews (Fink, 2017; Sue & Ritter, 2012). For this study, the online survey method was preferred to collect data from the participants for the following reasons:

- *Generalisability:* The purpose of the survey approach is to generalise the findings from the study sample to the entire population (Creswell, 2014; Cohen, Manion, & Morrison, 2013). Thus, the inferences in this study regarding student behaviour toward LMS can be generalised to all students who are registered at Saudi public universities.

- *Popularity in information systems:* The survey research method is the dominant approach in information systems (Orlikowski & Baroudi, 1991), technology acceptance (Choudrie & Dwivedi, 2005), and e-learning acceptance in particular (Abdullah & Ward, 2016). More specifically, *Research Industry Trends* reported that 78% of participants used online surveys during 2013, and 66% used online surveys most often compared with other quantitative methods (GRIT, 2013).
- *Measuring attitude:* Cohen et al. (2013) and Creswell (2014) reported that the survey research approach is appropriate when measuring individuals' attitudes, beliefs, experience, and behaviour. This present study collected quantitative data regarding student attitude and behaviour toward LMS. Furthermore, many hypotheses are proposed (see Chapter 3) to be empirically examined using the PLS-SEM technique, which cannot be achieved without the utilisation of the survey research approach.
- *Large and distributed population:* This investigation collected data from higher-education students in Saudi Arabia, of whom there are more than 1.3 million. These students are registered at various governmental universities located in different geographical regions of Saudi Arabia. The survey method approach is useful for collecting data from a large number of participants who are distributed across a wide geographical area (Cohen, Manion, & Morrison, 2013). Thus, online surveys are less expensive compared with mail surveys, telephone interviews, and personal interviews in terms of both cost and time (Bryman & Bell, 2015; Sekaran & Bougie, 2016).
- *Limited resources:* This research is limited in terms of time and financial budget. Unlike other survey methods, online surveys have the potential to accomplish a high response rate within a short period with no extra cost (Sue & Ritter, 2012). Furthermore, online surveys are cheap (no postage fee, telephone bills, travel tickets, papers, pens, etc.) and quick to administrate

(Bryman, 2016). With automated processes, the researcher does not need to enter and encode the collected data; thus, online surveys save time and energy (Sekaran & Bougie, 2016).

- *Online survey advantages:* Despite the disadvantages (e.g. the necessity of an Internet connection and dependency on technology), online surveys have many advantages for researchers. For example, online surveys are useful in minimising the problem of missing data. This issue is addressed by using mandatory fields (Hair, Hult, Ringle, & Sarstedt, 2017). More importantly, the interviewer effect, which might influence answers, is eliminated in online surveys as the interviewer is not present (Bryman & Bell, 2015). Finally, respondents can complete the survey anytime and anywhere at their own convenience (Cohen, Manion, & Morrison, 2013).

4.3.3 Cross-Sectional Design

The majority of studies have fallen into one of two research designs, either longitudinal or cross-sectional. Longitudinal studies are conducted several times with the same or different participants over a certain period (e.g. weeks, months, or years) (Cohen, Manion, & Morrison, 2013). Longitudinal design is associated with high cost and time, which explains why it is rarely used (Bryman & Bell, 2015). In contrast, cross-sectional design, or so-called social survey design (Bryman, 2016), investigates the target population only once within a specific period (Cohen, Manion, & Morrison, 2013). Cross-sectional studies are the most dominant design because of budget limitations, time restrictions, and the required effort (Sekaran & Bougie, 2016). For this study, a cross-sectional design was selected; thus, data were collected only once within a specific period. This decision was because of the utilisation of the PLS-SEM statistical technique (see Section 4.7.1), which requires examining a large number of participants. Furthermore, using a longitudinal design to collect data several times over a period is beyond the resources (time and cost) of this research.

Having discussed the selected research design, the following section describes the target population and justifies the selection of the sampling technique.

4.4 Population and Sampling

According to Hair et al. (2016), to obtain a representative sample, a set of procedures should be followed: (1) identify the population; (2) select the sampling frame; (3) choose the probability or non-probability sampling technique; (4) identify the sample size; and (5) plan the research sampling. In this section, the population of the study is explained, different sampling techniques are presented, the selected sampling method is justified, and the sample size is defined.

4.4.1 Population

The population of a study refers to all the units that are appropriate to the study aim and that share similar characteristics, including individuals, shops, cars, drugs, etc. (Hair, Celsi, Money, Samouel, & Page, 2016). According to Sue and Ritter (2012), population is the entire gathering of people, units, or objects to which the researcher desires to generalise the findings. Population can be defined as the entirety of elements from which the sample is to be chosen (Bryman & Bell, 2015).

For this study, the target population is higher-education students studying at public universities using LMS in Saudi Arabia. According to the Ministry of Education in Saudi Arabi, there are 28 public universities with 1,425,569 students, of whom 684,153 (48%) are male and 741,416 (52%) are female (Ministry of Education, 2017a). However, not all public universities use LMS; therefore, Shaqra University and University of Hafr Albatin were excluded. These exclusions reduced the number of public universities included in this study to 26, with 1,370,870 students, of whom 664,688 (48%) are male and 706,182 (52%) are female (Ministry of Education, 2017a). Thus, the target population of this study is 1,370,870 students.

4.4.2 Sampling Techniques

Data are necessary for conducting both quantitative and qualitative studies, and can be collected via various methods, as seen in the previous section. Sometimes, researchers tend to collect data from all units in the population (census); however, this is not realistic nor practical in most cases due to budget and time restrictions (Hair, Celsi, Money, Samouel, & Page, 2016). These limitations mean it is essential to identify a sample of the population with which to conduct the research. Bryman and Bell (2015) state that sampling is a key factor that contributes to the success of the research. 'Sample' refers to a small group of the population (Sue & Ritter, 2012) that is chosen for conducting the research (Bryman & Bell, 2015) and the selection of those units from the population (Hair, Hult, Ringle, & Sarstedt, 2017).

A sample of the population is mainly identified through either probability or non-probability sampling approaches (Sue & Ritter, 2012). In a probability approach, the sample is selected randomly, and each unit in the population has a known probability of being chosen (Bryman, 2016; Creswell, 2014). According to Cohen et al. (2013) and Hair et al. (2016), this approach is more likely to select a representative sample, meaning the findings can be generalised to a population. Therefore, quantitative research typically utilises the probability sampling approach (Hair, Celsi, Money, Samouel, & Page, 2016). On the other hand, the non-probability sampling approach involves selecting a sample based on the researcher's judgement, experience, or convenience (Cohen, Manion, & Morrison, 2013). In this approach, each object in the population does not have a known probability of being chosen, so the findings cannot be confidently generalised to a population (Sekaran & Bougie, 2016). Qualitative research typically utilises the non-probability sampling approach (Hair, Celsi, Money, Samouel, & Page, 2016). Table 4.3 describes the two sampling approaches and the most widely used sampling techniques in each approach.

Table 4.3 Sampling Approaches and Techniques

Approaches	Techniques	Definition
Probability Sampling Approach	Simple random sampling	Each unit in the population has an equal probability of being chosen.
	Systematic sampling	Involves choosing a random beginning point in the sampling frame and selecting each n^{th} object on the list.
	Stratified sampling	The sampling frame is divided either proportionally or disproportionally into identical subgroups (strata).
	Cluster sampling	Requires a set of procedures as follows: 1. Identify the characteristics of each cluster 2. Define the number of clusters to sample 3. Select clusters randomly 4. Identify the units in each cluster (sampling frame). 5. Use all units in the selected clusters or choose a probability sample from the clusters. 6. Identify the sample size if probability sample is selected.
	Multi-stage cluster sampling	Similar to cluster sampling, but involves multiple stages.
Non-probability Sampling Approach	Convenience sampling	The sample elements are selected based on their availability to participate in the research.
	Judgement/Purposive sampling	Involves the researcher's judgement to choose the elements of the sample.
	Snowball/Referral sampling	Uses probability techniques to choose the initial elements that help identify the other elements in the sample.
	Quota sampling	Similar to the stratified sampling, in which the sample elements are selected proportionally but on a convenience basis.

Sources: (Bryman, 2016; Hair, Celsi, Money, Samouel, & Page, 2016)

4.4.3 The Selected Sampling Technique

Selecting the appropriate sampling technique is important to ensure the accuracy of results. The selection relies on several considerations, including, but not limited to, the nature of the research, available resources, the aim of the research, and time and cost limitations (Hair, Celsi, Money, Samouel, & Page, 2016). After considering the differences between the sampling approaches, the multi-stage cluster-sampling technique was selected for this present study based on the following reasons:

- *Generalisability:* In a quantitative approach, researchers are usually concerned with the generalisability of the findings to the entire population, which can be achieved primarily by using a representative sample (Bryman & Bell, 2015). Researchers are more likely to select a representative sample by employing probability sampling techniques, of which multi-stage cluster sampling is an example (Bryman, 2016). Therefore, this sampling technique is beneficial when the researcher intends to generalise the findings to the population (Cohen, Manion, & Morrison, 2013).

- *Large and distributed population:* This study targeted more than 1.3 million higher-education students from various age groups, educational levels, universities, and of both genders who are widely dispersed across the Kingdom of Saudi Arabia. More accurately, this study sought a national sample with a very large population. Selecting one of the other probability techniques (e.g. simple random, systematic, or stratified sampling) would have complicated the data-collection process and might have required much communication and travelling between the 26 universities. Cohen et al. (2013) state that using simple random sampling with a large and distributed population produces extra administrative work. Consequently, this approach burdens the researcher with a great deal of extra time and cost. This present research has both a limited budget and time. Therefore, Bryman (2016) states a selected sampling technique is more appropriate for such a national study.
- *Difficult to obtain sampling frames:* The sampling frame is a list that includes comprehensive information about each subject in the population (Hair, Celsi, Money, Samouel, & Page, 2016). Using the other probability techniques necessitates obtaining the sampling frame from each public university in Saudi Arabia (26 sampling frames). This approach requires extra time, effort, and communication with the Ministry of Education and the 26 public universities in Saudi Arabia, which this study could not afford. Furthermore, access to student information is considered, at Saudi universities, a violation of privacy regulations in Saudi Arabia. However, using the multi-stage cluster-sampling technique, the researcher needed to communicate with only three public universities, which still required reasonable effort and time.

4.4.4 Sampling Procedures

This study followed the procedures of multi-stage cluster sampling suggested by Bryman (2016), Bryman and Bell (2015), Hair et al. (2016), and Sekaran and Bougie (2016). The steps of defining the study sample are described, below:

1. The population of the study was divided into clusters, with each cluster representing one public university adapting LMS for student use. The first stage of clustering resulted into 26 clusters (or universities), as summarised in Table 4.4. The clusters share similar characteristics, such as user type (students), educational levels, and gender balance, except the Islamic University of Madinah, which only has male students, Princess Nora bint Abdul Rahman University, which only has female students, and King Fahd University of Petroleum and Minerals, which only has male students.
2. The 26 clusters or universities were grouped based on the geographical regions. Hair et al. (2016) reported that geographical region sampling is the most commonly used method for cluster sampling. The second stage of clustering yielded three groups: Western Region (11 universities), Central Region (8 universities), and Eastern Region (7 universities), as summarised in Table 4.5, which reveals that the three regional clusters share similar characteristics, such as user type (students), educational levels, and gender balance. The selection of the three regions can be justified as the report of General Authority for Statistics, summarised in Table 1.1 in Section 1.7.1, showed that around two thirds of the population in Saudi Arabia is distributed in these three regions (General Authority for Statistics, 2010). In addition, targeting the 13 administrative regions in Saudi Arabia is beyond the resources (time and cost) of this research. Further, the three regions are located in different areas in the Kingdom of Saudi Arabia, which may enhance the representativity of the selected sample.
3. From each of the three regional clusters, one university was selected randomly. The selected universities were: King Abdulaziz University from Western

region, King Saud University from Central region, and Imam Abdulrahman Bin Faisal University from Eastern region.

4. A simple random sampling technique was employed within each of the selected universities.

Table 4.4 The Sample Clusters by Universities

	Region	University (Cluster)	Undergraduates		Postgraduates		Males		Females		Total
			Total	%	Total	%	Total	%	Total	%	
1	Western	Umm Al-Qura University	104,003	97.0	3,232	3.0	51,718	48.2	55,517	51.8	107,235
2		Islamic University of Madinah	14,353	78.4	3,956	21.6	18,309	100.0	0	0	18,309
3		King Abdulaziz University	169,948	96.5	6,239	3.5	94,307	53.5	81,880	46.5	176,187
4		Taibah University	66,674	95.9	2,852	4.1	28,711	41.3	40,815	58.7	69,526
5		Taif University	64,750	97.0	2,001	3.0	29,454	44.1	37,297	55.9	66,751
6		King Khaled University	64,521	95.9	2,768	4.1	28,077	41.7	39,212	58.3	67,289
7		Jazan University	61,109	99.4	341	0.6	25,939	42.2	35,511	57.8	61,450
8		Jeddah University	12,030	96.2	472	3.8	7,268	58.1	5,234	41.9	12,502
9		University of Bisha	16,768	95.9	714	4.1	4,952	28.3	12,530	71.7	17,482
10		Najran University	18,939	98.5	284	1.5	8,000	41.6	11,223	58.4	19,223
11		Al Baha University	25,388	96.8	832	3.2	12,351	47.1	13,869	52.9	26,220
12	Central	King Saud bin Abdulaziz University for Health Sciences	8,579	88.5	1,113	11.5	4,738	48.9	4,954	51.1	9,692
13		Princess Nora bint Abdul Rahman University	46,674	99.4	261	0.6	0	0	46,935	100.0	46,935
14		Saudi Electronic University	13,399	96.3	518	3.7	9,012	64.8	4,905	35.2	13,917
15		Majmaah University	19,944	99.5	109	0.5	11,185	55.8	8,868	44.2	20,053
16		Prince Sattam Bin Abdulaziz University	30,891	99.7	99	0.3	12,938	41.7	18,052	58.3	30,990
17		Imam Muhammad ibn Saud Islamic University	108,759	92.9	8,318	7.1	67,447	57.6	49,630	42.4	117,077
18		King Saud University	53,104	87.1	7,832	12.9	36,657	60.2	24,279	39.8	60,936
19		Qassim University	67,444	98.1	1,294	1.9	27,207	39.6	41,531	60.4	68,738
20	Eastern	King Fahd University of Petroleum and Minerals	10,020	86.6	1,548	13.4	11,568	100.0	0	0	11,568
21		King Faisal University	189,138	98.8	2,354	1.2	116,768	61.0	74,724	39.0	191,492
22		University of Hail	35,306	99.1	305	0.9	12,759	35.8	22,852	64.2	35,611
23		Al Jouf University	28,685	98.6	397	1.4	13,187	45.3	15,895	54.7	29,082
24		University of Tabuk	32,305	94.8	1,777	5.2	14,030	41.2	20,052	58.8	34,082
25		Northern Borders University	15,892	98.7	215	1.3	6,354	39.4	9,753	60.6	16,107

	Region	University (Cluster)	Undergraduates		Postgraduates		Males		Females		Total
			Total	**%**	**Total**	**%**	**Total**	**%**	**Total**	**%**	
26		Imam Abdulrahman Bin Faisal University	41,903	98.8	513	1.2	11,752	27.7	30,664	72.3	42,416
		Total	**1,320,526**	**96.3**	**50,344**	**3.7**	**664,688**	**48.5**	**706,182**	**51.5**	**1,370,870**

Source: (Ministry of Education, 2017a)

Table 4.5 The Sample Clusters by Regions

	University (Cluster)	Region	Undergraduate		Postgraduates		Male		Female		Total
			Total	**%**	**Total**	**%**	**Total**	**%**	**Total**	**%**	
1	Umm Al-Qura University	Western	618,483	96.3	23,691	3.7	309,086	48	333,088	52	642,174
2	Islamic University of Madinah										
3	King Abdulaziz University										
4	Taibah University										
5	Taif University										
6	King Khaled University										
7	Jazan University										
8	Jeddah University										
9	University of Bisha										
10	Najran University										
11	Al Baha University										
12	King Saud bin Abdulaziz University for Health Sciences	Central	348,794	94.7	19,544	5.3	169,184	46	199,154	54	368,338
13	Princess Nora bint Abdul Rahman University										
14	Saudi Electronic University										
15	Majmaah University										
16	Prince Sattam Bin Abdulaziz University										
17	Imam Muhammad ibn Saud Islamic University										
18	King Saud University										

	University (Cluster)	Region	Undergraduate		Postgraduates		Male		Female		Total
			Total	%	Total	%	Total	%	Total	%	
19	Qassim University										
20	King Fahd University of Petroleum and Minerals	Eastern	353,249	98.0	7,109	2.0	186,418	52	173,940	48	360,358
21	King Faisal University										
22	University of Hail										
23	Al Jouf University										
24	University of Tabuk										
25	Northern Borders University										
26	Imam Abdulrahman Bin Faisal University										

Source: (Ministry of Education, 2017a)

4.4.5 Sample Size

Before the data-collection stage, it is important to determine the appropriate sample size of the target population. Unfortunately, this process is complicated and depends on various considerations (Bryman, 2016). Those considerations include whether the research is quantitative or qualitative, the number of the variables, the investigated population, the variation of the population units, budget limitations, time constraints, results' generalisation, accuracy required, statistical analysis used, and confidence level (Hair, Celsi, Money, Samouel, & Page, 2016; Cohen, Manion, & Morrison, 2013). Nevertheless, the larger the sample the better for quantitative research in general (Bryman & Bell, 2015).

In probability sampling, as in the case of this study, the sample size can be determined based on either the researcher's judgement to represent the population, or on a table that calculates the sample size based on mathematical formulas (Cohen, Manion, & Morrison, 2013; Sue & Ritter, 2012). One of the most popular tables is that suggested by Krejcie and Morgan (1970). For this research, according to the table, they suggest that the sample size should be 384 students with a 5% confidence interval at a 95% confidence level.

In multivariate modelling, there are some guidelines to provide more solid answers for how large a sample should be. These guidelines can be used for some situations, such as large population size, budget limitations, and time constraints (Hair, Celsi, Money, Samouel, & Page, 2016). Sue and Ritter (2012) reported that the sample in multivariate studies should be at least 10 times larger than the number of indicators used. Accordingly, the sample size in this study should be 510. Nunnally (1978) recommends a sample size that is equivalent to 10 responses per construct (variable) in the research model; thus, at least 120 responses were required for this study. One popular guideline for multivariate modelling states that the sample size should be at least equivalent to 10 times the largest number of arrows directed at a single construct in the structural model (Barclay, Higgins, & Thompson, 1995). In this study, the largest number of arrows directed at a single construct is nine; thus, 90 responses are required.

However, scientists should approach this rough estimate with caution (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). Those guidelines fail to consider the effect of size, reliability, number of measures, or other elements that affect the power of the model (Hair, Sarstedt, Ringle, & Mena, 2012). The model's complexity and data characteristics should be considered when determining the sample size in PLS-SEM (Hair, Ringle, & Sarstedt, 2011). Hair, Hult et al. (2017) suggest that the sample size in PLS-SEM should be identified based on: (1) significance level, (2) statistical power, (3) coefficient of determination (R^2), and (4) the maximum number of arrows directed toward a latent construct. Typically, PLS-SEM studies have a significance level of 5%, a statistical power of 80%, and R^2 of at least 0.25 (Wong, 2013). According to Cohen (1992), the minimum sample size should be 150 when the maximum number of arrows pointing toward a construct is nine, a significance level of 5%, a statistical power of 80%, and R^2 of at least 0.10. However, researchers can use software to identify the statistical power and effect size specific for their models, such as G*Power (Faul, Erdfelder, Buchner, & Lang, 2009). According to G*Power version 3.1.9.2, 178 responses are required when the effect size is 0.15, the significance level is 5%, and the statistical power is 95%. Nevertheless, 833 responses were collected from respondents in this investigation, which means that the sample size exceeds all the recommendations mentioned above.

Having justified the selected sampling technique and sample size, the next section discusses the instrument's development and use in this research.

4.5 Instrumentation

This section provides more details about the online survey used for gathering data from the participants. The survey was designed according to a scientific methodology that is presented in several steps: (1) reviewing the previous literature, which could be the starting point for this tool; (2) pre-testing the developed instrument with experts to ensure the content and face validity; (3) translating the questionnaire survey into Arabic for the target population with clear terms and understandable wording; (4) conducting a pilot study to ensure the clarity and eliminate wording problems; and (5) examining the reliability of the questionnaire items to confirm the internal consistency of the used items. These steps are explained in the following sections.

4.5.1 Survey Development

When conducting a study, researchers can develop their own instrument, modify existing instruments, or use a pre-developed tool (Creswell, 2014). In line with previous studies concerning e-learning acceptance (Hwa, Hwei, & Peck, 2015; Majdalawi, Almarabeh, & Mohammad, 2014; Al-Adwan, Al- Adwan, & Smedley, 2013; Park, 2009; Mohammadi, 2015; Baharin, Lateh , Nathan, & Nawawi, 2015; Abdullah & Toycan, 2017; Lee, Hsiao, & Purnomo, 2014; Hsu & Chang, 2013; Tanduklangi, 2017), the survey items were adapted from questionnaires in the relevant literature about technology acceptance within the context of e-learning systems. The selected items are characterised as having high reliability and validity, according to the literature, for measuring the intended constructs. Appendices A and B include the English and Arabic versions of the developed survey. The instrument for this study comprises four sections plus the cover letter and consent form. These sections are described, below.

The first section has nine questions regarding the demographic characteristics of the participants: gender, age, university, educational level, field of study, computer skills, Internet skills, experience with LMS, and GPA. The aim of this section is to ensure that students from different backgrounds were included in this study.

The second section includes the eight usability constructs with 34 positive statements (see Table 4.6). Each construct was measured using multiple statements or indicators to produce more accurate estimations (Hair, Black, Babin, & Anderson, 2014; Hair, Hult, Ringle, & Sarstedt, 2017), to better reflect the correct response (Bryman & Bell, 2015), and to cover different parts of the measured concept (Bryman, 2016). For each statement, the participants were asked to select the answer that best represented their level of agreement. Following many usability studies (Scholtz, Mandela, Mahmud, & Ramayah, 2016; Thowfeeka & Abdul Salam, 2014; Junus, Santoso, Isal, & Utomo, 2015; Zaharias & Poylymenakou, 2009; Alkhattabi, 2015; Khedr, Hana, & Shollar, 2012), the statements were answered using a five-point Likert scale, in which (1) means strongly disagree and (5) means strongly agree. Sue and Ritter (2012) state that a five-point scale is usable for measuring the attitude and perception of respondents.

Table 4.6 The Second Section of the Online Survey

Constructs		Statements	Source
Content Quality	CQ01	The vocabularies used in Blackboard are appropriate for me (e.g. discussion board, content, assignments… etc.).	(Junus, Santoso, Isal, & Utomo, 2015; Zaharias & Poylymenakou, 2009; Zaharias, 2008)
	CQ02	Overall, the content of Blackboard is up-to-date.	
	CQ03	Overall, the content is organised in an appropriate sequence.	
	CQ04	Overall, there is sufficient content to support my learning.	
Learning Support	LS01	Blackboard provides tools that support my learning.	(Junus, Santoso, Isal, & Utomo, 2015; Ssemugabi & De Villiers, 2007; Zaharias, 2009; Oztekin, Kong, & Uysal, 2010)
	LS02	Blackboard supports individual and group learning.	
	LS03	The online help of Blackboard is always available.	
	LS04	The Blackboard manual is written clearly.	
	LS05	The Blackboard manual provides the information I need.	
Visual Design	VD01	Text, colours and layout used in Blackboard are consistent.	(Medina-Flores & Morales-Gamboa, 2015; Zaharias & Poylymenakou, 2009)
	VD02	The interface design of Blackboard is attractive to me.	
	VD03	Text and graphics of Blackboard are readable.	
	VD04	Important information is placed in areas most likely to attract my attention.	
System Navigation	SN01	I always know where I am in Blackboard.	(Gilani, et al., 2016; Medina-Flores & Morales-Gamboa, 2015; Zaharias, 2009)
	SN02	The navigational structure of Blackboard is convenient for me.	
	SN03	It is easy for me to find the information I need in Blackboard.	
	SN04	Links in Blackboard are working satisfactorily.	

Constructs		Statements	Source
	SN05	I can leave Blackboard at any time and easily return.	
Ease of Access	EOA01	It is easy for me to login to Blackboard.	(Medina-Flores & Morales-Gamboa, 2015; Junus, Santoso, Isal, & Utomo, 2015; Zaharias & Poylymenakou, 2009)
	EOA02	I can access Blackboard from different browsers.	
	EOA03	The pages and other elements of Blackboard download quickly.	
	EOA04	Blackboard is free from technical problems.	
System Interactivity	SI01	In general, Blackboard provides me with good synchronous and asynchronous communication tools (e.g. email, chat, forum).	(Zaharias & Poylymenakou, 2009; Junus, Santoso, Isal, & Utomo, 2015; Ssemugabi & De Villiers, 2007; Oztekin, Kong, & Uysal, 2010)
	SI02	Blackboard promotes my communication with teachers.	
	SI03	Blackboard facilitates my communication with students.	
	SI04	Blackboard helps me engage more with my learning.	
Instructional Assessment	IA01	Blackboard provides good self-assessment tools (e.g. exams, quizzes, case studies).	(Junus, Santoso, Isal, & Utomo, 2015; Zaharias, 2009)
	IA02	It is easy for me to use the self-assessment tools in Blackboard.	
	IA03	The self-assessment tools in Blackboard help me to understand the content of course.	
	IA04	The self-assessment tools in Blackboard measure my achievements of learning objectives.	
System Learnability	SL01	It is easy for me to learn how to use Blackboard.	(Lacka & Chong, 2016; Al-Khalifa, 2010; Zaharias & Poylymenakou, 2009)
	SL02	The results of clicking on buttons are predictable.	
	SL03	I do not need to read a lot to learn how to use Blackboard.	
	SL04	I can start using Blackboard with only online help.	

Table 4.6 does not include questions about the usage frequency of the help service of LMS (e.g. if Help is used, how many times) for several reasons. First, the objective of this section in the questionnaire is to measure the attitude of participants toward the LMS features rather than the usage frequency. Measuring the attitude toward the LMS features enables the researcher to examine the hypotheses proposed in Chapter 3 using the PLS-SEM statistical technique (see Section 4.7.1) and to measure the statistical significance of the adopted usability attributes, which is the main aim of this current study. In addition, the attitude toward the help service of LMS is stated in the construct of learning support, and the participants were asked about the availability of online help, the clarity of the LMS manual, and the sufficiency of the information provided

by the LMS manual (e.g. LS03, LS04, and LS05 in Table 4.6). Third, these usability constructs were adopted from previous literature on usability, technology acceptance, and e-learning, and their questions are characterised as having high reliability and validity for measuring the intended constructs. These questions have been adopted successfully in information systems and e-learning fields (Junus, Santoso, Isal, & Utomo, 2015; Oztekin, Kong, & Uysal, 2010; Ssemugabi & De Villiers, 2007; Zaharias, 2009), and the researcher followed other researchers in this regard, as the risk involved in asking self-developed questions is high. Finally, adopting further questions about the usage frequency of the LMS features increases the length of the questionnaire and the time needed for answering the questions, which may cause the frustration of participants and not completing the questionnaire. Nevertheless, measuring the usage frequency of the help service is important, and, therefore, it might be considered by future researchers.

The third section includes the four TAM constructs with 17 positive statements (see Table 4.7). For each statement, the participants were asked to select the answer that best represented their level of agreement. In accordance with the previous literature regarding e-learning acceptance (Ghazal, Aldowah, & Umar, 2018; Almarashdeh & Alsmadi, 2016; Majdalawi, Almarabeh, & Mohammad, 2014; Alkhalaf, 2013; Khedr, Hana, & Shollar, 2012; Kanwal & Rehman, 2017; Cuadrado-García, Ruiz-Molina, & Montoro-Pons, 2010), the statements were answered using a five-point Likert scale, in which (1) means strongly disagree and (5) means strongly agree.

Table 4.7 The Third Section of the Online Survey

Constructs		**Statements**	**Source**
Perceived Ease of Use	PEOU01	I find Blackboard flexible to interact with.	(Davis, 1989)
	PEOU02	It is easy for me to get Blackboard to do what I want it to do.	
	PEOU03	It is easy for me to become skilful at using Blackboard.	
	PEOU04	Overall, Blackboard is easy to use.	
Perceived Usefulness	PU01	Blackboard enables me to achieve tasks more quickly.	(Davis, 1989)
	PU02	Blackboard improves my learning performance.	
	PU03	Blackboard helps me to learn effectively.	

Constructs		Statements	Source
	PU04	Blackboard makes it easier for me to learn course content.	
	PU05	Overall, Blackboard is useful in my learning.	
Behavioural Intention	BI01	I would like to use Blackboard in all future courses.	(Ramírez Anormaliza, Sabate, & Audet Llinàs, 2016)
	BI02	I would recommend using Blackboard to others.	
	BI03	I would encourage my teachers to use Blackboard in courses.	
	BI04	I will continue using Blackboard in the future.	
Actual Use	AU01	I use Blackboard frequently.	(Mohammadi, 2015; Ramirez-Anormaliza, Tolozano-Benites, Astudillo-Quionez, & Suarez-Matamoros, 2017; Islam, 2013; Kurt, 2018)
	AU02	I tend to use Blackboard for as long as is necessary.	
	AU03	I have been using Blackboard regularly.	
	AU04	I usually get involved with Blackboard.	

The fourth section measures the students' utilisation level of eight features in LMS: course materials, announcements, assignments, discussion board, messages and email, grades, exams and quizzes and virtual classrooms. For each feature, the participants were asked to select the answer that best represented their level of utilisation. In line with previous studies concerning technology use (Back, et al., 2016; Dommett, 2018), this section was answered using a five-point Likert scale, in which (1) means never, (2) means rarely, (3) means sometimes, (4) means very often, and (5) means always.

4.5.2 Face Validity

Even well-developed surveys are sometimes unsuccessful in collecting reliable and valid data. Some researchers (Bryman & Bell, 2015; Bryman, 2016; Creswell, 2014; Field, 2013) emphasise the importance of pre-testing the developed instrument before conducting research to ensure the content or face validity, which refers to whether the survey items measure the desired content (Sekaran & Bougie, 2016). Sue and Ritter (2012) reported that the validity of the used survey can be threatened when the terminology and words are incorrect. Therefore, the content of the developed survey was tested before conducting the final version in this study.

The face validity is examined by asking experts to judge whether the developed survey measures the desired content (Bryman & Bell, 2015; Sekaran & Bougie, 2016). In this research, the developed questionnaire was tested in collaboration with five experts from relevant academic fields. The questionnaire was reviewed by experts from the United Kingdom, Nigeria, Oman, and Saudi Arabia. The details of those experts are provided in Table 4.8.

Table 4.8 The Examiners of Face Validity

	Expert	Position	Country	Experience
1	Malcolm Rutter	Lecturer	United Kingdom	HCI and usability
2	Sally Smith	Dean of Computing at Napier University	United Kingdom	Educational computing
3	Abdulhameed Alenezi	Dean of Computing at Aljouf University	Saudi Arabia	Saudi e-learning acceptance
4	Ali Tarhini	Assistant Professor	Oman	Technology and e-learning and acceptance
5	Maruff Oladejo	Assistant Professor	Nigeria	Education and e-learning acceptance

The face validity test was successful, resulting in many versions before reaching the final questionnaire. Several wording problems were raised. Various scale items were replaced. Different terminologies were exchanged for more appropriate terms. For example, one reviewer suggested replacing the term ‘learning management system’ with ‘Blackboard’ because students are more familiar with this term. Another academic proposed rephrasing the used features of the LMS, as used in the fourth section. Thus, this stage resulted in the questionnaire items being clear and understandable before the data-collection stage.

4.5.3 Translation

This study was conducted in the Kingdom of Saudi Arabia, where Arabic is the first language and which most students speak. Sekaran and Bougie (2016) assert that questionnaires should be available in the participant’s own language and using a clear and understandable wording and terms. This aspect is necessary to ensure that respondents understand the survey items and are not excluded from participation due to language barriers (Frandsen-Thorlacius, Hornbæk, Hertzum, & Clemmensen, 2009). Failure to understand the questions may lead to incorrect answers, biased responses (Sekaran & Bougie, 2016), and avoiding responding to the questions (Fink, 2017). Thus, the decision was made to translate the questionnaire from English into Arabic.

Selecting a person to translate a research questionnaire is challenging. Flink (2017) suggests using native speakers, as this reduces the time required for translating and revising the words of the questionnaire. For the purpose of this research, translators were carefully chosen based on the following: (1) must be native Arabic speakers and fluent in English, with high writing skills in both languages; (2) should have experience in interacting with students in Saudi Arabia; and (3) should be familiar with developing questionnaires in the Arabic language in particular. Table 4.9 provides information about the translators of the survey.

Table 4.9 The Translators of the Survey

	Experts	**Position**	**Field**	**Native Language**	**Experience with English**
1	Bassam Zafer	Associate Professor in Saudi Arabia	Software Engineering	Arabic	Lived in the UK for more than 10 years.
2	Ahmed Alshehri	Lecturer in Saudi Arabia and PhD candidate in the UK	Information Systems	Arabic	Lived in Australia for more than three years, and three years in the UK.

In this research, the translation of the questionnaire was achieved using the back-translation method proposed by Brislin (1986), which has been used by several studies on technology acceptance in Saudi Arabia (Alharbi & Drew, 2014; Baker, Al-Gahtani, & Hubona, 2010; Al-Gahtani, Hubona, & Wang, 2007; Alkhalaf, 2013; Aifan, 2015; AL-Ghamdi, 2012). According to this method, the survey instrument should be translated from the original language into the target language and vice versa, using experts who speak the two languages. Each expert performs the translation task independently. Finally, the original English version and the back-translated version are compared. Many rounds can be carried out before achieving a convergence.

To follow the back-translation method (Brislin, 1986), there was collaboration between two bilingual experts and one native English speaker from academic settings. The original questionnaire (English version) was sent to the first bilingual expert to translate the English version into Arabic. Then, the translated version was sent to the second bilingual expert to translate the Arabic version back into English. Finally, the two English versions were sent to a native English speaker, who is an assistant professor in the School of Computing at Edinburgh Napier University, to review whether there were any major differences between them. Fortunately, there were no significant differences.

After pre-testing and translating the questionnaire with the experts, there was a need to test the developed instrument with typical participants of the study. Therefore, a pilot study was conducted.

4.5.4 Pilot Study

Scholars (Fink, 2017; Hair, Celsi, Money, Samouel, & Page, 2016; Sekaran & Bougie, 2016; Bryman, 2016; Bryman & Bell, 2015) recommend researchers pilot their studies with a small number of typical participants. According to Sekaran and Bougie (2016), the pilot study is used to correct any lack of the required quality, to ensure the clarity of the questionnaire items, and to eliminate wording problems. It is even more necessary to conduct a pilot study in the case of online surveys, as with this study, because there will not be a person present to clarify any ambiguities (Bryman & Bell, 2015).

Paper-based questionnaires were employed for the pilot study to create a rapport with the participants, to collect the responses and offer feedback immediately, and to clarify any ambiguity of the questions for the participants. The questionnaire was distributed to a convenient sample of students at King Abdulaziz University in Saudi Arabia. The researcher explained the aim and objectives of this study, and the participants were given the opportunity to enquire about the survey.

Regarding the sample size of pilot studies, the number of responses in technology-acceptance studies is varied, but is usually relatively small compared with the main study. For example, Tarhini (2013) collected 65 questionnaires, Alenezi (2012) collected 46, Fathema (2013) only 20, and Abbasi (2011) 39. Following the guidelines of previous literature, 58 responses were received out of the 60 paper-based questionnaires used for the pilot study. This pilot study yielded a high response rate of 97%. However, 54 usable responses were used for data analysis because four responses were discounted due to missing data and suspicious responses.

After the data-collection stage, the students' responses were entered and encoded into the SPSS software version 23 to measure the constructs' reliability. Reliability refers to the constructs' internal consistency and ability to generate the same findings under the same situations (Field, 2013). Traditionally, social science studies utilise internal consistency to measure reliability using the Cronbach's alpha coefficient (Cronbach, 1951). Different researchers have used different reliability cut-off points. For instance, for some, a reliability value of 0.7 indicates acceptable reliability, while 0.8 indicates good reliability (Sekaran & Bougie, 2016; Bryman, 2016). Hair et al. (2011) and Hair, Hult et al. (2017) claim that reliability values between 0.6 and 0.7 are acceptable for exploratory research. The results of the reliability test are displayed in Table 4.10, which reveals that all the constructs except AU exceeded the suggested threshold. The other values ranged from 0.696 to 0.898, and the overall reliability value was 0.957.

Table 4.10 The Reliability of the Pilot Study

Constructs	Number of Indicators	Cronbach's Alpha
CQ	4	0.696
LS	5	0.785
VD	4	0.815
SN	5	0.742
EOA	4	0.712
SI	4	0.861
IA	4	0.702
SL	4	0.738
PEOU	4	0.898
PU	5	0.878
BI	4	0.887
AU	2	0.109
Overall	**49**	**0.957**

The AU construct comprised two questions. The first question measured how frequently students use the LMS. The question was answered using a five-point Likert scale, in which 1 means less than once a month, 2 means once a month, 3 means twice a month, 4 means three times a month, and 5 means more than three times a month. The second question measured the time students spend in each session with the LMS. This question was also answered using a five-point Likert scale, in which 1 means less than 30 minutes, 2 means from 30 minutes to one hour, 3 means one hour to two hours, 4 means two hours to three hours, and 5 means more than three hours. Although those questions were adapted from the previous literature on technology acceptance (Tarhini, 2013; Al-Gahtani, 2008), the reliability value of this variable was very low. Therefore, the decision was made to alter the questions for the AU construct before collecting the full data of the study.

4.6 Data Collection

Section 4.5 provides details about the development process of the instrument used in this research. In this section, the topics related to data collection, such as ethics and the procedures of data collection, are explained.

4.6.1 Ethical Considerations

Ethical considerations are crucial in social research and cannot be disregarded during the data-collection stages (Bryman, 2016). Following the regulations of Edinburgh Napier University, the Novi survey system (the online survey application offered and hosted by the university) was employed for data collection from the target population. The researcher included the consent form at the beginning of the online survey. On the first page, the researcher explained the aim and objectives of this study. The participants were informed that their participation in the online survey is completely voluntary and they may withdraw from it at any time without negative consequences. Should they not wish to answer any particular question or questions, they are free to decline to do so. The participants were instructed in what was expected from them and that the study should take no longer than 10 minutes to complete. It was stated that their responses are anonymised, their identifying information (e.g. name, email, and IP address) would not be collected, and that they would not be identified or identifiable in any report subsequently produced by the researcher. Furthermore, the participants were informed that the collected data may be submitted for publication. They were told that their agreement to participate in this study is not a waiver of any legal rights. Finally, the participants were provided with the supervisor and researcher’s email addresses in case they had further questions or concerns regarding the ethics of this study.

Following the regulations, approval was granted by the School of Computing at Edinburgh Napier University to begin the data-collection phase (see Appendix C). Furthermore, the researcher had to obtain approval letters from the three universities under investigation in Saudi Arabia as this study targeted students in Saudi public universities (see Appendix D).

4.6.2 Data-Collection Procedures

Emails were sent to 2,000 students registered in different academic programmes and various levels of education in the three universities: King Abdulaziz University, King Saud University, and Imam Abdulrahman Bin Faisal University. In this email, the students were asked to participate in the study, and the link to the survey was included. The online survey was available for three months during the autumn semester starting from 1st October 2017. Participation in the study was completely voluntary, and no incentives were provided to the participants.

Now the data collection has been explained, the following section provides information about data analysis and justifies the selection of the statistical technique.

4.7 Data Analysis

The analysis of the data was performed in two stages. First, the data were uploaded into SPSS version 23 to perform a preliminary data analysis, including data cleaning, descriptive statistics, response rate, and non-response bias test. In the second stage, the proposed model (see Chapter 3) was tested using the PLS-SEM technique with the software package SmartPLS 3 (Ringle, Wende, & Becker, 2015) as followed by e-learning acceptance studies (Ghazal, Aldowah, & Umar, 2018; Al-Gahtani, 2016; Amin, Afrin Azhar, & Akter, 2016; Salloum, Al-Emran, Shaalan, & Tarhini, 2018). This section briefly describes the PLS-SEM technique and justifies its selection for this study.

4.7.1 Partial Least Squares Structural Equation Modelling

Structural equation modelling is an extension of the first-generation multivariate analysis techniques, such as regression, factor analysis, and discriminant analysis, and allows a simultaneous testing of relationships between independent and dependent variables (Hair, Black, Babin, & Anderson, 2014). The approach can be applied through one of two methods: First, covariance-based structural equation modelling (CB-SEM) using software packages such as AMOS and LISREL; and second, PLS-SEM (or PLS path modelling) using software packages such as SmartPLS and PLS-Graph. Although both methods share the same primary objective – to examine the relationships between constructs – they differ statistically when testing the measurement model (Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016). The CB-SEM approach estimates the variance-covariance matrix; whereas, PLS-SEM explains the variance of an unobserved dependent variable (Henseler, Hubona, & Ray, 2017; Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Ringle, & Sarstedt, 2011). It is evident from Table 4.11 that the weaknesses of CB-SEM are the strengths of PLS-SEM, and vice versa. Therefore, researchers should not perceive the two techniques as being competitive, but as complementary (Hair, Ringle, & Sarstedt, 2011).

Table 4.11 The Differences between CB-SEM and PLS-SEM

Criteria	CB-SEM	PLS-SEM
Research goal	Confirm or compare theories	Develop or extend an existing theory or identify key drivers
Formative indicators	Difficult to examine	Supported
Sample size	Large sample size	Relatively small sample size
Data distribution	Normal distribution assumed	Normal distribution not assumed
Complex model	Supported	Perform better
Recursive model	Supported	Not supported

Source: (Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Ringle, & Sarstedt, 2011)

Following other studies in e-learning (Ghazal, Aldowah, & Umar, 2018; Al-Gahtani, 2016; Amin, Afrin Azhar, & Akter, 2016; Ramirez-Anormaliza, Tolozano-Benites, Astudillo-Quionez, & Suarez-Matamoros, 2017; Al-Azawei, Parslow, & Lundqvist, 2017), this research benefits from utilising the PLS-SEM technique using SmartPLS version 3 to analyse the collected data for the following reasons.

- *Widely adopted:* PLS-SEM has been widely employed in many fields, such as marketing (Hair, Sarstedt, Ringle, & Mena, 2012); international marketing (Henseler, Ringle, & Sinkovics, 2009); social sciences (Henseler, Hubona, & Ray, 2016); business (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014); human resource management (Ringle, Sarstedt, Mitchell, & Gudergan, 2018); hospitality (Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018); tourism (Do Valle & Assaker, 2016); and information systems (Ringle, Sarstedt, & Straub, 2012; Benitez-Amado, Henseler, & Castillo, 2017; Hair, Hollingsworth, Randolph, & Chong, 2017).
- *Overcoming the first-generation limitations:* First-generation multivariate analysis methods are incapable of testing latent (unobserved) variables, indirect effects, causal models, goodness-of-fit, and complex models (Lowry & Gaskin, 2014). However, second-generation methods (CB-SEM and PLS-SEM) can address those limitations. Second-generation methods do not invalidate the first-generation methods, but they are more appropriate for complex modelling (Lowry & Gaskin, 2014; Ong & Puteh, 2017).

- *Research objective:* CB-SEM is more convenient when the primary objective of the research is to confirm a pre-developed theory, compare theories, or test goodness-of-fit criteria; whereas, PLS-SEM is more convenient when the primary objective of the research is to extend an existing theory or identify key drivers (Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Ringle, & Sarstedt, 2011; Lowry & Gaskin, 2014; Hair, Sarstedt, Ringle, & Mena, 2012), which is the case with this present study. Ringle et al. (2018) reviewed studies published between 1985 and 2014 in human resource management and found that 26% of the studies used PLS-SEM primarily for theory development.
- *Complex model:* PLS-SEM enables researchers to examine complex models that include many independent and dependent variables (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Sarstedt, Ringle, & Hair, 2017; Henseler, Ringle, & Sinkovics, 2009; Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016). Previous reviews regarding PLS-SEM (Ringle, Sarstedt, & Straub, 2012; Hair, Sarstedt, Ringle, & Mena, 2012; Ringle, Sarstedt, Mitchell, & Gudergan, 2018; Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018; Do Valle & Assaker, 2016) found that the average number of constructs per model is between seven and eight; whereas, Shah and Goldstein (2006) revealed that the average number of constructs per model is five in CB-SEM models. Regarding measurement indicators, PLS-SEM studies (Ringle, Sarstedt, & Straub, 2012; Hair, Sarstedt, Ringle, & Mena, 2012; Ringle, Sarstedt, Mitchell, & Gudergan, 2018; Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018; Do Valle & Assaker, 2016) demonstrated that the average number of indicators per model is about 27. Shah and Goldstein (2006) revealed that the average number of indicators per model is only 16 in CB-SEM. These figures are unsurprising as the model fit in CB-SEM is negatively influenced by more indicators (Sarstedt, Ringle, & Hair, 2017). In this study, the proposed model comprises 12 constructs, 44 hypotheses, 51 indicators, and four moderating variables.
- *Focused model:* The model developed for this study is considered a ‘focused model’ because the number of independent variables is twice the number of

dependent variables, which is more appropriate for the prediction goal of PLS-SEM (Hair, Sarstedt, Ringle, & Mena, 2012). However, an 'unfocused model', in which the number of dependent variables is twice the number of independent variables, is more appropriate for the confirmation goal of CB-SEM (Hair, Sarstedt, Ringle, & Mena, 2012).

- *Non-normal distribution:* In empirical social studies, non-normal distribution is a common problem. Unlike PLS-SEM, CB-SEM assumes that data are normally distributed (Lowry & Gaskin, 2014; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). The PLS-SEM approach is characterised by its ability to handle data problems, such as non-normal data and small sample size (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Henseler & Sarstedt, 2013), as PLS-SEM is a non-parametric technique that does not assume data to be normally distributed (Hair, Hult, Ringle, & Sarstedt, 2017). Previous reviews (Ringle, Sarstedt, & Straub, 2012; Hair, Sarstedt, Ringle, & Mena, 2012; Ringle, Sarstedt, Mitchell, & Gudergan, 2018; Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014) found that the majority of studies have attributed the use of PLS-SEM to data non-normal distribution, small sample size, theory development, and model complexity.
- *Easy-to-use software package:* The PLS-SEM technique is implemented using quality, easy-to-use, and visually attractive software, such as SmartPLS (Sarstedt, Ringle, & Hair, 2017; Henseler & Sarstedt, 2013). SmartPLS is equipped with the required measures for model testing, such as measurement model analysis, path analysis, goodness-of-fit indices, and multigroup analysis.
- *Rarely used in usability:* The utilisation of the PLS-SEM technique for examining the influence of usability attributes has not received enough attention (Aziz & Kamaludin, 2014). Reviewing popular academic databases, including ScienceDirect, Springer, IEEE, ProQuest, ERIC, ACM, Emerald, and SAGE, revealed that this study is the first within the context of Saudi Arabia to investigate the usability factors influencing student usage of LMS via the PLS-SEM technique and SmartPLS.

To summarise, neither of the two techniques (CB-SEM and PLS-SEM) is superior, and the selection of the appropriate method is dependent on the aim of the research (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Hair, Sarstedt, Ringle, & Mena, 2012; Sarstedt, Ringle, & Hair, 2017). Nevertheless, when the sample is large (such as N=250) and a proper number of measures is used, both techniques produce similar results (Hair, Hult, Ringle, & Sarstedt, 2017). Several empirical studies (Nam, Kim, & Jin, 2018; Amaro, Abrantes, & Seabra, 2015) support this argument. The studies compared the two techniques and demonstrated that they produce similar results. Therefore, PLS-SEM is no less important than CB-SEM if properly used (Hair, Ringle, & Sarstedt, 2011).

4.8 Summary

In this chapter, the various methodologies used for this research were described. This study was conducted based on a positivist research paradigm that employed quantitative measures to collect empirical data from the target population. A survey research method and online surveys were found to be most appropriate for this investigation. This chapter explained the target population and the sampling size sufficient for this study and justified the selection of the multi-stage cluster-sampling technique. An online survey was developed, translated, and pre-tested twice with experts and typical participants. Finally, this chapter discussed the selection of the PLS-SEM technique using SmartPLS for data analysis.

Having established the research methodology, the next chapter preliminarily analyses the data collected from participants

CHAPTER 5: DATA ANALYSIS

5.1 Introduction

In the previous chapter, the quantitative data collection method used for this study was explained and justified. The current chapter introduces and analyses the results of the data collected from participants in Saudi higher education. The obtained data were exported from the Novi Survey system (the online survey application offered and hosted by Edinburgh Napier University) into Excel (xlsx) format. Using MS Excel 2016, an identification number was assigned to each case, and the data were encoded. After that, data were uploaded into the Statistical Package for the Social Sciences (SPSS) version 23, to perform the preliminary examination, response rate calculation, non-response bias test, and descriptive analysis.

In terms of the structure, the chapter begins by covering the preliminary examination of data, including missing data, outliers, unengaged responses, and normality. The response rate calculation and non-response bias test are conducted next. The section following presents the profile of respondents including gender, age, university, level of education, academic major, computer skills, internet skills, experience with LMS, and students' performance. Finally, the descriptive statistics of the constructs and the LMS features are shown.

5.2 Data Preliminary Examination

This examination is important in quantitative research and specifically when using SEM for data analysis (Hair, Hult, Ringle, & Sarstedt, 2017). Sue and Ritter (2012) stated that the collected data should be screened and cleaned from errors and incomplete answers. Even though the corrective actions are not always necessary, the examination is essential to ensure that the outputs of the multivariate analysis are correct (Hair, Black, Babin, & Anderson, 2014). Hair, Hult et al. (2017) emphasise that the issues of collected data, including strange response patterns, unengaged respondents, missing data, outliers, and data distribution, should be inspected. Therefore, those primary data issues are examined in the subsequent steps using SPSS.

5.2.1 Missing Data

Missing data is a common problem in behavioural (Schlomer, Bauman, & Card, 2010), marketing (Sarstedt & Mooi, 2014), and social science studies (Hair, Hult, Ringle, & Sarstedt, 2017). It is very rare when researchers do not face missing data problems (Hair, Black, Babin, & Anderson, 2014). Missing data arise when participants leave one or more questions unanswered in the questionnaire (Sekaran & Bougie, 2016). Missing data is a problem that reduces the available data for analysis and might produce erroneous findings that lead to bias in the results (Hair, Black, Babin, & Anderson, 2014). The effect of missing data is specifically important when using the SEM technique for data analysis (Hair, Hult, Ringle, & Sarstedt, 2017) as it is not designed to analyse incomplete data (Jamil, 2012; Kline, 2012). For instance, the Bootstrapping function, which is used for examining relationships between constructs in SmartPLS, cannot be calculated when the sample includes missing data.

In the current study, 851 responses were submitted by the respondents. All questions in the online survey were designed to be mandatory, and the survey could not be submitted without answering all the questions. Thus, the submitted responses did not include any missing data. The outliers are considered in the next section.

5.2.2 Outliers

A typical example of unreasonable answers is outliers, which occurs when one response is excessively different from other responses (Sekaran & Bougie, 2016). Hair, Black et al. (2014) defined outliers as cases with unusual values (either too low or too high values) that make these cases distinct from other cases. Outliers can affect the data validity (Hair, Celsi, Money, Samouel, & Page, 2016), impact the data distribution (Hair, Black, Babin, & Anderson, 2014), and bias statistical tests (Field, 2013). Therefore, it is crucial to detect and handle outliers.

Kline (2016) has defined two types of outliers: (1) univariate outliers and (2) multivariate outliers. Univariate outliers can be encountered when a case has an excessive value on an individual variable (Kline, 2016). Univariate detection of outliers entails identifying the cases with variable values that are either extremely low or extremely high (Sarstedt & Mooi, 2014). This type of outliers can be identified using minimum and maximum values and graphs (Sekaran & Bougie, 2016). By doing so, three cases (330, 706, and 755) qualified as univariate outliers with extreme values on the variable of LMS experience (-1, -1, and 2016), respectively (see Table 5.1). Following the recommendations of Hair et al. (2016), those values are unreasonable, and, therefore, they were eliminated.

Table 5.1 Univariate Outliers

Case ID	**LMS Experience**
330	-1
706	-1
755	2016

The second type of outlier is known as a multivariate outlier, which occurs when a case has excessive values on two or more variables (Kline, 2016). To achieve the multivariate detection of outliers, the Mahalanobis distance (D^2) was used as suggested by Hair, Black et al. (2014) and Kline (2016). The Mahalanobis distance indicates the case's distance from the means of independent variables (Field, 2013). As a rule of thumb for large samples (N > 80) in multivariate analysis, cases with $D^2/df > 3$ or 4 with $p < .001$ are considered influential outliers (Hair, Black, Babin, & Anderson, 2014). *Df* refers to the number of independent variables, so *df* is 11 in this research. Table 5.2 demonstrates that 12 cases are candidates for multivariate outliers. One case (ID: 303) exceeded the threshold, while the other 11 cases are between 3.07 and 3.70. However, scholars (Kline, 2016; Hair, Black, Babin, & Anderson, 2014) stated that outliers should not be eliminated unless there is a strong evidence that they do not belong to the target population. Furthermore, it is expected to have some outliers with a large sample, which is the case in this study, that do not affect the results substantially (Parke, 2013). Therefore, multivariate outlier cases addressed in Table 5.2 were retained.

Table 5.2 Multivariate Outliers

Case ID	**Mahalanobis D^2**	D^2/df	**p-Value**
303	79.36	7.22	$p < .001$
600	40.68	3.70	$p < .001$
238	40.33	3.67	$p < .001$
710	38.28	3.48	$p < .001$
452	37.44	3.40	$p < .001$
105	36.78	3.34	$p < .001$
252	35.40	3.22	$p < .001$
212	34.50	3.14	$p < .001$
648	34.43	3.13	$p < .001$
179	34.42	3.13	$p < .001$
605	33.96	3.09	$p < .001$
099	33.71	3.07	$p < .001$

5.2.3 Unengaged Responses

In this regard, unengaged responses are meant to be suspicious response patterns where respondents select an individual answer for all or a large number of questions (Ibrahim, Wong, & Shiratuddin, 2015). It is also known as straight lining (Hair, Hult, Ringle, & Sarstedt, 2017). Another type of suspicious response patterns is diagonal lining, which can be detected using visual inspection (Hair, Hult, Ringle, & Sarstedt, 2017). Suspicious response patterns are considered evidence that such respondents are not engaged in the survey.

Following other studies in technology acceptance (Hana, Kimb, & Kiatkawsin, 2017; Alomary, 2017; Maroufkhani, Nourani, & Bin Boerhannoeddin, 2015), the standard deviation was computed for each case to detect straight lining patterns. Cases with a value of 0 were subjected for deleting as they are considered suspicious response patterns. It was found that 15 respondents (0.87% of received responses) were not completely engaged in the survey (see Table 5.3). The respondents had given the same answer to every question. The 15 cases were identified as straight lining patterns, and, therefore, those cases were dropped from data analysis.

Table 5.3 Unengaged Responses

Case ID	Minimum Value	Maximum Value	Standard Deviation
121	1	1	0.000
137	5	5	0.000
152	5	5	0.000
155	1	1	0.000
246	3	3	0.000
290	1	1	0.000
298	3	3	0.000
312	3	3	0.000
373	5	5	0.000
386	3	3	0.000
412	3	3	0.000
418	3	3	0.000
419	1	1	0.000
682	3	3	0.000
721	5	5	0.000

While screening all cases, two unreasonable cases (025 and 316) were identified. In case 025, the respondent mentioned that she has 22 years of LMS experience while her age was 22 years, and her educational level was undergraduate. In the other case (316), the respondent mentioned that he has 43 years of LMS experience while his age was 21 years, and his educational level was undergraduate. Therefore, the decision was made to replace their LMS experience with the mean (2.32) as recommended by Gaskin (2013).

5.2.4 Normality

Normality refers to the data distribution of a single variable (Field, 2013). In the best case scenario, data will take a bell-shaped curve to indicate a normal distribution (Hair, Celsi, Money, Samouel, & Page, 2016). The normality test is one of the early measures required to verify that the data collected are appropriate for statistical data analysis. In other words, data not normally distributed might affect the reliability and validity of multivariate data analysis (Hair, Black, Babin, & Anderson, 2014). Even though PLS-SEM is a non-parametric tool that does not assume normal data (Hair, Hult, Ringle, & Sarstedt, 2017; Garson, 2016), it is important to ensure that data collected are not extremely non-normal (Hair, Hult, Ringle, & Sarstedt, 2017).

In terms of measuring the data distribution, researchers of SEM (Hair, Hult, Ringle, & Sarstedt, 2017; Kline, 2016; Hair, Black, Babin, & Anderson, 2014) recommended using two values to measure the shape of data distribution: skewness and kurtosis. Skewness refers to measuring the symmetry of the data distribution, while kurtosis refers to the height of the distribution (Field, 2013). Positive skewness value indicates that the distribution is skewed to left, and negative skewness value indicates that the distribution is skewed to right (Kline, 2016). Positive kurtosis indicates that the distribution is too peaked, and negative kurtosis indicates that the distribution is too flat (Kline, 2016).

While the optimum values of skewness and kurtosis are zero (Cohen, Manion, & Morrison, 2013), the threshold of skewness and kurtosis is controversial. According to Hair, Hult et al. (2017) and Hair et al. (2016), the values of skewness and kurtosis should be within the range of ±1. Hair, Black et al. (2014) and Field (2013) reported that the widely used threshold is ±2.58 for .01 significance level and ±1.96 for .05 significance level. The results of the normality test in Table 5.4 show that the values of skewness and kurtosis for the 12 constructs of the model were within the range of ±1, which demonstrate that data distribution is not a problem for the 12 constructs and model testing in the next chapter. However, the values of skewness and kurtosis for the majority of the demographic variables were not within the range of ±1, which indicate that data is not normally distributed for these demographic variables. Detailed skewness and kurtosis values for each indicator are provided in Appendix E.

Table 5.4 Results of Normality Test

	Variables	Skewness		Kurtosis	
		Statistic	**Std. Error**	**Statistic**	**Std. Error**
Model Constructs	AU	-0.279	0.085	-0.556	0.169
	BI	-0.611	0.085	-0.642	0.169
	CQ	-0.445	0.085	-0.310	0.169
	EOA	-0.435	0.085	-0.285	0.169
	IA	-0.339	0.085	-0.463	0.169
	LS	-0.148	0.085	-0.416	0.169
	PEOU	-0.460	0.085	-0.405	0.169
	PU	-0.417	0.085	-0.556	0.169
	SI	-0.200	0.085	-0.784	0.169
	SL	-0.536	0.085	-0.343	0.169

	Variables	Skewness		Kurtosis	
		Statistic	Std. Error	Statistic	Std. Error
	SN	-0.318	0.085	-0.581	0.169
	VD	-0.305	0.085	-0.660	0.169
Demographic Variables	Gender	-0.735	0.085	-1.463	0.169
	Age	1.782	0.085	3.187	0.169
	University	0.353	0.085	-0.734	0.169
	Level of education	1.745	0.085	1.046	0.169
	Academic major	0.712	0.085	-1.496	0.169
	Computer skills	0.060	0.085	-0.411	0.169
	Internet skills	-0.133	0.085	-1.289	0.169
	Experience	1.408	0.085	3.499	0.169
	GPA	-2.148	0.085	4.138	0.169

Having cleaned and screened data, the next section provides more information about the number of responses used for data analysis.

5.3 Response Rate

For this study, the target population is higher-education students who are studying at public universities using LMS in Saudi Arabia. A total of 2,000 online surveys were distributed to the students registered at the three universities under investigation. A total of 851 responses were submitted by participants, equivalent to a response rate of 42.55%. After the preliminary examination for missing data, outliers, normality, and unengaged responses, 833 responses (41.65% response rate) were used for data analysis. This indicates that the minimum sample size required for this study has been achieved (see Section 4.4.5).

5.4 Non-Response Bias

The problem of non-response bias occurs in survey research when respondents are different from those who did not respond (Berg, 2005). It is difficult to obtain the data of all non-respondents to be compared with the data of respondents. In this way, it was assumed that the characteristics of those who did not respond are like those who responded late to check non-response bias (Hakami, 2018; Abbasi, 2011; Ameen, Willis, & Shah, 2018; Chandio, 2011). Consistent with early research in technology acceptance (Abbasi, 2011; Ameen, Willis, & Shah, 2018), the demographic information and 12 constructs were contrasted between the early responses (first 50) and the late responses (last 50) as these responses were obtained at different points of time. Mann-Whitney U test was employed to assess non-response bias by comparing the first 50 responses and the last 50 responses across the variables. The results presented in Table 5.5 demonstrate that the significance values of all variables are above 0.05. This implies that there is no statistically significant difference between the first 50 and the last 50 responses, and non-response bias is not a serious limitation in this research.

Table 5.5 Results of Non-Response Bias Test

	Variables	**Mann-Whitney U**	**Wilcoxon W**	**Z**	**Sig. (2-tailed)**
Model Constructs	AU	1203.000	2478.000	-0.326	0.745
	BI	1201.500	2476.500	-0.339	0.735
	CQ	1128.500	2403.500	-0.842	0.400
	EOA	1042.500	2317.500	-1.437	0.151
	IA	1149.500	2424.500	-0.697	0.486
	LS	1171.000	2446.000	-0.546	0.585
	PEOU	1068.500	2343.500	-1.258	0.209
	PU	1190.000	2465.000	-0.415	0.678
	SI	1136.000	2411.000	-0.789	0.430
	SL	1071.000	2346.000	-1.242	0.214
	SN	1055.000	2330.000	-1.348	0.178
	VD	1225.000	2500.000	-0.173	0.862
Demographic Variables	Gender	1075.000	2350.000	-1.395	0.163
	Age	1039.000	2314.000	-1.471	0.141
	University	1200.000	2475.000	-0.427	0.669
	Level of education	1150.000	2425.000	-1.036	0.300
	Academic major	1225.000	2500.000	-0.209	0.835
	Computer skills	1244.000	2519.000	-0.047	0.962
	Internet skills	1027.500	2302.500	-1.748	0.080
	Experience	1222.500	2497.500	-0.193	0.847
	GPA	1036.000	2311.000	-1.476	0.140

5.5 Profile of Respondents

Besides the collected responses about the variables that might influence student use of LMS, the online survey also obtained information about the personal and demographic characteristics of respondents. The profile of respondents, including gender, age, university, level of education, academic major, computer skills, internet skills, experience with LMS, and performance, demonstrates that students from different demographic groups are covered in this study. The respondents' demographic information is presented in the following subsections.

5.5.1 Gender

The participants were asked to select their gender either (1) male or (2) female. The results in Table 5.6 show that 32.8% of respondents are male students, and 67.2% are female students.

Table 5.6 Gender groups of Respondents

Gender	Frequency	Percent
Male	273	32.8
Female	560	67.2
Total	**833**	**100**

5.5.2 Age

Age was measured based on a ratio scale, and the participants were asked to enter how old they were. The respondents' age is presented in Table 5.7. The results indicate that 193 students (22.81%) are below 20 years old, 576 students (68.09%) are between 20 and 30 years old, and 77 students (9.10%) are above 30 years old. According to the normality test (Section 5.2.4) and the frequency values, the values of the respondents' age are not normally distributed. Therefore, the median was reported for this variable as recommended by Field (2013).

Table 5.7 Age Distribution of Respondents

Age	Frequency	Percent	Median
17	5	.6	21
18	57	6.8	
19	125	15.0	
20	161	19.3	
21	94	11.3	
22	94	11.3	
23	75	9.0	
24	29	3.5	
25	29	3.5	

Age	Frequency	Percent	Median
26	23	2.8	
27	16	1.9	
28	17	2.0	
29	14	1.7	
30	18	2.2	
31	10	1.2	
32	10	1.2	
33	11	1.3	
34	9	1.1	
35	9	1.1	
36	7	.8	
37	3	.4	
38	6	.7	
39	3	.4	
40	3	.4	
43	2	.2	
44	1	.1	
45	1	.1	
46	1	.1	

5.5.3 University

The participants' university variable was measured based on a nominal scale, and the students were asked to select the university in which they registered (1) King Abdulaziz University, (2) King Saud University, or (3) Imam Abdulrahman Bin Faisal University. It was found that most responses were received from students at King Saud University with 418 responses (50.2%) followed by King Abdulaziz University with 375 responses (45%). A few responses were received from students at Imam Abdulrahman Bin Faisal University. This is because fewer participants were invited, as the number of students registered at this university is the smallest compared with the other two universities. Furthermore, the deanship of e-learning at Imam Abdulrahman Bin Faisal University was recently established, and, thus, the use of LMS might be still in early stages. The students' responses including the frequencies and percentage are presented in Table 5.8.

Table 5.8 Universities of Respondents

University	Frequency	Percent
King Abdulaziz University	375	45.0
King Saud University	418	50.2
Imam Abdulrahman Bin Faisal University	40	4.8

5.5.4 Level of Education

The level of education was measured based on an ordinal scale, and the students were asked to select their level either (1) undergraduate or (2) postgraduate. The online survey was answered by 690 undergraduate students (82.8%) and 143 postgraduate students (17.2%) (see Table 5.9). Compatible with the reports of the Ministry of Education in Saudi Arabia, the overwhelming majority of students in this research are undergraduate students (Ministry of Education, 2017a).

Table 5.9 Educational Level of Respondents

Level of Education	Frequency	Percent
Undergraduate	690	82.8
Postgraduate	143	17.2
Total	**833**	**100**

5.5.5 Academic Major

The students' responses about their academic major including the frequencies and percentage are presented in Table 5.10. A nominal scale was used to measure this variable, and the students were asked to select their academic major either (1) science or (2) art. Science students are specialised in medicine, applied sciences (e.g. engineering and computer science), and natural sciences (e.g. biology, physics and chemistry). Art students are specialised in humanities and social sciences (e.g. history, religious studies, education, languages, and management). The results reveal that 556 (66.7%) of respondents are specialised in science, and 277 (33.3%) of respondents are art students.

Table 5.10 Academic Major of Respondents

Academic Major	Frequency	Percent
Science	556	66.7
Art	277	33.3
Total	**833**	**100**

5.5.6 Computer Skills

The computer skills variable was measured based on an ordinal scale, and the students responded by either (1) novice, (2) moderate, or (3) expert computer skills. The online survey was answered by 44 students (5.3%) having novice computer skills, 528 students (63.4%) having moderate computer skills, and 261 students (31.3%) having expert computer skills (see Table 5.11). This shows that more than 94% of higher-educational students in Saudi Arabia maintained a high degree of computer skills, which might indicate that the students had the skills needed to use computer-based educational systems. Next, the responses of the internet skills variable are analysed.

Table 5.11 Computer Skills of Respondents

Computer Skills	**Frequency**	**Percent**
Novice	44	5.3
Moderate	528	63.4
Expert	261	31.3
Total	**833**	**100**

5.5.7 Internet Skills

The students' internet skills item was measured based on an ordinal scale, and the students responded by either (1) novice, (2) moderate, or (3) expert internet skills. The online survey was answered by 13 students (1.6%) having novice internet skills, 429 students (51.5%) having moderate internet skills, and 391 students (46.9%) having expert internet skills (see Table 5.12). This shows that more than 98% of higher-educational students in Saudi Arabia maintained a high degree of internet skills, which might indicate that the students had the technical skills needed to use web-based educational systems.

Table 5.12 Internet Skills of Respondents

Computer Skills	**Frequency**	**Percent**
Novice	13	1.6
Moderate	429	51.5
Expert	391	46.9
Total	**833**	**100**

5.5.8 Experience

The experience with LMS was measured based on a ratio scale, and the participants were asked to enter how many years they have been using LMS. The respondents' experience with LMS is presented in Table 5.13. As this variable was measured in terms of the number of years, the value of 0.10 indicates 1 month of experience, and the value of 2.32 indicates 2 years and 4 months of experience. The results indicate that 519 students (61.35%) have less than 2 years of experience, and 327 students (38.65%) have more than 2 years of experience. According to the normality test (Section 5.2.4) and the frequency values, the values of the respondents' experience with LMS are not normally distributed. Therefore, the median was reported for this variable as recommended by Field (2013). Next, the students' GPA scores are analysed.

Table 5.13 LMS Experience of Respondents

Experience (years)	Frequency	Percent	Median
0.00	45	5.4	2.0
0.10	1	.1	
0.50	5	.6	
1.00	253	30.4	
1.50	2	.2	
2.00	203	24.4	
2.32	2	.2	
2.50	2	.2	
3.00	157	18.8	
4.00	92	11.0	
5.00	43	5.2	
6.00	12	1.4	
7.00	6	.7	
8.00	3	.4	
9.00	1	.1	
10.00	6	.7	

5.5.9 Performance

This variable examines the students' academic performance in terms of GPA and was measured based on a ratio scale. The participants were asked to enter their GPA, which is presented in Table 5.14. The results show that students from different GPA groups are included in this study, and 496 students (58.63%) have a GPA score between 4.01

and 5.00. According to the normality test (Section 5.2.4), the values of the respondents' GPA are not normally distributed. Therefore, the median was reported for this variable as recommended by Field (2013).

Table 5.14 GPA Scores of Respondents

GPA	Frequency	Percent	Median
0.00 – 2.00	60	7.09	4.29
2.00 – 3.00	67	7.92	
3.01 – 4.00	220	26.36	
4.01 – 5.00	486	58.63	

The next two sections display the analysis of the descriptive statistics of the 12 constructs and LMS features used by students.

5.6 Descriptive Statistics of the Constructs

Table 5.15 displays the descriptive statistics of the independent and dependent variables, including number of indicators, the minimum and maximum values, mean, and standard deviation. For each indicator, the respondents were asked to select the answer that best represented their level of agreement based on a five-point Likert scale. The results show that the mean values of the constructs ranged between 3.27 (1.099) and 3.65 (1.019), which indicate that most respondents in this study have a positive attitude toward LMS. This result is consistent with prior research in Saudi LMS (Al-Aulamie, 2013; Alenezi, 2011; Alshorman & Bawaneh, 2018). Furthermore, all indicators maintain small standard deviation (SD) values, which implies that the responses are close to the mean.

Table 5.15 Descriptive Statistics of Constructs

Constructs	Indicators	Minimum	Maximum	Mean	Standard Deviation
AU	4	1	5	3.44	1.05
BI	4	1	5	3.63	1.24
CQ	4	1	5	3.52	0.97
EOA	4	1	5	3.56	0.97
IA	4	1	5	3.42	1.07
LS	5	1	5	3.28	0.98
PEOU	4	1	5	3.48	1.07
PU	5	1	5	3.45	1.13
SI	4	1	5	3.27	1.10

SL	4	1	5	3.65	1.02
SN	5	1	5	3.46	1.03
VD	4	1	5	3.27	1.11

5.7 Descriptive Statistics of the Features

The descriptive statistics of the LMS features, including the frequencies, percentage, mean, and standard deviation, are presented in Table 5.16. These features are course materials, announcements, assignments, discussion board, messages and email, grades, exams and quizzes, and virtual classrooms. For each feature, the respondents selected the answer that best represented their level of utilisation. In general, the overall mean (3.03) indicate that participants have a moderate utilisation level of LMS. The results reveal that the students always use course materials, assignments, messages and emails, grades, and exams and quizzes.

Table 5.16 Descriptive Statistics of LMS Features

Features		Never	Rarely	Sometimes	Very Often	Always	Mean	Standard Deviation
Course Materials	F	91	104	163	181	294	3.58	1.363
	%	10.9	12.5	19.6	21.7	35.3		
Announcements	F	387	129	141	68	108	2.26	1.437
	%	46.5	15.5	16.9	8.2	13.0		
Assignments	F	112	90	157	171	303	3.56	1.414
	%	13.4	10.8	18.8	20.5	36.4		
Discussion Board	F	332	163	146	97	95	2.35	1.395
	%	39.9	19.6	17.5	11.6	11.4		
Messages and email	F	209	113	140	145	226	3.08	1.548
	%	25.1	13.6	16.8	17.4	27.1		
Grades	F	120	74	133	160	346	3.65	1.451
	%	14.4	8.9	16.0	19.2	41.5		
Exams and Quizzes	F	180	93	147	134	279	3.29	1.548
	%	21.6	11.2	17.6	16.1	33.5		
Virtual Classes	F	359	109	132	74	159	2.48	1.561
	%	43.1	13.1	15.8	8.9	19.1		

5.8 Summary

In this chapter, a point-by-point clarification of the data analysis process was provided. The data were uploaded into the SPSS package to perform the preliminary examination, non-response bias, profile of respondents, and descriptive analysis of the constructs and LMS features.

The chapter began by the preliminary examination of the collected data including missing data, outliers, normality, and unengaged responses. As all questions in the online survey were designed to be mandatory, it was not possible to submit an incomplete form. Using minimum and maximum values and graphs (Sekaran & Bougie, 2016), three cases were qualified as univariate outliers with extreme values on the variable of LMS experience. Following the suggestions of Hair et al. (2016), those values were deemed to be unreasonable, and, therefore, they were deleted. Using Mahalanobis distance, one case was a candidate for multivariate outliers. In order to test for normality, the researcher used skewness and kurtosis values to measure the shape of data distribution (Hair, Hult, Ringle, & Sarstedt, 2017; Kline, 2016; Hair, Black, Babin, & Anderson, 2014), and it was found that the data is normally distributed. Furthermore, 15 cases were identified as straight-lining patterns, and, thus, they were dropped. Finally, two unreasonable responses were replaced by the parameter means as recommended by Gaskin (2013).

A total of 2,000 online surveys were distributed to the students registered at the three investigated universities. A total of 851 responses (42.55% response rate) were submitted by participants, and 833 responses (41.65% response rate) were used for data analysis. Using t-test to compare the mean values of the early and late respondents, Section 5.4 provided evidence that non-response bias is not a problem in this research.

The third section displayed the profile of respondents including age, gender, university, level of education, academic major, computer skills, internet skills, experience with LMS, and performance. This demonstrated that students from different personal and demographic groups were covered in this research.

In the following section (Section 5.6), the descriptive statistics of the independent and dependent constructs in the proposed model, including the frequencies, percentage, mean, and standard deviation, were displayed. The overall mean (3.46) demonstrated that most students expressed generally a positive attitude toward LMS.

The last section of this chapter showed the descriptive statistics of the LMS features (course materials, announcements, assignments, discussion board, messages and email, grades, exams and quizzes, and virtual classrooms) used by students. The results revealed that students in higher-educational institutions in Saudi Arabia use LMS features moderately.

The next chapter supplies more details about the proposed model testing using the PLS-SEM technique and SmartPLS software. The results obtained from the model testing are discussed further in Chapter 7.

CHAPTER 6: MODEL TESTING

6.1 Introduction

In the research methodology chapter, the selection of the PLS-SEM technique for data analysis and model testing was discussed and justified. In the previous chapter, data were uploaded into the SPSS software to perform the preliminary examination, response rate calculation, non-response bias test, and descriptive analysis. For this chapter, data were exported from SPSS in .csv format and imported into the SmartPLS software version 3.2.7 to perform further analysis and model testing. According to several researchers (Hair, Hult, Ringle, & Sarstedt, 2017; Henseler, Hubona, & Ray, 2017; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018), when using PLS-SEM for model testing, a multi-stage procedure should be followed: (1) measurement model assessment and (2) structural model assessment. This multi-stage approach is followed in this chapter to evaluate the proposed model as shown in the next sections.

6.2 Measurement Model Assessment

The measurement model, so-called outer model, refers to the relationships between the constructs and their indicators (Henseler & Sarstedt, 2013; Hair, Ringle, & Sarstedt, 2011; Henseler, Ringle, & Sinkovics, 2009; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Benitez-Amado, Henseler, & Castillo, 2017). In other words, the measurement model refers to how the constructs are measured via indicators (Hair, Sarstedt, Ringle, & Gudergan, 2018). As SEM provides researchers with the ability to measure one variable using multiple indicators to enhance the accuracy of the measure (Hair, Hult, Ringle, & Sarstedt, 2017), it is crucial to address the reliability and validity of the used indicators in multivariate analysis (Hair, Black, Babin, & Anderson, 2014). Furthermore, if the measurement model evaluation does not meet the minimum requirements of reliability and validity, the structural model evaluation in the second stage has no value (Henseler, Hubona, & Ray, 2016; Hair, Sarstedt, Ringle, & Mena, 2012; Henseler, Hubona, & Ray, 2017). Researchers (Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Ringle, & Sarstedt, 2013; Hair, Ringle, & Sarstedt, 2011; Henseler, Ringle, & Sinkovics, 2009; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Henseler, Ringle, & Sarstedt, 2015) provided guidelines for evaluating and reporting the measurement model, including indicator reliability, construct reliability, convergent validity, and discriminant validity. Table 6.1 summarises the criteria used for evaluating the measurement model in this study. Review studies on PLS-SEM (Ringle, Sarstedt, & Straub, 2012; Hair, Sarstedt, Ringle, & Mena, 2012; Ringle, Sarstedt, Mitchell, & Gudergan, 2018; Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Hair, Hollingsworth, Randolph, & Chong, 2017) found that researchers usually report those criteria when examining the measurement model.

Table 6.1 Criteria of Measurement Model Assessment

Validity Type	Criteria	Guidelines	References
Indicator reliability	Loadings	Loading ≥ 0.7	(Chin, 1998)
Construct reliability	Cronbach's alpha (CA)	CA ≥ 0.7	(Cronbach, 1951)
	Composite reliability (CR)	CR ≥ 0.7	(Hair, Hult, Ringle, & Sarstedt, 2017)
Convergent validity	Average variance extracted (AVE)	AVE ≥ 0.5	(Fornell & Larcker, 1981)
Discriminant validity	Cross loadings	loading > its cross loadings on the other constructs	(Chin, 1998)
	Fornell-Larcker criterion	√AVE > correlation with other constructs	(Fornell & Larcker, 1981)
	Heterotrait-Monotrait Ratio (HTMT)	Constructs' correlation ≤ 0.90	(Henseler, Ringle, & Sarstedt, 2015)

Given those criteria and guidelines, the results of measures' reliability and validity assessments are presented in the following subsections.

6.2.1 Indicator Reliability

The reliability of indicators is measured in terms of outer loadings (Hair, Ringle, & Sarstedt, 2011). High outer loadings mean that the indicators of a construct have a large degree of similarity (Hair, Hult, Ringle, & Sarstedt, 2017). Loadings vary between 0 and 1, and the value closer to 1 indicates more reliability (Garson, 2016). In respect to the threshold of outer loadings, researchers (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Hair, Ringle, & Sarstedt, 2011; Hair, Hult, Ringle, & Sarstedt, 2017; Henseler, Ringle, & Sinkovics, 2009; Chin, 1998) recommended that the indicators' reliability is achieved when the outer loading of each indicator is above 0.7. Using PLS algorithm with 1,000 iterations, the results presented in Table 6.2 demonstrate that all indicators are reliable except AU02 and SN05. Those two indicators did not meet the recommended threshold; therefore, they were removed.

Table 6.2 Results of Measurement Model Assessment

Constructs	**Indicators**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
AU	AU01	0.922	0.880	0.926	0.807
	AU02	0.502			
	AU03	0.920			
	AU04	0.851			
BI	BI01	0.923	0.946	0.961	0.861
	BI02	0.935			
	BI03	0.919			
	BI04	0.935			
CQ	CQ01	0.796	0.835	0.890	0.670
	CQ02	0.834			
	CQ03	0.850			
	CQ04	0.793			
EOA	EOA01	0.758	0.807	0.874	0.635
	EOA02	0.773			
	EOA03	0.876			
	EOA04	0.777			
IA	IA01	0.826	0.916	0.941	0.800
	IA02	0.921			
	IA03	0.935			
	IA04	0.893			
LS	LS01	0.801	0.874	0.908	0.665
	LS02	0.806			
	LS03	0.810			
	LS04	0.819			
	LS05	0.839			
PEOU	PEOU01	0.893	0.909	0.936	0.785
	PEOU02	0.878			
	PEOU03	0.866			
	PEOU04	0.907			
PU	PU01	0.885	0.946	0.959	0.823
	PU02	0.919			
	PU03	0.931			
	PU04	0.909			

Constructs	**Indicators**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
	PU05	0.891			
SI	SI01	0.823	0.878	0.916	0.732
	SI02	0.868			
	SI03	0.871			
	SI04	0.859			
SL	SL01	0.885	0.872	0.913	0.724
	SL02	0.851			
	SL03	0.869			
	SL04	0.795			
SN	SN01	0.892	0.882	0.920	0.743
	SN02	0.896			
	SN03	0.916			
	SN04	0.731			
	SN05	0.666			
VD	VD01	0.877	0.879	0.917	0.733
	VD02	0.859			
	VD03	0.855			
	VD04	0.834			

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

6.2.2 Construct Reliability

Assessing the reliability of the measurement model is crucial as the lack of reliability may lead to biased results in the structural model evaluation (Hair, Sarstedt, Ringle, & Mena, 2012). Reliability refers to the indicators' internal consistency and their ability to generate the same findings under the same situations (Field, 2013). Traditionally, social science studies utilise internal consistency to measure the reliability using Cronbach's alpha (CA) (Cronbach, 1951). Hair et al. (2012) reviewed studies using PLS-SEM in the 30 highly-rated marketing journals and published between 1981 and 2010. Assessing 204 papers revealed that the internal consistency reliability of the indicators is usually measured using both Cronbach's alpha and composite reliability (CR) (Hair, Sarstedt, Ringle, & Mena, 2012). Cronbach's alpha tends to underrate the reliability values, whereas composite reliability tends to overrate the reliability values (Hair, Hult, Ringle, & Sarstedt, 2017; Sarstedt, Ringle, & Hair, 2017). Furthermore, Cronbach's alpha values increase by increasing the number of indicators (Field, 2013). Therefore, Hair, Hult et al. (2017) and Sarstedt et al. (2017) recommended researchers to report the results of both measures, Cronbach's alpha (low values) and composite reliability (high values).

The reliability coefficient must be within the range of 0 and 1, in which a value closer to 1 indicates higher reliability. However, researchers have used different cut-off points for the appropriate reliability. A reliability value of 0.7 indicates acceptable reliability and 0.8 indicates good reliability (Sekaran & Bougie, 2016). Hair et al. (2011) stated that reliability values between 0.6 and 0.7 are acceptable for exploratory research. While Hair, Hult et al. (2017) consider values between 0.7 and 0.9 appropriate. The results of a reliability test by calculating Cronbach's alpha and composite reliability are displayed in Table 6.2. The Cronbach's alpha coefficient values range from 0.807 to 0.946, whereas the composite reliability values range from 0.874 to 0.961. Those findings provide evidence of the high reliability of the constructs.

6.2.3 Convergent Validity

Convergent validity refers to the extent to which an indicator is positively correlated with other indicators in the same construct (Sekaran & Bougie, 2016). In the view of Henseler et al. (2009), convergent validity means that indicators present the same constructs. Convergent validity is achieved when the outer loading of each indicator is above 0.7 and average variance extracted (AVE) of each construct is 0.5 or above (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Hair, Ringle, & Sarstedt, 2011; Hair, Hult, Ringle, & Sarstedt, 2017; Garson, 2016; Benitez-Amado, Henseler, & Castillo, 2017). The AVE refers to the grand mean of the squared loadings of the indicators of a construct (Hair, Hult, Ringle, & Sarstedt, 2017; Sarstedt, Ringle, & Hair, 2017). When the AVE of a construct is 0.5 or above, more than the half of the variance of the construct's measures is explained (Chin, 1998). Table 6.2 shows that AVE values exceed 0.5 demonstrating the convergent reliability of the constructs.

6.2.4 Discriminant Validity

Discriminant validity means that a construct is different from other constructs in the model and captures the intended variable (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). In other words, each construct should have more correlation with its indicators than with the indicators of the other constructs (Hair, Hult, Ringle, & Sarstedt, 2017). Some researchers (Henseler, Hubona, & Ray, 2016; Hair, Hult, Ringle, & Sarstedt, 2017) recommended measuring discriminant validity using cross loadings, Fornell-Larcker criteria, and Heterotrait-Monotrait Ratio.

According to Hair, Hult et al. (2017), cross loadings is typically the first method to evaluate the discriminant validity of measures. The cross loadings approach ensures that the indicator is not improperly assigned to another construct (Henseler, Hubona, & Ray, 2016). More specifically, the outer loading of an indicator on its construct should be higher than its cross loadings on the other constructs (Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Ringle, & Sarstedt, 2011). Compared with Fornell-Larcker criteria, cross loadings examine the discriminant validity on the indicator level (Henseler, Ringle, & Sinkovics, 2009). The discriminant validity test was conducted in SmartPLS, and the results of the cross loadings assessment presented in Table 6.3 provide evidence on discriminant validity.

Table 6.3 Results of Cross Loadings

	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU01	**0.92**	0.58	0.48	0.36	0.47	0.48	0.53	0.58	0.49	0.46	0.44	0.39
AU03	**0.92**	0.54	0.46	0.35	0.48	0.46	0.52	0.57	0.48	0.44	0.47	0.37
AU04	**0.85**	0.46	0.39	0.31	0.39	0.41	0.45	0.48	0.40	0.39	0.36	0.30
BI01	0.51	**0.92**	0.49	0.44	0.54	0.49	0.59	0.70	0.53	0.53	0.48	0.41
BI02	0.59	**0.94**	0.58	0.47	0.62	0.57	0.68	0.77	0.62	0.60	0.57	0.50
BI03	0.52	**0.92**	0.47	0.43	0.50	0.44	0.58	0.66	0.53	0.52	0.47	0.42
BI04	0.57	**0.94**	0.53	0.45	0.55	0.50	0.63	0.70	0.56	0.56	0.51	0.46
CQ01	0.39	0.49	**0.80**	0.46	0.54	0.56	0.58	0.51	0.49	0.55	0.57	0.52
CQ02	0.42	0.48	**0.83**	0.44	0.52	0.56	0.54	0.51	0.51	0.49	0.51	0.54
CQ03	0.42	0.46	**0.85**	0.47	0.54	0.59	0.57	0.50	0.55	0.54	0.59	0.62
CQ04	0.40	0.41	**0.79**	0.43	0.57	0.66	0.49	0.52	0.57	0.45	0.50	0.52
EOA01	0.25	0.32	0.40	**0.76**	0.39	0.38	0.47	0.35	0.39	0.49	0.48	0.39
EOA02	0.28	0.37	0.39	**0.77**	0.38	0.41	0.45	0.36	0.36	0.44	0.43	0.38

	AU	BI	CQ	EOA	IA	LS	PEOU	PU	SI	SL	SN	VD
EOA03	0.35	0.43	0.48	**0.88**	0.47	0.45	0.51	0.45	0.46	0.50	0.52	0.48
EOA04	0.33	0.41	0.49	**0.78**	0.45	0.45	0.48	0.39	0.43	0.44	0.52	0.50
IA01	0.38	0.51	0.53	0.45	**0.83**	0.54	0.55	0.59	0.61	0.54	0.52	0.48
IA02	0.44	0.55	0.61	0.49	**0.92**	0.64	0.67	0.64	0.66	0.66	0.65	0.58
IA03	0.49	0.57	0.65	0.50	**0.94**	0.69	0.67	0.69	0.70	0.66	0.65	0.58
IA04	0.46	0.51	0.57	0.45	**0.89**	0.62	0.62	0.65	0.66	0.60	0.58	0.51
LS01	0.46	0.49	0.68	0.48	0.57	**0.80**	0.55	0.61	0.61	0.51	0.51	0.51
LS02	0.37	0.42	0.57	0.35	0.58	**0.81**	0.51	0.59	0.63	0.47	0.47	0.47
LS03	0.42	0.43	0.59	0.43	0.56	**0.81**	0.53	0.55	0.60	0.47	0.51	0.45
LS04	0.39	0.42	0.53	0.43	0.55	**0.82**	0.52	0.49	0.53	0.47	0.54	0.53
LS05	0.40	0.42	0.56	0.46	0.57	**0.84**	0.54	0.53	0.57	0.49	0.56	0.54
PEOU01	0.51	0.63	0.62	0.56	0.65	0.60	**0.89**	0.67	0.64	0.68	0.69	0.64
PEOU02	0.52	0.57	0.60	0.52	0.63	0.60	**0.88**	0.63	0.60	0.67	0.65	0.57
PEOU03	0.45	0.55	0.52	0.51	0.58	0.53	**0.87**	0.61	0.54	0.73	0.57	0.50
PEOU04	0.49	0.61	0.61	0.53	0.62	0.57	**0.91**	0.65	0.56	0.76	0.67	0.59
PU01	0.54	0.66	0.59	0.43	0.65	0.60	0.69	**0.89**	0.66	0.59	0.53	0.49
PU02	0.54	0.67	0.55	0.40	0.64	0.61	0.62	**0.92**	0.67	0.54	0.49	0.44
PU03	0.56	0.71	0.57	0.45	0.67	0.64	0.66	**0.93**	0.69	0.59	0.53	0.49
PU04	0.55	0.69	0.55	0.44	0.67	0.63	0.64	**0.91**	0.64	0.55	0.51	0.45
PU05	0.58	0.74	0.57	0.48	0.62	0.61	0.66	**0.89**	0.65	0.59	0.53	0.45
SI01	0.41	0.51	0.57	0.50	0.63	0.63	0.58	0.58	**0.82**	0.55	0.51	0.50
SI02	0.43	0.46	0.54	0.41	0.62	0.60	0.53	0.59	**0.87**	0.47	0.48	0.47
SI03	0.41	0.45	0.50	0.37	0.59	0.61	0.52	0.57	**0.87**	0.45	0.46	0.46
SI04	0.49	0.63	0.60	0.47	0.66	0.63	0.63	0.72	**0.86**	0.56	0.56	0.56
SL01	0.41	0.55	0.58	0.53	0.63	0.54	0.74	0.58	0.54	**0.89**	0.62	0.54
SL02	0.45	0.55	0.56	0.55	0.65	0.54	0.70	0.59	0.56	**0.85**	0.63	0.55
SL03	0.38	0.48	0.49	0.49	0.54	0.47	0.68	0.48	0.46	**0.87**	0.58	0.48
SL04	0.39	0.45	0.48	0.40	0.51	0.47	0.60	0.48	0.46	**0.80**	0.49	0.46
SN01	0.42	0.49	0.58	0.49	0.57	0.53	0.64	0.48	0.49	0.60	**0.89**	0.63
SN02	0.41	0.47	0.61	0.50	0.61	0.58	0.66	0.51	0.56	0.60	**0.90**	0.70
SN03	0.45	0.52	0.62	0.53	0.62	0.59	0.69	0.54	0.54	0.64	**0.92**	0.66
SN04	0.35	0.39	0.49	0.63	0.50	0.49	0.51	0.42	0.45	0.53	**0.73**	0.51
VD01	0.29	0.39	0.55	0.46	0.49	0.50	0.54	0.42	0.48	0.49	0.60	**0.88**
VD02	0.33	0.39	0.54	0.44	0.49	0.53	0.50	0.43	0.52	0.43	0.60	**0.86**
VD03	0.34	0.42	0.59	0.51	0.50	0.51	0.59	0.43	0.47	0.57	0.63	**0.86**
VD04	0.39	0.46	0.61	0.47	0.58	0.55	0.58	0.48	0.55	0.55	0.67	**0.83**

Another method to assess the discriminant validity is the one suggested by Fornell and Larcker (1981) who suggested that the square root of a construct's AVE should be larger than its correlation with other constructs. This means that the construct has more variance with its indicators than with the other constructs in the model (Hair, Hult, Ringle, & Sarstedt, 2017). In comparison with cross loadings, Fornell-Larcker criteria examine the discriminant validity on the construct level (Henseler, Ringle, & Sinkovics, 2009). Table 6.4 shows that the square root of each construct's AVE, presented on the diagonal line, are larger than the construct's correlation with other constructs. According to Fornell-Larcker criteria, the constructs maintain discriminant validity.

Table 6.4 Results of Fornell-Larcker Discriminant Validity

	AU	BI	CQ	EOA	IA	LS	PEOU	PU	SI	SL	SN	VD
AU	**0.90**											
BI	0.59	**0.93**										
CQ	0.50	0.56	**0.82**									
EOA	0.38	0.48	0.55	**0.80**								
IA	0.50	0.60	0.66	0.53	**0.90**							
LS	0.50	0.54	0.72	0.53	0.70	**0.82**						
PEOU	0.56	0.67	0.66	0.60	0.70	0.65	**0.89**					
PU	0.61	0.77	0.62	0.49	0.72	0.68	0.72	**0.91**				
SI	0.51	0.61	0.65	0.52	0.74	0.72	0.66	0.73	**0.86**			
SL	0.48	0.60	0.62	0.59	0.69	0.59	0.80	0.63	0.60	**0.85**		
SN	0.48	0.55	0.67	0.61	0.67	0.63	0.73	0.57	0.59	0.69	**0.86**	
VD	0.40	0.49	0.67	0.55	0.60	0.61	0.65	0.51	0.59	0.60	0.73	**0.86**

One recent method for measuring the discriminant validity in PLS-SEM is the Heterotrait-Monotrait Ratio (HTMT), which was developed by Henseler et al. (2015). They argued that neither Fornell-Larcker criteria nor cross loadings method is able to reliably identify the discriminant validity problems. When two constructs are exactly correlated, the cross loadings method does not report a lack of discriminant validity. Likewise, Fornell-Larcker criteria performs inadequately when the outer loadings are very close. HTMT represents the estimate for the construct's correlation with the other constructs, that should be smaller than one (Henseler, Hubona, & Ray, 2016). A correlation closer to one shows a lack of discriminant validity. Henseler et al. (2015) suggested a threshold of 0.90 when the constructs are conceptually similar and 0.85 when the constructs are conceptually different. The results of HTMT assessment in Table 6.5 range between 0.443 and 0.896, indicating the discriminant validity of the constructs.

Table 6.5 Results of HTMT Discriminant Validity

	AU	BI	CQ	EOA	IA	LS	PEOU	PU	SI	SL	SN
BI	0.640										

	AU	BI	CQ	EOA	IA	LS	PEOU	PU	SI	SL	SN
CQ	0.574	0.624									
EOA	0.451	0.548	0.672								
IA	0.549	0.639	0.754	0.613							
LS	0.568	0.589	0.841	0.628	0.774						
PEOU	0.619	0.717	0.760	0.698	0.765	0.728					
PU	0.664	0.808	0.701	0.553	0.770	0.746	0.777				
SI	0.574	0.654	0.752	0.606	0.818	0.822	0.735	0.790			
SL	0.543	0.650	0.724	0.694	0.764	0.676	0.896	0.690	0.674		
SN	0.535	0.596	0.775	0.738	0.742	0.722	0.810	0.623	0.668	0.779	
VD	0.443	0.527	0.784	0.650	0.668	0.697	0.721	0.560	0.661	0.677	0.825

Following the multi-stage procedure (Hair, Hult, Ringle, & Sarstedt, 2017; Henseler, Hubona, & Ray, 2017; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018), this section demonstrates the reliability and validity of the measurement model. The next section therefore proceeds with the structural model evaluation.

6.3 Structural Model Assessment

The structural model, also known as inner model, refers to the relationships between the constructs themselves (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Benitez-Amado, Henseler, & Castillo, 2017), and its assessment includes evaluating the relationships between the constructs in the model (Henseler & Sarstedt, 2013; Hair, Ringle, & Sarstedt, 2011; Henseler, Ringle, & Sinkovics, 2009). Researchers (Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Ringle, & Sarstedt, 2013; Hair, Ringle, & Sarstedt, 2011; Henseler, Ringle, & Sinkovics, 2009; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Henseler, Ringle, & Sarstedt, 2015) provided guidelines for evaluating and reporting the structural model, including collinearity, path coefficients, coefficient of determination (R^2), and cross-validated redundancy (Q^2). Table 6.6 summarises the criteria used for evaluating the structural model in this study. Review studies on PLS-SEM (Ringle, Sarstedt, & Straub, 2012; Hair, Sarstedt, Ringle, & Mena, 2012; Ringle, Sarstedt, Mitchell, & Gudergan, 2018; Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Hair, Hollingsworth, Randolph, & Chong, 2017) found that researchers usually report those criteria when examining the structural model.

Table 6.6 Criteria of Structural Model Assessment

Criteria	Guidelines	References
Collinearity	VIF < 5 or tolerance > 2	(Hair, Ringle, & Sarstedt, 2011; Hair, Hult, Ringle, & Sarstedt, 2017)
Path coefficients	Use bootstrapping with 10,000 sub-samples Significance: $p \leq 0.05$ Sign: one-tailed option	(Hair, Hollingsworth, Randolph, & Chong, 2017; Hair, Hult, Ringle, & Sarstedt, 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)
Cross-validated redundancy (Q^2)	Use blindfolding $Q^2 > 0$	(Chin, 1998)

Given those criteria and guidelines, the results of those assessments are presented in the following subsections.

6.3.1 Collinearity

Collinearity occurs when there is a high correlation between two constructs, which produces interpretation issues (Hair, Hult, Ringle, & Sarstedt, 2017). If more than two constructs are involved, it refers to multicollinearity. Collinearity can be assessed using the variance inflation factor (VIF), which is obtained by dividing one by tolerance referring to the variance explained by one independent construct not explained by the other independent constructs (Hair, Hult, Ringle, & Sarstedt, 2017; Benitez-Amado, Henseler, & Castillo, 2017). A VIF value of 5 or higher (tolerance value of 0.20 or lower) indicates a high collinearity (Hair, Ringle, & Sarstedt, 2011; Hair, Hult, Ringle, & Sarstedt, 2017). Table 6.7 shows that all VIF values are below the cut-off point providing evidence that the collinearity of independent constructs is not critical.

Table 6.7 Results of VIF Values

Constructs	AU	BI	PEOU	PU
BI	1.000			
CQ			2.802	2.813

Constructs	AU	BI	PEOU	PU
EOA			1.837	1.848
IA			3.099	3.113
LS			2.920	2.928
PEOU		2.085		3.801
PU		2.085		
SI			2.794	2.852
SL			2.481	3.217
SN			3.084	3.202
VD			2.566	2.577

6.3.2 Path Coefficients

Path coefficients refer to the estimates of the relationships between the model's constructs (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). Those coefficients range from +1 to -1, where +1 means a strong positive relationship, 0 means a weak or non-existence relationship, and -1 means a strong negative relationship (Garson, 2016). When assessing PLS path, studies should report path coefficients beside the significance level, t-value, and p-value (Hair, Sarstedt, Ringle, & Mena, 2012). Ringle et al. (2012) reviewed studies that used PLS-SEM and were published in MIS Quarterly between 1992 and 2011 and concluded that the majority of studies had reported path coefficients, significance level, t-value, and p-value when examining the structural model. Therefore, those values are reported for the path analysis test.

In SmartPLS, testing the hypotheses and path coefficients entails the utilisation of Bootstrapping, a non-parametric statistical approach that draws many sub-samples from the sample data and examines models for each sub-sample (Hair, Black, Babin, & Anderson, 2014). 10,000 sub-samples were used for bootstrapping as recommended by researchers (Hair, Hollingsworth, Randolph, & Chong, 2017; Hair, Hult, Ringle, & Sarstedt, 2017). Furthermore, the one-tailed option was employed as the hypotheses were proposed to be positive (see Chapter 3). Following studies in e-learning (Ghazal, Aldowah, & Umar, 2018; Al-Gahtani, 2016; Amin, Afrin Azhar, & Akter, 2016; Ramirez-Anormaliza, Tolozano-Benites, Astudillo-Quionez, & Suarez-Matamoros, 2017; Al-Azawei, Parslow, & Lundqvist, 2017; Hakami, 2018) and the majority of studies in other domains (Hair, Hult, Ringle, & Sarstedt, 2017), this research benefits from utilising a significance level of 0.05. Consequently, hypotheses or relationships with a p-value larger than 0.05 are rejected (Hair, Hult, Ringle, & Sarstedt, 2017).

The results of hypothesis and direct relationship testing are presented in Table 6.8, showing that 14 out of 20 path relationships in the structural model were positively significant. The findings demonstrate that the path PU → BI is the strongest (β = 0.595), whereas the path EOA → PEOU is the weakest (β = 0.054). PEOU is affected by six independent variables, namely CQ, SN, EOA, SI, IA, and SL. In terms of PU, CQ, LS, SI, IA, and PEOU are positively significant. The students' behavioural intention to use LMS is significantly influenced by PEOU (β = 0.239) and PU (β = 0.595). Furthermore, student use of LMS is significantly affected by BI (β = 0.590). Accordingly, hypotheses H1, H2 H4, H7, H9, H11, H12, H13, H14, H15, H17, H18, H19, and H20 are accepted.

Table 6.8 Results of Path Analysis

H#	Paths	Coefficients (β)	t-Value	p-Value	Adjusted R^2	Result
H1	CQ → PEOU	0.055^{*}	1.865	0.031	0.734	Accept
H3	LS → PEOU	0.046	1.461	0.072		Reject
H5	VD → PEOU	0.053	1.619	0.053		Reject
H7	SN → PEOU	0.176^{***}	5.016	0.000		Accept
H9	EOA → PEOU	0.054^{*}	1.964	0.025		Accept
H11	SI → PEOU	0.124^{***}	3.830	0.000		Accept
H13	IA → PEOU	0.059^{*}	1.747	0.040		Accept
H15	SL → PEOU	0.440^{***}	14.088	0.000		Accept
H2	CQ → PU	0.065^{*}	1.847	0.032	0.667	Accept
H4	LS → PU	0.158^{***}	4.473	0.000		Accept
H6	VD → PU	-0.102^{**}	2.919	0.002		Reject
H8	SN → PU	-0.065	1.606	0.054		Reject
H10	EOA → PU	-0.014	0.457	0.324		Reject
H12	SI → PU	0.272^{***}	6.888	0.000		Accept
H14	IA → PU	0.220^{***}	5.566	0.000		Accept
H16	SL → PU	0.014	0.315	0.376		Reject
H17	PEOU → PU	0.352^{***}	6.140	0.000		Accept
H18	PEOU → BI	0.239^{***}	6.091	0.000	0.615	Accept
H19	PU → BI	0.595^{***}	15.769	0.000		Accept
H20	BI → AU	0.590^{***}	21.401	0.000	0.347	Accept

*** p<.001, ** p<.01, * p<.05 (one-tailed test)

6.3.3 Coefficient of Determination

Coefficient of determination (R^2) refers to the effect of independent variables on the dependent latent variables (Hair, Sarstedt, Ringle, & Mena, 2012), which is one of the quality measures of the structural model (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). Hair et al. (2012) reviewed 204 paper using PLS-SEM and found that R^2 is the main criterion for the structural model assessment. Along the same lines, Ringle et al. (2012) reviewed studies that used PLS-SEM in information systems and revealed that R^2 had been reported in 105 models out of 109. R^2 estimates vary from 0 to 1, in which 0 means low explained variance and 1 means high explained variance. Researchers have used a different cut-off of R^2 value. For example, Hair et al. (2011) in marketing research described that R^2 values of 0.25, 0.50, or 0.75 are low, moderate, or high, respectively. In business research, Chin (1998) suggested that R^2 with 0.19, 0.33, or 0.67 are low, moderate, or high, respectively.

Researchers should report the adjusted R^2 values that consider the number of the independent variables and sample size (Henseler, Hubona, & Ray, 2016; Hair, Hult, Ringle, & Sarstedt, 2017). Adding more independent variables leads to an increase in R^2 values; however, the adjusted R^2 recompenses this issue by taking into account the complexity of the model (Hair, Hult, Ringle, & Sarstedt, 2017). Furthermore, the adjusted R^2 values are useful in assessing the quality of various models or comparing the model across different contexts (Henseler, Hubona, & Ray, 2016). The adjusted R^2 can be calculated using the following equation, in which *n* is the sample size and *k* is the number of the independent variables (Hair, Hult, Ringle, & Sarstedt, 2017).

$$R_{adj}^2 = 1 - (1 - R^2).\frac{n-1}{n-k-1}$$

Table 6.8 presents the result of adjusted R^2. The findings demonstrate that the independent variables explain 73% of the variance in PEOU, and SL explains the most compared with the other variables. Regarding PU, the independent variables account for 67% of the variance in PU, and PEOU contributes the most. Both PEOU and PU explain 62% of the variance in BI. According to Hair et al. (2011) and Chin (1998), those adjusted R^2 estimates are substantial, which indicate the high quality of the proposed model.

6.3.4 Cross-Validated Redundancy

Cross-validated redundancy (Q^2) assesses the predictive relevance of the structural model (Hair, Hult, Ringle, & Sarstedt, 2017). Even though Q^2 is important for evaluating the quality of structural models, reviewing 109 models revealed that Q^2 values were not reported in any of the reviewed models (Ringle, Sarstedt, & Straub, 2012; Hair, Sarstedt, Ringle, & Mena, 2012). The Q^2 value is identified based on a blindfolding procedure, a sample reuse technique that excludes some data and predicts the excluded data using the estimation of the model parameters (Hair, Ringle, & Sarstedt, 2011). The smaller the difference, the higher Q^2 and the predictive power of the structural model. Table 6.9 shows that the Q^2 value of each dependent variable are larger than zero, which demonstrates the predictive relevance of the dependent variables.

Table 6.9 Results of Cross-Validated Redundancy (Q^2)

Constructs	The Sum of the Squared Observations (SSO)	The Sum of the Squared Prediction Error (SSE)	Q^2 (=1-SSE/SSO)
PEOU	3,332.00	1,496.92	0.551
PU	4,165.00	1,992.08	0.522
BI	3,332.00	1,654.35	0.503
AU	2,499.00	1,831.11	0.267

Following the multi-stage procedure (Hair, Hult, Ringle, & Sarstedt, 2017; Henseler, Hubona, & Ray, 2017; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018), this section establishes the structural model assessment, and the researcher, therefore, proceeds with the model fit evaluation in the subsequent section.

6.4 Goodness-of-Fit

Goodness-of-fit (GoF) refers to how well a model fits the empirical data (Hair, Hult, Ringle, & Sarstedt, 2017). When the model has an ill fit, the model delivers less information than the data have (Henseler, Hubona, & Ray, 2017). PLS-SEM was originally developed for prediction without GoF indices (Sarstedt, Ringle, & Hair, 2017). Unlike PLS-SEM, users of CB-SEM depend, to a great degree, on GoF criteria (Ringle, Sarstedt, Mitchell, & Gudergan, 2018). Several GoF criteria have been produced for PLS-SEM, such as standardised root mean square residual (SRMR), normed fit index (NFI), and the root mean square residual covariance (RMS_{theta}).

However, researchers (Hair, Hult, Ringle, & Sarstedt, 2017; Sarstedt, Ringle, & Hair, 2017; Henseler, Hubona, & Ray, 2017; Henseler, Hubona, & Ray, 2016) have questioned the usefulness of using those GoF criteria for validating PLS-SEM models and argued that the criteria are more relevant to CB-SEM. Hair, Hult et al. (2017) claimed that GoF should not be transferred to PLS-SEM as the two techniques (CB-SEM and PLS-SEM) have different objectives and use different methods for estimating the model's values. CB-SEM tends to minimise the covariance matrix parameters to explain models, whereas PLS-SEM maximises the explained variance of dependent constructs to predict models (Henseler, Hubona, & Ray, 2017; Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Ringle, & Sarstedt, 2011). Explaining and predicting the model perspective are two different concepts in multivariate analysis (Sarstedt, Ringle, & Hair, 2017); therefore, Henseler and Sarstedt (2013) asserted that the term 'fit' varies between CB-SEM and PLS-SEM. Furthermore, those criteria in PLS-SEM are still in their early stages and need further development to be robust (Hair, Hult, Ringle, & Sarstedt, 2017). Hu and Bentler (1998) did not recommend the use of NFI as it increases for models with a large number of variables and indicators. Likewise, Henseler and Sarstedt (2013) empirically examined the global GoF index developed by Tenenhaus, Amato, and Vinzi (2004) and concluded that the index is not able to distinguish between valid and invalid PLS models. Consequently, it was recommended (Ringle, Sarstedt, Mitchell, & Gudergan, 2018; Henseler & Sarstedt, 2013; Sarstedt, Ringle, & Hair, 2017) that researchers should depend on the model's predictive criteria (e.g. path coefficients, R^2, and Q^2) rather than GoF criteria. This might explain why past reviews (Hair, Sarstedt, Ringle, & Mena, 2012; Ringle, Sarstedt, Mitchell, & Gudergan, 2018; Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018) found that GoF indices have not been used by the majority of PLS-SEM studies.

It has been argued (Henseler, Hubona, & Ray, 2017; Henseler, Hubona, & Ray, 2016) that SRMR (Hu & Bentler, 1998) is the only approximate model fit index for PLS-SEM validation, forming 'the sum of the squared differences between the model-implied and the empirical correlation matrix' (Henseler, Hubona, & Ray, 2016, p. 28). Researchers (Benitez-Amado, Henseler, & Castillo, 2017; Hair, Hult, Ringle, & Sarstedt, 2017; Henseler, Hubona, & Ray, 2017) recommended a cut-off point suggested by Hu and Bentler (1998) of 0.08 in order to indicate that the model has a good fit. The examination of the current model fit demonstrates that the SRMR is equal to 0.061 indicating that the model had a good fit.

Having examined the measurement model, structural models, and model fit, the subsequent stage is to examine the differences between students in the acceptance of LMS based on their demographic characteristics.

6.5 Differences in the Acceptance of Learning Management Systems

After assessing the relationships between the model's variables for the full set of data, the next step is to assess how the effect of the usability attributes on the acceptance and use of LMS differ between students in Saudi public universities based on their demographic characteristics, gender, age, level of education, and experience. This is important in order to provide answers for the second research question. The same guidelines employed to assess the measurement and structural models of the full data set (see Section 6.2 and 6.3) are used to evaluate the model for each demographic group (Hair, Hult, Ringle, & Sarstedt, 2017; Sarstedt, Henseler, & Ringle, 2011). Those criteria are summarised in Table 6.10.

Table 6.10 Criteria of the Model Assessment for Each Group

Assessment Type	Criteria	Guidelines	References
Measurement model	Indicator reliability	Loading ≥ 0.7	(Chin, 1998)
	Construct reliability	CA ≥ 0.7	(Cronbach, 1951)
		CR ≥ 0.7	(Hair, Hult, Ringle, & Sarstedt, 2017)
	Convergent validity	AVE ≥ 0.5	(Fornell & Larcker, 1981)
	Discriminant validity	√AVE > correlation with other constructs	(Fornell & Larcker, 1981)
Structural model	Path coefficients	Use bootstrapping with 10,000 sub-samples Significance: $p \leq 0.05$ Sign: one-tailed option	(Hair, Hollingsworth, Randolph, & Chong, 2017; Hair, Hult, Ringle, & Sarstedt, 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)

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

Given those criteria and guidelines, the reliability and validity tests and path coefficients are examined for each demographic group in the following subsections.

6.5.1 Gender

The gender variable was measured based on a nominal scale (categorical) , and, therefore, there is no need for further refinement (Henseler & Fassott, 2010; Hair, Black, Babin, & Anderson, 2014). The results show that 273 of respondents are male and 560 are female students. Each group exceeds the minimum sample size recommended by Hair, Hult et al. (2017) and Cohen (1992) (significance = 5%, minimum R^2 = 0.25, and sample size = 56) and by Kock and Hadaya (2018) (significance = 5%, minimum R^2 = 0.25, and sample size = 88). Having done these checks, the researcher then proceeded with the measurement and structural models' assessment.

Table 6.11 and Table 6.12 display the results of the measurement model assessment for male and female students using PLS algorithm with 1,000 iterations. As can be seen in Table 6.11, the loadings, Cronbach's alpha, composite reliability of each construct in both sub-samples exceed the cut-off point providing evidence of the high reliability of the constructs. Furthermore, AVE values are above 0.5, and, therefore, all constructs have adequate convergent validity.

Table 6.11 Results of Measurement Model Assessment for Gender

Indicators	Male Students				Female Students			
	Loadings > 0.7	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
AU01	0.930	0.904	0.940	0.839	0.917	0.865	0.917	0.788
AU03	0.935				0.910			
AU04	0.881				0.832			
BI01	0.892	0.925	0.946	0.815	0.938	0.956	0.968	0.884
BI02	0.907				0.950			
BI03	0.895				0.930			
BI04	0.919				0.943			
CQ01	0.828	0.841	0.893	0.677	0.768	0.827	0.885	0.659
CQ02	0.839				0.827			
CQ03	0.836				0.855			
CQ04	0.787				0.795			
EOA01	0.780	0.832	0.889	0.667	0.741	0.792	0.865	0.618
EOA02	0.831				0.736			
EOA03	0.886				0.871			
EOA04	0.765				0.789			
IA01	0.842	0.926	0.948	0.819	0.811	0.908	0.936	0.785
IA02	0.921				0.919			
IA03	0.946				0.927			
IA04	0.909				0.883			
LS01	0.835	0.900	0.926	0.715	0.778	0.854	0.895	0.631
LS02	0.852				0.772			
LS03	0.832				0.801			
LS04	0.840				0.801			
LS05	0.869				0.819			
PEOU01	0.905	0.925	0.947	0.817	0.886	0.898	0.929	0.765
PEOU02	0.902				0.865			
PEOU03	0.897				0.844			
PEOU04	0.913				0.903			
PU01	0.900	0.946	0.959	0.824	0.874	0.945	0.958	0.820
PU02	0.909				0.923			
PU03	0.935				0.928			
PU04	0.898				0.914			
PU05	0.895				0.886			
SI01	0.835	0.898	0.929	0.766	0.814	0.865	0.907	0.710
SI02	0.893				0.849			
SI03	0.892				0.856			

Indicators	Male Students				Female Students			
	Loadings > 0.7	CA > 0.7	CR > 0.7	AVE > 0.5	Loadings > 0.7	CA > 0.7	CR > 0.7	AVE > 0.5
SI04	0.880				0.851			
SL01	0.897	0.875	0.914	0.728	0.874	0.867	0.909	0.715
SL02	0.852				0.846			
SL03	0.851				0.875			
SL04	0.810				0.784			
SN01	0.883	0.888	0.923	0.751	0.895	0.876	0.916	0.734
SN02	0.893				0.896			
SN03	0.917				0.916			
SN04	0.765				0.704			
VD01	0.891	0.894	0.926	0.759	0.867	0.870	0.911	0.719
VD02	0.881				0.849			
VD03	0.866				0.847			
VD04	0.846				0.829			

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

The values of Fornell-Larcker discriminant validity for both genders are shown in Table 6.12. The results 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. By doing so, the measurement model assessment is successful for both sub-samples.

Table 6.12 Results of Fornell-Larcker Discriminant Validity for Gender

Male Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	**0.92**											
BI	0.58	**0.90**										
CQ	0.56	0.59	**0.82**									
EOA	0.42	0.53	0.63	**0.82**								
IA	0.59	0.58	0.69	0.53	**0.91**							
LS	0.57	0.56	0.75	0.54	0.73	**0.85**						
PEOU	0.56	0.69	0.73	0.65	0.71	0.68	**0.90**					
PU	0.63	0.76	0.67	0.50	0.74	0.72	0.75	**0.91**				
SI	0.60	0.60	0.70	0.54	0.75	0.79	0.73	0.74	**0.88**			
SL	0.56	0.64	0.65	0.64	0.72	0.64	0.84	0.68	0.68	**0.85**		
SN	0.54	0.64	0.73	0.68	0.73	0.71	0.76	0.66	0.68	0.74	**0.87**	
VD	0.49	0.55	0.72	0.57	0.65	0.68	0.70	0.61	0.69	0.65	0.76	**0.87**
Female Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	**0.89**											
BI	0.59	**0.94**										
CQ	0.45	0.54	**0.81**									
EOA	0.36	0.46	0.51	**0.79**								
IA	0.43	0.61	0.63	0.52	**0.89**							
LS	0.45	0.53	0.69	0.52	0.67	**0.80**						
PEOU	0.55	0.66	0.62	0.56	0.69	0.62	**0.88**					
PU	0.59	0.77	0.59	0.47	0.70	0.65	0.70	**0.91**				
SI	0.45	0.61	0.61	0.50	0.72	0.68	0.62	0.71	**0.84**			
SL	0.42	0.57	0.59	0.55	0.66	0.55	0.77	0.60	0.54	**0.85**		

SN	0.43	0.50	0.63	0.58	0.63	0.58	0.71	0.51	0.53	0.65	**0.86**	
VD	0.33	0.45	0.64	0.53	0.57	0.57	0.62	0.45	0.52	0.56	0.72	**0.85**

Table 6.13 presents the path analysis of the two sub-samples using the bootstrapping technique with 10,000 sub-samples, as recommended by Hair, Hollingsworth et al. (2017) and Hair, Hult et al. (2017). In terms of the male students' sample, the path coefficients are not similar to the overall sample. More accurately, the paths SN → PEOU, EOA → PEOU, IA → PEOU, CQ → PU, and VD → PU are different. The highest significant path is BI → AU ($\beta = 0.583$), whereas the lowest significant path is SI → PEOU ($\beta = 0.146$). Regarding female students, there are somewhat different results from the pooled sample in CQ → PEOU, LS → PEOU, EOA → PEOU, and SN → PU. The strongest significant path is PU → BI ($\beta = 0.613$), whereas the weakest significant path is CQ → PU ($\beta = 0.070$). For both male and female students, the variance explained by the independent variables is highest in PEOU, followed by PU and BI.

Table 6.13 Results of Path Analysis for Gender

Paths	**Male Students**		**Female Students**		**Pooled Sample**	
	β	**Adj. R^2**	**β**	**Adj. R^2**	**β**	**Adj. R^2**
CQ → PEOU	0.182^{***}	0.782	0.001	0.708	0.055^{*}	0.734
LS → PEOU	-0.022		0.081^{*}		0.046	
VD → PEOU	0.061		0.044		0.053	
SN → PEOU	0.076		0.223^{***}		0.176^{***}	
EOA → PEOU	0.059		0.038		0.054^{*}	
SI → PEOU	0.146^{*}		0.112^{**}		0.124^{***}	
IA → PEOU	0.006		0.092^{*}		0.059^{*}	
SL → PEOU	0.500^{***}		0.416^{***}		0.440^{***}	
CQ → PU	0.048	0.677	0.070^{*}	0.653	0.065^{*}	0.667
LS → PU	0.183^{**}		0.146^{***}		0.158^{***}	
VD → PU	-0.053		-0.121^{**}		-0.102^{**}	
SN → PU	-0.004		-0.089^{*}		-0.065	
EOA → PU	-0.053		0.004		-0.014	
SI → PU	0.198^{**}		0.301^{***}		0.272^{***}	
IA → PU	0.250^{***}		0.193^{***}		0.220^{***}	
SL → PU	-0.011		0.026		0.014	
PEOU → PU	0.349^{***}		0.364^{***}		0.352^{***}	
PEOU → BI	0.280^{***}	0.614	0.224^{***}	0.618	0.239^{***}	0.615
PU → BI	0.554^{***}		0.613^{***}		0.595^{***}	
BI → AU	0.583^{***}	0.338	0.592^{***}	0.350	0.590^{***}	0.347

*** $p<.001$, ** $p<.01$, * $p<.05$, β: path coefficient, Adj. R^2: adjusted coefficient of determination

6.5.2 Age

The age variable was measured using a ratio scale, and, therefore, there is a need for further refinement (Henseler & Fassott, 2010; Hair, Black, Babin, & Anderson, 2014). It was concluded (Iacobucci, Posavac, Karde, Schneider, & Popovich, 2015) that the median-split method is quite common in analysis and there is no strong reason that prevents one from using it. Using the median-split procedures (median = 21), there are 442 students within the younger students' group (median <= 21) and 391 students within the older students' group (median > 21). Each group exceeds the minimum sample size recommended by Hair, Hult et al. (2017), Cohen (1992), and Kock and Hadaya (2018). Thus, the researcher proceeded with the measurement and structural models' assessment.

Table 6.14 and Table 6.15 display the results of the measurement model assessment for younger and older students using the PLS algorithm with 1,000 iterations. As can be seen, the loadings, Cronbach's alpha, composite reliability, convergent validity, and discriminant validity of each construct in both sub-samples exceed the cut-off point providing evidence of the high reliability and validity of the constructs.

Table 6.14 Results of Measurement Model Assessment for Age

Indicators	**Younger Students**				**Older Students**			
	Loadings > 0.7	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
AU01	0.924	0.881	0.926	0.808	0.918	0.878	0.925	0.804
AU03	0.916				0.924			
AU04	0.854				0.847			
BI01	0.922	0.944	0.960	0.857	0.921	0.947	0.962	0.862
BI02	0.932				0.937			
BI03	0.914				0.923			
BI04	0.934				0.934			
CQ01	0.817	0.843	0.895	0.681	0.762	0.825	0.884	0.657
CQ02	0.842				0.823			
CQ03	0.845				0.857			
CQ04	0.794				0.797			
EOA01	0.751	0.799	0.869	0.624	0.754	0.818	0.881	0.649
EOA02	0.749				0.796			
EOA03	0.868				0.889			
EOA04	0.786				0.777			
IA01	0.821	0.910	0.937	0.789	0.832	0.924	0.947	0.816

Indicators	Younger Students				Older Students			
	Loadings > 0.7	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
IA02	0.908				0.938			
IA03	0.931				0.940			
IA04	0.889				0.899			
LS01	0.823	0.890	0.919	0.695	0.774	0.849	0.892	0.623
LS02	0.787				0.833			
LS03	0.837				0.773			
LS04	0.853				0.768			
LS05	0.868				0.796			
PEOU01	0.898	0.913	0.939	0.794	0.883	0.901	0.931	0.771
PEOU02	0.899				0.846			
PEOU03	0.852				0.885			
PEOU04	0.914				0.898			
PU01	0.894	0.948	0.960	0.827	0.869	0.943	0.957	0.816
PU02	0.919				0.918			
PU03	0.936				0.924			
PU04	0.906				0.913			
PU05	0.890				0.891			
SI01	0.818	0.885	0.920	0.743	0.830	0.869	0.910	0.718
SI02	0.881				0.851			
SI03	0.869				0.873			
SI04	0.877				0.834			
SL01	0.886	0.880	0.918	0.736	0.885	0.862	0.906	0.707
SL02	0.859				0.842			
SL03	0.887				0.842			
SL04	0.797				0.792			
SN01	0.901	0.890	0.925	0.756	0.876	0.868	0.911	0.721
SN02	0.906				0.882			
SN03	0.920				0.911			
SN04	0.738				0.716			
VD01	0.892	0.890	0.924	0.752	0.857	0.861	0.906	0.706
VD02	0.853				0.872			
VD03	0.866				0.833			
VD04	0.856				0.797			

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

Table 6.15 Results of Fornell-Larcker Discriminant Validity for Age

Younger Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	**0.90**											
BI	0.61	**0.93**										
CQ	0.54	0.60	**0.83**									
EOA	0.43	0.51	0.56	**0.79**								
IA	0.57	0.67	0.71	0.55	**0.89**							
LS	0.57	0.58	0.75	0.55	0.70	**0.83**						
PEOU	0.59	0.68	0.69	0.60	0.74	0.65	**0.89**					
PU	0.65	0.79	0.65	0.50	0.76	0.69	0.71	**0.91**				
SI	0.60	0.63	0.67	0.54	0.77	0.75	0.67	0.76	**0.86**			
SL	0.52	0.64	0.64	0.57	0.72	0.59	0.83	0.65	0.62	**0.86**		
SN	0.55	0.60	0.73	0.66	0.72	0.64	0.76	0.60	0.62	0.71	**0.87**	

Younger Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
VD	0.49	0.56	0.73	0.60	0.63	0.62	0.68	0.53	0.62	0.64	0.77	**0.87**
Older Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	**0.90**											
BI	0.56	**0.93**										
CQ	0.43	0.50	**0.81**									
EOA	0.33	0.46	0.55	**0.81**								
IA	0.40	0.50	0.59	0.50	**0.90**							
LS	0.40	0.49	0.68	0.51	0.69	**0.79**						
PEOU	0.50	0.66	0.63	0.60	0.64	0.65	**0.88**					
PU	0.56	0.74	0.59	0.48	0.65	0.67	0.73	**0.90**				
SI	0.39	0.56	0.62	0.49	0.69	0.69	0.65	0.68	**0.85**			
SL	0.43	0.54	0.59	0.62	0.64	0.60	0.77	0.60	0.57	**0.84**		
SN	0.37	0.47	0.58	0.57	0.59	0.62	0.68	0.52	0.55	0.65	**0.85**	
VD	0.27	0.38	0.60	0.49	0.57	0.59	0.60	0.49	0.55	0.54	0.68	**0.84**

Table 6.16 presents the path analysis of the two sub-samples. In terms of the younger students' sample, four path coefficients are varied from the pooled sample CQ → PEOU, EOA → PEOU, SI → PEOU, and CQ → PU. The highest significant path is PU → BI (β = 0.620), whereas the lowest significant path is IA → PEOU (β = 0.088). The variance explained by the independent variables is highest in PEOU (R^2 = 0.762 or 76.2%) followed by PU (R^2 = 0.690 or 69.0%). Regarding older students, the paths EOA → PEOU, IA → PEOU, CQ → PU, and VD → PU are different from the pooled sample. The strongest significant path is BI → AU (β = 0.564) followed by PU → BI (β = 0.560), whereas the weakest significant path is CQ → PEOU (β = 0.075) followed by SN → PEOU (β = 0.145). The explained variance is strongest in PEOU (R^2 = 0.692 or 69.2%) followed by PU (R^2 = 0.637 or 63.7%).

Table 6.16 Results of Path Analysis for Age

Paths	**Younger Students**		**Older Students**		**Pooled Sample**	
	β	**Adj. R^2**	**β**	**Adj. R^2**	**β**	**Adj. R^2**
CQ → PEOU	0.025	0.762	0.075^{*}	0.692	0.055^{*}	0.734
LS → PEOU	0.056		0.063		0.046	
VD → PEOU	0.056		0.056		0.053	
SN → PEOU	0.189^{***}		0.145^{**}		0.176^{***}	
EOA → PEOU	0.047		0.072		0.054^{*}	
SI → PEOU	0.073		0.166^{***}		0.124^{***}	
IA → PEOU	0.088^{*}		0.027		0.059^{*}	
SL → PEOU	0.471^{***}		0.405^{***}		0.440^{***}	
CQ → PU	0.074	0.690	0.052	0.637	0.065^{*}	0.667
LS → PU	0.132^{**}		0.196^{***}		0.158^{***}	
VD → PU	-0.128^{**}		-0.061		-0.102^{**}	
SN → PU	-0.064		-0.082		-0.065	

Paths	Younger Students		Older Students		Pooled Sample	
	β	**Adj. R^2**	**β**	**Adj. R^2**	**β**	**Adj. R^2**
EOA → PU	-0.008	0.643	-0.013	0.574	-0.014	0.615
SI → PU	0.309^{***}		0.211^{***}		0.272^{***}	
IA → PU	0.283^{***}		0.154^{**}		0.220^{***}	
SL → PU	0.047		-0.017		0.014	
PEOU → PU	0.262^{***}		0.447^{***}		0.352^{***}	
PEOU → BI	0.233^{***}	0.643	0.246^{***}	0.574	0.239^{***}	0.615
PU → BI	0.620^{***}		0.560^{***}		0.595^{***}	
BI → AU	0.605^{***}	0.365	0.564^{***}	0.317	0.590^{***}	0.347

*** p<.001, ** p<.01, * p<.05, β: path coefficient, Adj. R^2: adjusted coefficient of determination

6.5.3 Level of Education

The level of education variable was measured based on a nominal scale (categorical) , and, therefore, there is no need for further refinement (Henseler & Fassott, 2010; Hair, Black, Babin, & Anderson, 2014). The results show that 690 of the respondents are undergraduate and 143 are postgraduate students. Each group exceeds the minimum sample size recommended by Hair, Hult et al. (2017), Cohen (1992), and Kock and Hadaya (2018). The investigation therefore proceeded with the measurement and structural models' assessment.

Table 6.17 and Table 6.18 display the results of the measurement model assessment for the undergraduate and the postgraduate students using the PLS algorithm with 1,000 iterations. The loadings, Cronbach's alpha, composite reliability of each construct in both sub-samples exceed the cut-off point except the loadings of LS04 (0.625) and LS05 (0.663) for the postgraduate students. Consequently, both indicators were eliminated for the two groups before proceeding with the discriminant validity assessment. Furthermore, AVE values are above 0.5, and, therefore, all constructs have an adequate convergent validity.

Table 6.17 Results of Measurement Model Assessment for Education

Indicators	Undergraduate Students				Postgraduate Students			
	Loadings > 0.7	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
AU01	0.921	0.882	0.927	0.809	0.936	0.869	0.918	0.791
AU03	0.917				0.937			
AU04	0.860				0.786			

Indicators	Undergraduate Students				Postgraduate Students			
	Loadings > 0.7	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
BI01	0.919	0.944	0.960	0.856	0.941	0.955	0.968	0.882
BI02	0.933				0.943			
BI03	0.915				0.937			
BI04	0.934				0.935			
CQ01	0.795	0.831	0.888	0.665	0.793	0.857	0.903	0.700
CQ02	0.833				0.850			
CQ03	0.844				0.884			
CQ04	0.788				0.817			
EOA01	0.760	0.802	0.871	0.629	0.768	0.838	0.892	0.675
EOA02	0.780				0.752			
EOA03	0.864				0.927			
EOA04	0.764				0.828			
IA01	0.826	0.914	0.940	0.796	0.826	0.928	0.949	0.824
IA02	0.917				0.943			
IA03	0.933				0.941			
IA04	0.889				0.916			
LS01	0.808	0.883	0.914	0.682	0.764	0.793	0.853	0.539
LS02	0.807				0.793			
LS03	0.814				0.807			
LS04	0.838				0.625			
LS05	0.860				0.663			
PEOU01	0.894	0.910	0.937	0.787	0.881	0.900	0.931	0.770
PEOU02	0.882				0.846			
PEOU03	0.863				0.885			
PEOU04	0.909				0.898			
PU01	0.887	0.946	0.959	0.823	0.867	0.942	0.956	0.813
PU02	0.919				0.916			
PU03	0.932				0.922			
PU04	0.906				0.928			
PU05	0.893				0.874			
SI01	0.823	0.878	0.916	0.733	0.824	0.869	0.910	0.718
SI02	0.865				0.876			
SI03	0.870				0.872			
SI04	0.865				0.815			
SL01	0.886	0.872	0.912	0.723	0.880	0.875	0.914	0.728
SL02	0.850				0.856			
SL03	0.868				0.874			
SL04	0.795				0.800			
SN01	0.894	0.886	0.922	0.749	0.867	0.854	0.903	0.700
SN02	0.900				0.859			
SN03	0.918				0.897			
SN04	0.736				0.712			
VD01	0.884	0.882	0.918	0.738	0.852	0.863	0.907	0.708
VD02	0.858				0.864			
VD03	0.856				0.847			
VD04	0.838				0.802			

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

The values of Fornell-Larcker discriminant validity for the undergraduate and the postgraduate students are shown in Table 6.18. The results 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. This indicates that the measurement model assessment is successful for both sub-samples.

Table 6.18 Results of Fornell-Larcker Discriminant Validity for Education

Undergraduate Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	**0.90**											
BI	0.62	**0.93**										
CQ	0.50	0.56	**0.82**									
EOA	0.39	0.48	0.55	**0.79**								
IA	0.52	0.61	0.67	0.53	**0.89**							
LS	0.50	0.53	0.71	0.49	0.66	**0.86**						
PEOU	0.57	0.67	0.66	0.59	0.70	0.61	**0.89**					
PU	0.62	0.77	0.62	0.47	0.72	0.68	0.72	**0.91**				
SI	0.53	0.61	0.64	0.50	0.74	0.72	0.66	0.74	**0.86**			
SL	0.50	0.61	0.63	0.58	0.70	0.57	0.81	0.64	0.61	**0.85**		
SN	0.51	0.56	0.68	0.63	0.68	0.59	0.74	0.59	0.61	0.71	**0.87**	
VD	0.41	0.50	0.69	0.58	0.62	0.57	0.65	0.52	0.61	0.62	0.75	**0.86**
Postgraduate Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	**0.89**											
BI	0.44	**0.94**										
CQ	0.46	0.55	**0.84**									
EOA	0.34	0.55	0.57	**0.82**								
IA	0.38	0.49	0.61	0.55	**0.91**							
LS	0.42	0.45	0.67	0.53	0.64	**0.84**						
PEOU	0.46	0.63	0.72	0.69	0.69	0.66	**0.88**					
PU	0.53	0.73	0.62	0.59	0.67	0.64	0.75	**0.90**				
SI	0.43	0.52	0.67	0.62	0.70	0.67	0.68	0.65	**0.85**			
SL	0.35	0.47	0.57	0.63	0.60	0.47	0.73	0.54	0.53	**0.85**		
SN	0.25	0.44	0.56	0.55	0.57	0.43	0.66	0.44	0.48	0.54	**0.84**	
VD	0.29	0.43	0.56	0.40	0.51	0.43	0.62	0.48	0.47	0.47	0.62	**0.84**

Table 6.19 presents the path analysis of the two sub-samples. In terms of the undergraduate students' sample, the path coefficients are not similar to the overall sample. More accurately, the paths CQ → PEOU, EOA → PEOU, IA → PEOU, and CQ → PU are different. The highest significant path is BI → AU (β = 0.616), whereas the lowest significant path is VD → PU (β = -0.122). Regarding the postgraduate students, there are quite different results from the pooled sample. Nine paths LS → PEOU, VD → PEOU, SI → PEOU, IA → PEOU, CQ → PU, LS → PU, VD → PU, SN → PU, and SI → PU are varied. The strongest significant path is PU → BI (β =

0.583), whereas the weakest significant path is SN → PEOU (β = 0.123). For both the undergraduate and the postgraduate students' sample, the variance explained by the independent variables is highest in PEOU, followed by PU and BI.

Table 6.19 Results of Path Analysis for Level of Education

Paths	Undergraduates		Postgraduates		Pooled Sample	
	β	Adj. R^2	β	Adj. R^2	β	Adj. R^2
CQ → PEOU	0.042	0.734	0.142^{**}	0.756	0.055^{*}	0.734
LS → PEOU	0.024		0.154^{**}		0.046	
VD → PEOU	0.044		0.146^{**}		0.053	
SN → PEOU	0.188^{***}		0.123^{*}		0.176^{***}	
EOA → PEOU	0.045		0.152^{*}		0.054^{*}	
SI → PEOU	0.127^{***}		0.059		0.124^{***}	
IA → PEOU	0.054		0.078		0.059^{*}	
SL → PEOU	0.468^{***}		0.267^{***}		0.440^{***}	
CQ → PU	0.051	0.678	0.051	0.626	0.065^{*}	0.667
LS → PU	0.184^{***}		0.099		0.158^{***}	
VD → PU	-0.122^{**}		0.046		-0.102^{**}	
SN → PU	-0.036		-0.178^{*}		-0.065	
EOA → PU	-0.021		0.127		-0.014	
SI → PU	0.283^{***}		0.084		0.272^{***}	
IA → PU	0.220^{***}		0.241^{**}		0.220^{***}	
SL → PU	0.026		-0.096		0.014	
PEOU → PU	0.328^{***}		0.495^{***}		0.352^{***}	
PEOU → BI	0.245^{***}	0.625	0.191^{*}	0.536	0.239^{***}	0.615
PU → BI	0.597^{***}		0.583^{***}		0.595^{***}	
BI → AU	0.616^{***}	0.379	0.442^{***}	0.190	0.590^{***}	0.347

*** p<.001, ** p<.01, * p<.05, β: path coefficient, Adj. R^2: adjusted coefficient of determination

6.5.4 Experience

The experience variable was measured using a ratio scale, and, therefore, there is a need for further refinement (Henseler & Fassott, 2010; Hair, Black, Babin, & Anderson, 2014). Using the median-split procedures (median = 2.0), there are 509 students within the less-experienced group (median <= 2.0) and 324 students within the more-experienced group (median > 2.0). Each group exceeds the minimum sample size recommended by Hair, Hult et al. (2017), Cohen (1992), and Kock and Hadaya (2018). Having done these checks, the researcher then proceeded with the measurement and structural models' assessment.

Table 6.20 and Table 6.21 display the results of the measurement model assessment for less-experienced and more-experienced students using the PLS algorithm with 1,000 iterations. As can be seen, the loadings, Cronbach's alpha, composite reliability, convergent validity, and discriminant validity of each construct in both sub-samples exceed the cut-off point providing evidence of the high reliability and validity of the constructs.

Table 6.20 Results of Measurement Model Assessment for Experience

Indicators	**Less-Experienced Students**				**More-Experienced Students**			
	Loadings > 0.7	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**	**Loadings > 0.7**	**CA > 0.7**	**CR > 0.7**	**AVE > 0.5**
AU01	0.925	0.881	0.927	0.808	0.915	0.871	0.920	0.794
AU03	0.918				0.920			
AU04	0.852				0.836			
BI01	0.934	0.946	0.961	0.860	0.896	0.943	0.959	0.854
BI02	0.930				0.941			
BI03	0.915				0.919			
BI04	0.930				0.940			
CQ01	0.817	0.843	0.895	0.680	0.755	0.823	0.883	0.655
CQ02	0.842				0.821			
CQ03	0.843				0.861			
CQ04	0.795				0.797			
EOA01	0.750	0.801	0.871	0.628	0.765	0.815	0.879	0.644
EOA02	0.753				0.801			
EOA03	0.879				0.869			
EOA04	0.782				0.772			
IA01	0.834	0.918	0.942	0.804	0.809	0.913	0.939	0.795
IA02	0.915				0.930			
IA03	0.936				0.932			
IA04	0.897				0.890			
LS01	0.829	0.885	0.916	0.685	0.752	0.855	0.896	0.633
LS02	0.810				0.803			
LS03	0.828				0.784			
LS04	0.824				0.811			
LS05	0.846				0.825			
PEOU01	0.905	0.914	0.939	0.795	0.868	0.897	0.929	0.765
PEOU02	0.890				0.856			
PEOU03	0.854				0.886			
PEOU04	0.916				0.888			
PU01	0.895	0.950	0.961	0.832	0.864	0.939	0.954	0.804
PU02	0.922				0.913			
PU03	0.934				0.927			
PU04	0.911				0.907			
PU05	0.900				0.872			
SI01	0.823	0.891	0.925	0.755	0.822	0.855	0.902	0.696
SI02	0.893				0.822			
SI03	0.888				0.848			

SI04	0.869				0.845			
SL01	0.889	0.883	0.919	0.740	0.875	0.848	0.898	0.688
SL02	0.857				0.836			
SL03	0.882				0.842			
SL04	0.811				0.761			
SN01	0.902	0.888	0.924	0.754	0.869	0.868	0.911	0.720
SN02	0.907				0.881			
SN03	0.919				0.910			
SN04	0.731				0.721			
VD01	0.881	0.883	0.919	0.740	0.867	0.871	0.912	0.722
VD02	0.859				0.862			
VD03	0.853				0.854			
VD04	0.847				0.813			

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

Table 6.21 Results of Fornell-Larcker Discriminant Validity for Experience

Less-Experienced Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	**0.90**											
BI	0.61	**0.93**										
CQ	0.54	0.60	**0.83**									
EOA	0.41	0.52	0.59	**0.79**								
IA	0.53	0.65	0.68	0.54	**0.90**							
LS	0.55	0.58	0.75	0.55	0.71	**0.83**						
PEOU	0.58	0.68	0.69	0.63	0.73	0.68	**0.89**					
PU	0.65	0.80	0.66	0.52	0.76	0.71	0.74	**0.91**				
SI	0.57	0.65	0.68	0.55	0.75	0.75	0.68	0.76	**0.87**			
SL	0.49	0.61	0.62	0.59	0.69	0.61	0.82	0.65	0.61	**0.86**		
SN	0.51	0.58	0.71	0.63	0.70	0.67	0.74	0.62	0.61	0.68	**0.87**	
VD	0.44	0.52	0.70	0.57	0.60	0.63	0.65	0.53	0.61	0.61	0.75	**0.86**
More-Experienced Students												
	AU	**BI**	**CQ**	**EOA**	**IA**	**LS**	**PEOU**	**PU**	**SI**	**SL**	**SN**	**VD**
AU	**0.89**											
BI	0.53	**0.92**										
CQ	0.42	0.48	**0.81**									
EOA	0.31	0.39	0.50	**0.80**								
IA	0.43	0.51	0.62	0.51	**0.89**							
LS	0.43	0.49	0.68	0.50	0.67	**0.80**						
PEOU	0.50	0.64	0.61	0.54	0.65	0.61	**0.88**					
PU	0.54	0.71	0.55	0.42	0.63	0.64	0.69	**0.90**				
SI	0.40	0.54	0.59	0.45	0.72	0.69	0.63	0.67	**0.83**			
SL	0.43	0.56	0.63	0.57	0.68	0.58	0.75	0.59	0.57	**0.83**		
SN	0.39	0.46	0.59	0.58	0.61	0.58	0.70	0.48	0.55	0.68	**0.85**	
VD	0.29	0.40	0.63	0.50	0.60	0.59	0.63	0.47	0.54	0.58	0.69	**0.85**

Table 6.22 presents the path coefficients of the two sub-samples. In terms of the less-experienced students' sample, the significant path coefficients are identical to the overall sample. The highest significant path is PU → BI ($\beta = 0.661$), whereas the lowest significant path is EOA → PEOU ($\beta = 0.066$). The variance explained by the independent variables is highest in PEOU ($R^2 = 0.768$ or 76.8%) followed by PU (R^2

= 0.707 or 70.7%). Regarding more-experienced students, seven paths CQ → PEOU, VD → PEOU, EOA → PEOU, IA → PEOU, CQ → PU, VD → PU, and SN → PU vary from the pooled sample. The strongest significant path is BI → AU (β = 0.526), whereas the weakest significant path is VD → PEOU (β = 0.112). The explained variance is strongest in PEOU (R^2 = 0.663 or 66.3%) followed by PU (R^2 = 0.596 or 59.6%).

Table 6.22 Results of Path Analysis for Experience

Paths	Less-Experienced Students		More-Experienced Students		Pooled Sample	
	β	**Adj. R^2**	**β**	**Adj. R^2**	**β**	**Adj. R^2**
CQ → PEOU	0.077*	0.768	0.038	0.663	0.055*	0.734
LS → PEOU	0.050		0.041		0.046	
VD → PEOU	0.016		0.112*		0.053	
SN → PEOU	0.162***		0.193***		0.176***	
EOA → PEOU	0.066*		0.039		0.054*	
SI → PEOU	0.098*		0.161**		0.124***	
IA → PEOU	0.077*		0.029		0.059*	
SL → PEOU	0.473***		0.370***		0.440***	
CQ → PU	0.075*	0.707	0.038	0.596	0.065*	0.667
LS → PU	0.128**		0.217***		0.158***	
VD → PU	-0.123**		-0.064		-0.102**	
SN → PU	-0.021		-0.161**		-0.065	
EOA → PU	-0.015		-0.009		-0.014	
SI → PU	0.296***		0.244***		0.272***	
IA → PU	0.279***		0.115*		0.220***	
SL → PU	-0.002		0.069		0.014	
PEOU → PU	0.302***		0.410***		0.352***	
PEOU → BI	0.190***	0.656	0.301***	0.542	0.239***	0.615
PU → BI	0.661***		0.499***		0.595***	
BI → AU	0.609***	0.370	0.526***	0.275	0.590***	0.347

*** p<.001, ** p<.01, * p<.05, β: path coefficient, Adj. R^2: adjusted coefficient of determination

Having investigated the measurement and structural models of each demographic group, the next section examines the moderating effect of the demographic characteristics on the relationships in the proposed model.

6.6 Moderating Effect

After assessing the relationships between the model's variables, the next step is to assess the moderating effect of four demographic characteristics, namely gender, age, level of education, and experience on the proposed relationships. This is important to provide answers for the third research question. The moderating influence occurs when a variable affects the strength or direction of a relationship between two latent variables (Henseler & Fassott, 2010). The observed heterogeneity, depending on observable characteristics (e.g. age and gender), can be measured using the multigroup analysis (MGA) (Hair, Hult, Ringle, & Sarstedt, 2017; Sarstedt, Henseler, & Ringle, 2011). Therefore, the MGA was used for examining the moderating effect of the four demographic characteristics on the relationships in this study.

There are prerequisites for examining the significant differences between groups using the MGA (Hair, Sarstedt, Ringle, & Gudergan, 2018; Matthews, 2017; Henseler, Ringle, & Sarstedt, 2016). Table 6.23 summarises the criteria used for evaluating the MGA in this study. First, each group in the moderator variable must be evaluated using the measurement model criteria, which were discussed previously in this chapter (see Section 6.5) (Hair, Black, Babin, & Anderson, 2014; Hair, Hult, Ringle, & Sarstedt, 2017). After establishing the measurement model, the analysis of MGA requires assessing the measurement invariance (Hair, Sarstedt, Ringle, & Gudergan, 2018; Matthews, 2017; Henseler, Ringle, & Sarstedt, 2016; Sarstedt, Henseler, & Ringle, 2011) to ensure that the difference between groups is not generated from using different measures across the groups (Hair, Sarstedt, Ringle, & Gudergan, 2018). The measurement invariance of the composite models approach (MICOM) (Henseler, Ringle, & Sarstedt, 2016) has been employed in PLS-SEM to establish measurement invariance, a three-step procedure: (1) ‘configural invariance’, (2) ‘compositional invariance’, and (3) ‘equality of composite mean values and variances’. Finally, the analysis of the significant difference in path coefficients between the groups is conducted (Hair, Black, Babin, & Anderson, 2014; Hair, Hult, Ringle, & Sarstedt, 2017).

Table 6.23 Criteria of the MGA

Validity Type	Criteria	Guidelines	References
Measurement invariance of the	Configural invariance	Use the same indicators, scale, treatment, and	(Henseler, Ringle, & Sarstedt, 2016)

Validity Type	Criteria	Guidelines	References
composite models (MICOM)		algorithm for both groups	
	Compositional invariance	correlation ≥ 5% quantile	(Matthews, 2017; Henseler, Ringle, & Sarstedt, 2016; Hair, Sarstedt, Ringle, & Gudergan, 2018)
Significant differences in path coefficients	Permutation test	Permutations = 5,000 Significance: $p \leq 0.05$ Two-tailed option	(Matthews, 2017)

Given those criteria, the measurement invariance and significant differences in path coefficients are examined for each moderator in the following subsections.

6.6.1 Gender

The gender moderator variable was measured based on a nominal scale (categorical) , and, therefore, there is no need for further refinement (Henseler & Fassott, 2010; Hair, Black, Babin, & Anderson, 2014). The results show that 273 of respondents are male and 560 are female students. Each group exceeds the minimum sample size recommended by Hair, Hult et al. (2017), Cohen (1992), and Kock and Hadaya (2018). Having done these checks, the researcher then proceeded with the other prerequisites of the MGA.

Next, the MICOM procedure was executed. For step 1, configural invariance requires the compared groups to be measured using the same indicators, scale, treatment, and algorithm settings (Henseler, Ringle, & Sarstedt, 2016), and, therefore, the configural invariance is established for the gender moderator variable. Regarding step 2 of MICOM, compositional invariance is fulfilled when the construct scores are not significantly different across the groups (Hair, Hult, Ringle, & Sarstedt, 2017). Thus, compositional invariance assesses the correlation between the construct scores of the compared groups (Hair, Sarstedt, Ringle, & Gudergan, 2018). As the permutation test in SmartPLS 3 is capable of assessing compositional invariance (Hair, Sarstedt, Ringle, & Gudergan, 2018; Matthews, 2017), it was run with 5,000 permutations and two-tailed option at a 0.05 significance level, as recommended by Matthews (2017).

Table 6.24 shows that the compositional invariance is demonstrated for the gender moderator variable, as the original correlation between construct scores is larger or equal to the 5% quantile correlation (Matthews, 2017; Henseler, Ringle, & Sarstedt, 2016; Hair, Sarstedt, Ringle, & Gudergan, 2018). When the configural and compositional invariance are met, partial measurement invariance is evident, and researchers can proceed to compare the groups using the MGA (Hair, Sarstedt, Ringle, & Gudergan, 2018; Henseler, Ringle, & Sarstedt, 2016).

Table 6.24 Results of Compositional Invariance for Gender

Constructs	Original Correlation	Correlation Permutation Mean	5% Quantile Correlation	Permutation p-Value
AU	1.000	1.000	0.999	0.702
BI	1.000	1.000	1.000	0.024
CQ	1.000	1.000	0.999	0.702
EOA	0.999	0.999	0.997	0.420
IA	1.000	1.000	1.000	0.987
LS	1.000	1.000	0.999	0.379
PEOU	1.000	1.000	1.000	0.713
PU	1.000	1.000	1.000	0.846
SI	1.000	1.000	1.000	0.100
SL	1.000	1.000	1.000	0.564
SN	1.000	1.000	0.999	0.361
VD	1.000	1.000	0.999	0.936

After establishing the measurement invariance, the statistically significant differences between male and female students were examined. Unlike the liberal parametric test and the one-tailed PLS-MGA, the permutation test is non-parametric, two-tailed, more conservative, and recommended by researchers (Hair, Sarstedt, Ringle, & Gudergan, 2018; Matthews, 2017; Sarstedt, Henseler, & Ringle, 2011). Therefore, the permutation test was employed for this study and run with 5,000 permutations and a two-tailed option at a 0.05 significance level, as suggested by Matthews (2017). Table 6.25 shows that gender moderates only one relationship between CQ → PEOU (supporting H21a). More specifically, this relationship is stronger for male compared with female students. Therefore, the findings suggest accepting hypothesis H21a – gender moderates the effect of CQ on students' PEOU of LMS.

Table 6.25 Results of Permutation Test for Gender

Paths	β for Male Students	β for Female Students	Difference	Permutation p-Value
CQ → PEOU	0.182***	0.001	0.181*	0.035
LS → PEOU	-0.022	0.081*	-0.103	0.138
VD → PEOU	0.061	0.044	0.017	0.819
SN → PEOU	0.076	0.223***	-0.147	0.056
EOA → PEOU	0.059	0.038	0.021	0.725
SI → PEOU	0.146*	0.112**	0.033	0.628
IA → PEOU	0.006	0.092*	-0.085	0.248
SL → PEOU	0.500***	0.416***	0.084	0.212
CQ → PU	0.048	0.070*	-0.022	0.779
LS → PU	0.183**	0.146***	0.037	0.640
VD → PU	-0.053	-0.121**	0.068	0.378
SN → PU	-0.004	-0.089*	0.085	0.324
EOA → PU	-0.053	0.004	-0.057	0.378
SI → PU	0.198**	0.301***	-0.103	0.225
IA → PU	0.250***	0.193***	0.057	0.516
SL → PU	-0.011	0.026	-0.037	0.690
PEOU → PU	0.349***	0.364***	-0.016	0.908
PEOU → BI	0.280***	0.224***	0.056	0.516
PU → BI	0.554***	0.613***	-0.059	0.465
BI → AU	0.583***	0.592***	-0.009	0.876

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

6.6.2 Age

The age moderator variable was measured using a ratio scale, and, therefore, there is a need for further refinement (Henseler & Fassott, 2010; Hair, Black, Babin, & Anderson, 2014). Using the median-split procedures (median = 21), there are 442 students within the younger students' group (median <= 21) and 391 students within the older students' group (median > 21). Each group exceeds the minimum sample size recommended by Hair, Hult et al. (2017), Cohen (1992), and Kock and Hadaya (2018). Thus, the researcher proceeded with the other prerequisites of the MGA.

Following the MGA stages, the MICOM procedure was executed next. As the two groups used the same indicators, scale, treatment, and algorithm, the configural invariance is established for the age moderator variable (Henseler, Ringle, & Sarstedt, 2016). For step 2 of MICOM, Table 6.26 shows that the compositional invariance is demonstrated, as the original correlation between scores construct is larger or equal to the 5% quantile correlation (Matthews, 2017; Henseler, Ringle, & Sarstedt, 2016; Hair, Sarstedt, Ringle, & Gudergan, 2018). As the configural and compositional invariance were met, the next step is to compare the groups using the MGA (Hair, Sarstedt, Ringle, & Gudergan, 2018; Henseler, Ringle, & Sarstedt, 2016).

Table 6.26 Results of Compositional Invariance for Age

Constructs	Original Correlation	Correlation Permutation Mean	5% Quantile Correlation	Permutation p-Value
AU	1.000	1.000	0.999	0.626
BI	1.000	1.000	1.000	0.708
CQ	1.000	1.000	0.999	0.931
EOA	1.000	0.999	0.998	0.598
IA	1.000	1.000	1.000	0.652
LS	0.999	1.000	0.999	0.023
PEOU	1.000	1.000	1.000	0.053
PU	1.000	1.000	1.000	0.824
SI	1.000	1.000	1.000	0.372
SL	1.000	1.000	1.000	0.136
SN	1.000	1.000	0.999	0.979
VD	1.000	1.000	0.999	0.197

Using the permutation test, Table 6.27 shows that age has no moderating effect on the relationships between the model’s variables.

Table 6.27 Results of Permutation Test for Age

Paths	β for Younger Students	β for Older Students	Difference	Permutation p-Value
CQ → PEOU	0.025	0.075^{*}	-0.050	0.414
LS → PEOU	0.056	0.063	-0.007	0.916
VD → PEOU	0.056	0.056	-0.001	0.994
SN → PEOU	0.189^{***}	0.145^{**}	0.044	0.531
EOA → PEOU	0.047	0.072	-0.026	0.646
SI → PEOU	0.073	0.166^{***}	-0.093	0.149
IA → PEOU	0.088^{*}	0.027	0.061	0.383
SL → PEOU	0.471^{***}	0.405^{***}	0.067	0.294
CQ → PU	0.074	0.052	0.022	0.756
LS → PU	0.132^{**}	0.196^{***}	-0.064	0.384
VD → PU	-0.128^{**}	-0.061	-0.067	0.364
SN → PU	-0.064	-0.082	0.018	0.818
EOA → PU	-0.008	-0.013	0.005	0.933
SI → PU	0.309^{***}	0.211^{***}	0.098	0.218
IA → PU	0.283^{***}	0.154^{**}	0.129	0.098
SL → PU	0.047	-0.017	0.064	0.487
PEOU → PU	0.262^{***}	0.447^{***}	-0.186	0.116
PEOU → BI	0.233^{***}	0.246^{***}	-0.013	0.866
PU → BI	0.620^{***}	0.560^{***}	0.060	0.435

Paths	β for Younger Students	β for Older Students	Difference	Permutation p-Value
BI → AU	0.605***	0.564***	0.041	0.458

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

6.6.3 Level of Education

The level of education moderator variable was measured based on a nominal scale (categorical) , and, therefore, there is no need for further refinement (Henseler & Fassott, 2010; Hair, Black, Babin, & Anderson, 2014). The results show that 690 of the respondents are undergraduate and 143 are postgraduate students. Each group exceeds the minimum sample size recommended by Hair, Hult et al. (2017), Cohen (1992), and Kock and Hadaya (2018). The investigation therefore proceeded with the other prerequisites of the MGA.

In the next stage, the MICOM procedure was executed. Following Henseler, Ringle et al. (2016), the configural invariance is established for the level of education moderator variable. For step 2 of MICOM, Table 6.28 shows that the compositional invariance is demonstrated, as the original correlation between construct scores is larger or equal to the 5% quantile correlation (Matthews, 2017; Henseler, Ringle, & Sarstedt, 2016; Hair, Sarstedt, Ringle, & Gudergan, 2018). As the configural and compositional invariance conditions were met, the researcher proceeded to compare the groups using the MGA (Hair, Sarstedt, Ringle, & Gudergan, 2018; Henseler, Ringle, & Sarstedt, 2016).

Table 6.28 Results of Compositional Invariance for Level of Education

Constructs	Original Correlation	Correlation Permutation Mean	5% Quantile Correlation	Permutation p-Value
AU	0.999	1.000	0.999	0.054
BI	1.000	1.000	1.000	0.079
CQ	1.000	0.999	0.998	0.754
EOA	0.998	0.999	0.995	0.257
IA	1.000	1.000	1.000	0.476
LS	0.999	1.000	0.999	0.103
PEOU	1.000	1.000	1.000	0.403
PU	1.000	1.000	1.000	0.282
SI	1.000	1.000	0.999	0.702
SL	1.000	1.000	0.999	0.696

Constructs	Original Correlation	Correlation Permutation Mean	5% Quantile Correlation	Permutation p-Value
SN	0.999	1.000	0.999	0.096
VD	1.000	1.000	0.999	0.532

Next, the statistically significant differences between the undergraduate and the postgraduate students were examined using the permutation test with 5,000 permutations and a two-tailed option at a 0.05 significance level, as recommended by Matthews (2017). Table 6.29 shows that level of education moderates two out of the 20 relationships: SL → PEOU (supporting H33h) and BI → AU (supporting H38). More specifically, both relationships are stronger for the undergraduate students compared with the postgraduate students. Therefore, the findings suggest accepting the two hypotheses H33h and H38 and rejecting the other hypotheses in Table 6.29.

Table 6.29 Results of Permutation Test for Level of Education

Paths	β for Undergraduates	β for Postgraduates	Difference	Permutation p-Value
CQ → PEOU	0.042	0.142^{**}	-0.100	0.233
LS → PEOU	0.024	0.154^{**}	-0.130	0.116
VD → PEOU	0.044	0.146^{**}	-0.102	0.249
SN → PEOU	0.188^{***}	0.123^{*}	0.065	0.490
EOA → PEOU	0.045	0.152^{*}	-0.107	0.149
SI → PEOU	0.127^{***}	0.059	0.068	0.445
IA → PEOU	0.054	0.078	-0.024	0.805
SL → PEOU	0.468^{***}	0.267^{***}	0.201^{*}	0.018
CQ → PU	0.051	0.051	-0.001	0.994
LS → PU	0.184^{***}	0.099	0.085	0.361
VD → PU	-0.122^{**}	0.046	-0.168	0.094
SN → PU	-0.036	-0.178^{*}	0.142	0.195
EOA → PU	-0.021	0.127	-0.148	0.076
SI → PU	0.283^{***}	0.084	0.199	0.071
IA → PU	0.220^{***}	0.241^{**}	-0.021	0.848
SL → PU	0.026	-0.096	0.122	0.311
PEOU → PU	0.328^{***}	0.495^{***}	-0.166	0.292
PEOU → BI	0.245^{***}	0.191^{*}	0.054	0.610
PU → BI	0.597^{***}	0.583^{***}	0.015	0.889
BI → AU	0.616^{***}	0.442^{***}	0.174^{*}	0.014

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

6.6.4 Experience

The experience moderator variable was measured using a ratio scale, and, therefore, there is a need for further refinement (Henseler & Fassott, 2010; Hair, Black, Babin,

& Anderson, 2014). Using the median-split procedures (median = 2.0), there are 509 students within the less-experienced group (median <= 2.0) and 324 students within the more-experienced group (median > 2.0). Each group exceeds the minimum sample size recommended by Hair, Hult et al. (2017), Cohen (1992), and Kock and Hadaya (2018). Having done these checks, the researcher then proceeded with the other prerequisites of the MGA.

After that, the MICOM procedure was executed. As the two groups used the same indicators, scale, treatment and algorithm, the configural invariance is established for the age moderator variable (Henseler, Ringle, & Sarstedt, 2016). For step 2 of MICOM, Table 6.30 shows that the compositional invariance is demonstrated, as the original correlation between scores construct is larger or equal to the 5% quantile correlation (Matthews, 2017; Henseler, Ringle, & Sarstedt, 2016; Hair, Sarstedt, Ringle, & Gudergan, 2018). As the configural and compositional invariance were met, the next step is to compare the groups using the MGA (Hair, Sarstedt, Ringle, & Gudergan, 2018; Henseler, Ringle, & Sarstedt, 2016).

Table 6.30 Results of Compositional Invariance for Experience

Constructs	Original Correlation	Correlation Permutation Mean	5% Quantile Correlation	Permutation p-Value
AU	1.000	1.000	0.999	0.659
BI	1.000	1.000	1.000	0.830
CQ	1.000	1.000	0.999	0.930
EOA	0.999	0.999	0.997	0.565
IA	1.000	1.000	1.000	0.312
LS	1.000	1.000	0.999	0.525
PEOU	1.000	1.000	1.000	0.360
PU	1.000	1.000	1.000	0.779
SI	1.000	1.000	1.000	0.631
SL	1.000	1.000	1.000	0.860
SN	1.000	1.000	0.999	0.457
VD	1.000	1.000	0.999	0.249

The permutation test in Table 6.31 reveals that experience moderates two out of 20 relationships: IA → PU (supporting H40g) and PU → BI (supporting H43), and both relationships are stronger for students with less experience. Therefore, the findings suggest accepting the two hypotheses H40g and H43 and rejecting the other hypotheses in Table 6.31.

Table 6.31 Results of Permutation Test for Experience

Paths	β for Less-Experienced Students	β for More-Experienced Students	Difference	Permutation p-Value
CQ → PEOU	0.077*	0.038	0.039	0.531
LS → PEOU	0.050	0.041	0.009	0.892
VD → PEOU	0.016	0.112*	-0.096	0.166
SN → PEOU	0.162***	0.193***	-0.032	0.663
EOA → PEOU	0.066*	0.039	0.027	0.633
SI → PEOU	0.098*	0.161**	-0.063	0.345
IA → PEOU	0.077*	0.029	0.048	0.491
SL → PEOU	0.473***	0.370***	0.104	0.110
CQ → PU	0.075*	0.038	0.037	0.610
LS → PU	0.128**	0.217***	-0.089	0.249
VD → PU	-0.123**	-0.064	-0.059	0.415
SN → PU	-0.021	-0.161**	0.139	0.096
EOA → PU	-0.015	-0.009	-0.006	0.923
SI → PU	0.296***	0.244***	0.053	0.526
IA → PU	0.279***	0.115*	0.164*	0.041
SL → PU	-0.002	0.069	-0.072	0.448
PEOU → PU	0.302***	0.410***	-0.108	0.398
PEOU → BI	0.190***	0.301***	-0.110	0.174
PU → BI	0.661***	0.499***	0.162*	0.036
BI → AU	0.609***	0.526***	0.083	0.133

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

6.7 Summary

In this chapter, a step-by-step clarification of the model testing process was provided. The data were exported from SPSS in .csv format and imported into SmartPLS 3 software version 3.2.7 to perform further analysis and model testing.

In the first section, the measurement model was assessed in terms of indicator reliability, construct reliability, convergent validity, and discriminant validity. The assessment resulted in removing two indicators (NAV05 and AU02) as they did not meet the recommended threshold of 0.7. The other results demonstrated the reliability and validity of the measurement model, and the analysis therefore proceeded with the structural model evaluation.

Following the multi-stage approach, the structural model was assessed in terms of collinearity, path coefficients, R^2, and Q^2. More importantly, this stage examined the proposed paths and hypotheses between the constructs. The results revealed that 14 out of 20 path relationships in the structural model were positively significant. This suggested accepting hypotheses H1, H2 H4, H7, H9, H11, H12, H13, H14, H15, H17, H18, H19, and H20 and rejecting H3, H5, H6, H8, H10, and H16.

Having established the measurement model, structural model, and model fit, the subsequent stage examined the differences between students in the acceptance of LMS based on their demographic characteristics. This section showed that each demographic group was affected by different usability attributes. The last section assessed the moderating effect of the four demographic characteristics on the relationships between the constructs (CQ, LS, VD, SN, EOA, SI, IA, SL, PEOU, PU, BI, and AU). The results in Section 6.6 revealed that only five out of 80 hypotheses were supported.

This chapter presented the results of the model testing, which includes measures, relationships, GoF, differences in the acceptance, and moderating effect assessment. The next chapter interprets these findings and discusses their relationship to the past literature.

CHAPTER 7: DISCUSSION

7.1 Introduction

In the previous two chapters, the collected data were analysed using SPSS and SmartPLS software. The next chapter (Chapter 8) focuses on the recommendations for practitioners, the study contributions, and research limitations. In this chapter, the results obtained from the data analysis stage are discussed in detail. Chapter 7 discusses the justification for the acceptance or rejection of the proposed hypotheses, explains the obtained results, and compares the findings with the previous literature regarding LMS acceptance. This chapter is divided into three sections. First, Chapter 7 discusses the direct relationships between the independent and dependent variables in the structural model. The second section discusses the differences in the students' acceptance of LMS based on their demographic characteristics of gender, age, level of education, and experience. Finally, the effect of the four personal moderators (gender, age, level of education, and LMS experience) on the proposed relationships between the independent and dependent variables is explored.

7.2 Proposed Model

Section 6.3.2 contains the results obtained from the path analysis using the bootstrapping technique and SmartPLS software. In this section, the direct relationships between the usability variables (CQ, LS, VD, SN, EOA, SI, IA, and SL) and the dependent variables (PEOU, PU, BI, and AU) are discussed. This section answers the first question in this study, which is concerned with the factors that affect student use of LMS in Saudi higher education.

The results of testing the proposed hypotheses are provided in Figure 7.1. The findings indicate that 14 out of 20 path relationships in the structural model are positively significant and supported. In line with the previous literature regarding Saudi e-learning (Al-Aulamie, 2013; Alenezi, 2011; Al-Mushasha, 2013), the structural model examination demonstrated the relationships between the TAM constructs (PEOU, PU, BI, and AU) for an LMS in the context of higher-educational institutions in Saudi Arabia. The results of testing the proposed hypotheses are discussed in the following subsections.

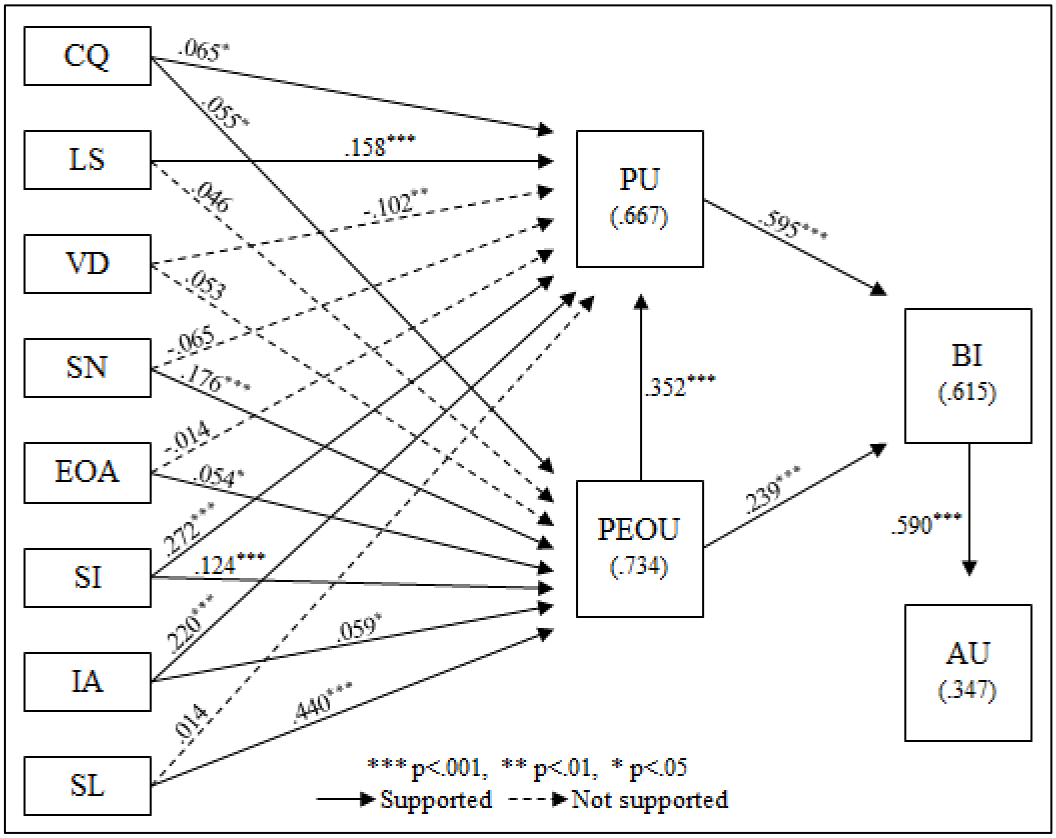

Figure 7.1 Results of Hypotheses Testing

7.2.1 Content Quality

In this study, CQ is the extent to which students in Saudi universities believe that LMS have good content. It was hypothesised, in the proposed model, that CQ has a direct positive influence on students' PEOU of LMS (H1). The results reveal that CQ has a significant effect on PEOU ($\beta = 0.055$, $p < 0.05$), and, thus, H1 is accepted. This result implies that when students perceive that LMS have good content, students are more likely to perceive their use of them to be somewhat easy to use. One possible interpretation is that students prefer LMS that have easy to reach, updated, sufficient, and well-organised content, which, consequently, facilitates their education. In line with this result, other researchers empirically found (Lee, Hsiao, & Purnomo, 2014; Shah, Bhatti, Iftikhar, Qureshi, & Zaman, 2013; Bhatiasevi, 2011; Alkandari, 2015; Salloum, 2018; Lau & Woods, 2009) that the CQ of e-learning systems is a determinant of students' PEOU. Therefore, this study provides evidence for the existence of a positive effect of CQ on students' PEOU of LMS in Saudi Arabia.

Moreover, it was hypothesised that CQ has a direct positive influence on students' PU of LMS (H2). The path analysis demonstrates that CQ is a significant predictor for PU ($\beta = 0.065$, $p < 0.05$), and, thus, H2 is accepted. This result indicates that if the content of LMS is not appropriate, students perceive the system to be less useful, which, in turn, affects the students' use of LMS. One reasonable justification for this result is that, when LMS have appropriate, up-to-date, sufficient, and properly organised content, students believe their academic performance to be enhanced, so they consider LMS to be useful for their education. This result conflicts with the findings of Kang and Shin (2015), who found no effect of CQ on PU in the context of virtual classes, which is not the case in this study. Kang and Shin (2015) attribute their result to the existence of teachers in synchronous e-learning that might reduce the influence of CQ. In contrast with Kang and Shin (2015), many studies in e-learning (Ghazal, Aldowah, & Umar, 2018; Al-Rahmi, et al., 2018; Alkandari, 2015; Damnjanovic, Jednak, & Mijatovic, 2015; Lee, Hsiao, & Purnomo, 2014; Lwoga, 2014; Al-Aulamie, 2013; Shah, Bhatti, Iftikhar, Qureshi, & Zaman, 2013; Khedr, Hana, & Shollar, 2012; Bhatiasevi, 2011; Terzis & Economides, 2011; Poelmans, Wessa, Milis, Bloemen, & Doom, 2008; Zhang, Liu, Yan, & Zhang, 2017; Salloum, 2018) have demonstrated the effect of CQ on students' PU. Therefore, this study agrees with the majority of previous literature and supports the presence of a positive influence of CQ on students' PU of LMS in Saudi public universities.

7.2.2 Learning Support

According to Zaharias and Poylymenakou (2009), LS refers to the ability of LMS to provide students in higher-educational institutions in Saudi Arabia with the tools and features needed to support their learning activities. In this study, it was proposed that LS has a direct positive influence on students' PEOU of LMS (H3). The results reveal that LS does not have a significant effect on PEOU ($\beta = 0.046$, $p = 0.072$), and, thus, H3 is rejected. Hence, this study concludes that there is an absence of the effect of LS on students' PEOU of LMS in Saudi Arabia. Therefore, attention related to increasing the ease of use should focus on areas in which the influence on students is more pronounced.

On the other hand, it was hypothesised that LS has a direct positive influence on students' PU of LMS (H4). The path analysis demonstrated that LS is a significant predictor for PU ($\beta = 0.158$, $p < 0.001$), and, thus, H4 is accepted. This result implies that when students perceive that LMS provide good LS, they are more likely to perceive them to be useful. More specifically, students prefer to use LMS that have appropriate and sufficient tools to support their education with help, which augments their perception of the usefulness of the systems. Thus, this study supports the notion that LS is a significant predictor for PU of LMS in Saudi Arabia.

7.2.3 Visual Design

Visual design refers to the degree to which the interface layout of LMS are appropriate and attractive to students in Saudi higher education (Scholtz, Mandela, Mahmud, & Ramayah, 2016). The researcher assumed that VD has a direct positive influence on students' PEOU of LMS (H5). The results of the structural model assessment unexpectedly disclosed the lack of this relationship, indicating that VD is not a determinant for students' PEOU of LMS in Saudi Arabia. Rejecting hypothesis H5 contradicts e-learning research (Al-Aulamie, 2013; Khedr, Hana, & Shollar, 2012; Theng & Sin, 2012; Liu, Chen, Sun, Wible, & Kuo, 2010; Jeong, 2011; Thong, Hong,

& Tam, 2002). Nevertheless, the non-existence of VD influence on PEOU can be attributed to the following reason: The majority of participants in this study had more than two years' experience with LMS, and more than 94% of students expressed moderate and high level computer and Internet skills. The students' wide exposure to computer and Internet technology, LMS in particular, and their advanced technical skills might contribute to minimising the significance of the interface VD. Furthermore, Cyr, Head, and Ivanov (2006) investigated the effect of VD on the constructs of the TAM model. They found that VD is more related to 'enjoyable user experience', and, therefore, VD affected enjoyment more than PEOU and PU. In summary, this study found an absence of VD effects on students' PEOU of LMS in Saudi higher education.

In terms of PU, it was proposed that VD has a direct positive influence on students' Regarding PU, it was proposed that VD has a direct positive influence on students' PU of LMS (H6). The examination findings reveal VD negatively affects PU ($\beta = -0.102$, $p < 0.01$), and, thus, H6 is rejected. This study found that when students perceive that LMS have good interface VD, they are more likely not to perceive them as useful. Nevertheless, reviewing the literature revealed that the relationship between VD and PU in e-learning systems is indeterminate. For example, Cho et al. (2009) and Khedr et al. (2012) demonstrated the above effect; whereas, Al-Aulamie (2013), Jeong (2011), and Parsazadeh et al. (2017) found that VD does not influence students' PU. Furthermore, the finding of this study can be justified, because most of the participants expressed advanced computer and Internet skills, indicating that they have computer self-efficacy, which has been found to negatively affect PU in e-learning research (Abdullah, Ward, & Ahmed, 2016; Aypay, Celik, Aypay, & Sever, 2012). Additionally, the interface VD might exist at the expense of a system's usefulness. In other words, developers should be aware that an attractive user interface is not necessarily a criterion in trying to increase student perceptions of usefulness. In summary, this study supports the presence of a negative effect of VD on students' PU of LMS in Saudi Arabia.

7.2.4 System Navigation

According to Naveh et al. (2012), SN refers to the degree to which the organisation of LMS is understandable and appropriate for students in higher education in Saudi Arabia. In this study, it was hypothesised that SN has a direct positive influence on students' PEOU of LMS (H7). The results reveal that SN has a significant effect on PEOU ($\beta = 0.176$, $p < 0.001$), and, thus, H7 is accepted. This result means that when the navigational structure of LMS is convenient for students, they are more likely to perceive the system to be easy to use. One possible interpretation is that students favour LMS enabling them to find information, to predict links, and to leave and return easily, which, consequently, makes navigation between the course elements easier. Supporting this result, other researchers have empirically found (Khan & Qutab, 2016; Theng & Sin, 2012; Thong, Hong, & Tam, 2002; Jeong, 2011) that the navigation of e-learning is a substantial determinant of students' PEOU. Therefore, this study provides evidence of the existence of a positive effect of SN on students' PEOU of LMS in Saudi Arabia.

Moreover, it was hypothesised that SN has a direct positive influence on students' PU of LMS (H8). The path analysis demonstrated that SN is not a significant predictor for PU ($\beta = -0.065$, $p = 0.054$), and, thus, H8 is rejected. This finding is unexpected, as past literature regarding information systems (Khan & Qutab, 2016; Scholtz, Mandela, Mahmud, & Ramayah, 2016; Green & Pearson, 2011) demonstrated that SN is an important predictor for PU. However, Jeong (2011) investigated the use of an e-library in Korea and found that SN does not influence students' PU. Furthermore, contrasting studies (Khan & Qutab, 2016; Scholtz, Mandela, Mahmud, & Ramayah, 2016; Green & Pearson, 2011) were not conducted in the domain of e-learning systems. In short, this study concludes that easy navigation does not influence Saudi students' PU of LMS.

7.2.5 Ease of Access

For this current research, EOA refers to the degree to which students in Saudi higher education can access LMS without difficulty from the login process to the course content (Naveh, Tubin, & Pliskin, 2012; Park, 2009). The finding supports hypothesis H9, which states that EOA has a direct positive influence on students' PEOU of LMS, ($\beta = 0.054$, $p < 0.05$). Thus, the researcher accepted hypothesis H9. This result confirmed that when students perceive an LMS as easy to access, they are more likely to perceive it as easy to use. Nevertheless, the path coefficient indicates that the relationship between EOA and PEOU is the weakest significant relationship compared with the other relationships. This result is perhaps understandable, as many IT infrastructure and telecommunication projects have been taking place recently in Saudi Arabia under the Vision 2030 initiative (Vision 2030, 2016); therefore, most students do not have problems with accessibility and Internet connection and can login to the system at any time and from anywhere. This finding is consistent with several empirical studies in e-learning (Tran, 2016; Kang & Shin, 2015; Lee, Hsiao, & Purnomo, 2014; Al-Aulamie, 2013; Park, 2009; Lee, 2008; Thong, Hong, & Tam, 2002; Aziz & Kamaludin, 2014; Salloum, 2018). However, this relationship is not in line with Kanwal and Rehman (2017), who explained their result as occurring because the virtual university, in which their study was conducted, has its own private network distributed across Pakistan. Additionally, their study was carried out in a different context (Pakistan) with only computing and business students at a completely virtual university. Nevertheless, this present study supports the presence of a positive effect of EOA on students' PEOU of LMS in Saudi Arabia.

Regarding EOA → PU, it was hypothesised that PU is directly affected by EOA of LMS (H10). However, this study provides evidence that EOA does not influence PU ($\beta = -0.014$, $p = 0.324$), and, thus, H10 is rejected. The results demonstrate that the students' perception of EOA of LMS does not play an important role in their view of the usefulness of LMS. Although Al-Aulamie (2013) empirically accepted hypothesis H10 in a Saudi students' context, that author investigated the effect of EOA on PU using only undergraduate students. Furthermore, Parsazadeh et al. (2017) conducted their study with Malaysian diploma engineering students at a single institution. Finally, rejecting hypothesis H10 is in accordance with most past literature on LMS (Kang & Shin, 2015; Park, 2009; Aziz & Kamaludin, 2014; Lee, 2008; Thong, Hong, & Tam, 2002).

7.2.6 System Interactivity

The SI variable is defined as the degree to which students in Saudi universities believe that LMS have good communication tools. In this study, it was assumed that SI has a direct positive influence on students' PEOU of LMS (H11). The results reveal that SI has a significant effect on PEOU ($\beta = 0.124$, $p < 0.001$), and, thus, H11 is accepted. This result indicates that when students perceive that LMS have good interactivity, they are more likely to perceive them as easy to use. A plausible interpretation is that the communication tools provided by the LMS were easy to use, uncomplicated, and limitation-free regarding time and place, which contributed to an increase in the students' belief about the user friendliness of the systems. Although some studies (Pituch & Lee, 2006; Baleghi-Zadeh, Ayub, Mahmud, & Daud, 2017) regarding e-learning systems contradict this finding, both these studies were conducted using only undergraduate students enrolled at a single institution (university) in Taiwan and Malaysia, respectively. Nevertheless, the result of this study is compatible with most previous research on e-learning (Huang & Liaw, 2018; Tran, 2016; Baharin, Lateh , Nathan, & Nawawi, 2015; Lin, Persada, & Nadlifatin, 2014; Liaw, 2008; Alkandari, 2015; Freitas, Ferreira, Garcia, & Kurtz, 2017; Li, Duan, Fu, & Alford, 2012). Therefore, this study provides evidence of the existence of a positive effect of SI on students' PEOU of LMS in Saudi Arabia.

Also, it was proposed that PU is positively affected by SI of LMS (H12). Examining the relationships between the independent and dependent variables disclosed that SI positively impacts PU ($\beta = 0.272$, $p < 0.001$), and, thus, H12 is accepted. More specifically, SI → PU is the second strongest path among the external variables. This result indicates that without a positive perception of LMS interactivity, the students' PU of LMS decreases, and this impacts their views regarding the effectiveness of the LMS to enhance their learning. As highlighted elsewhere (Alkandari, 2015), the relative advantages of LMS are that they are rich with asynchronous and synchronous tools that facilitate the students' communication with each other and with teachers. This finding is consistent with previous literature on e-learning (Theng & Sin, 2012; Baharin, Lateh , Nathan, & Nawawi, 2015; Baleghi-Zadeh, Ayub, Mahmud, & Daud, 2017; Huang & Liaw, 2018; Lin, Persada, & Nadlifatin, 2014; Al-Harbi, 2011; Alkandari, 2015; Parsazadeh, Zainuddin, Ali, & Rezaei, 2017). Therefore, this study found evidence of a positive effect of SI on students' PU of LMS in Saudi Arabia.

7.2.7 Instructional Assessment

In this study, IA measures the degree to which students in higher education in Saudi Arabia believe that LMS have good tools for formative assessment. It was hypothesised, in the proposed model, that IA has a direct positive influence on students' PEOU (H13) and PU (H14) of LMS. The results reveal that IA significantly effects both PEOU ($\beta = 0.059$, $p < 0.05$) and PU ($\beta = 0.220$, $p < 0.001$), and, thus, hypotheses H13 and H14 are accepted. These results imply that when students are provided with good assessment tools, they are more likely to perceive LMS as being easy to use and useful. One possible interpretation is that students prefer LMS that have easy-to-use self-assessment tools that enable them to understand the content of a course and measure their achievements via learning objectives. This ability, in turn, makes the students' education process easy and valuable. Therefore, this study provides evidence regarding the existence of a positive effect of IA on students' PEOU and PU of LMS in Saudi Arabia.

7.2.8 System Learnability

Applying Nielsen's (1993) definition, SL refers to the degree to which students in higher education in Saudi Arabia can learn how to use LMS without difficulty. The findings support hypothesis H15, which states that SL has a direct positive influence on students' PEOU of LMS, ($\beta = 0.440$, $p < 0.001$). Thus, hypothesis H15 is accepted. The path coefficient indicates that the relationship between SL and PEOU is the strongest significant relationship compared with the other external variables. This result confirms the importance of SL as a factor in the students' use of LMS in Saudi Arabia and suggests that when students perceive LMS to be easy to learn, they are more likely to perceive it to be easy to use. This effect can be explained because e-learning systems are a relatively new technology in the education system of Saudi Arabia; therefore, students require an easy-to-learn LMS. This finding is well aligned with several empirical studies on information systems (Gül, 2017; Scholtz, Mandela, Mahmud, & Ramayah, 2016; Aziz & Kamaludin, 2014). Therefore, this study finds evidence for the presence of a strong and positive effect of SL on students' PEOU of LMS in Saudi Arabia.

Regarding SL → PU, it was assumed that PU is directly affected by the SL of LMS (H16). However, this study found that SL does not have an influence on PU ($\beta = 0.014$, $p = 0.376$), and, thus, H16 is rejected. The results demonstrate that an easy-to-learn LMS does not play an important role in students' decisions regarding the usefulness of LMS in their education. Although other studies on information systems (Gül, 2017; Scholtz, Mandela, Mahmud, & Ramayah, 2016; Aziz & Kamaludin, 2014) confirm the relationship between SL and PU, these three studies did not examine e-learning systems, did not survey students, and were not conducted in Saudi Arabia. In short, this present study rejects the influence of SL on students' PU of LMS in Saudi Arabia.

7.2.9 Perceived Ease of Use

For the current research, PEOU is taken to mean the extent to which students in Saudi universities believe that utilising LMS does not require significant effort (Davis, 1986). In this study, it was hypothesised that PEOU has a direct positive influence on students' PU of LMS (H17). The results reveal that PEOU positively affects PU ($\beta = 0.352$, $p < 0.001$), and, thus, H17 is accepted. This result confirms that when students perceive LMS to be easy to use, they are more likely to perceive it as being useful. In other words, students prefer LMS that require little effort to use, which, in turn, enhances their perception toward the usefulness of these systems. This result can be justified in that an easy-to-use LMS saves students' time and effort, enabling them to learn more easily, effectively, and quickly (Hakami, 2018). The finding is consistent with technology models, such as the TAM (Davis, Bagozzi, & Warshaw, 1989); the A-TAM (Taylor & Todd, 1995a); the TAM2 (Venkatesh & Davis, 2000); the model of PEOU determinants (Venkatesh, 2000); and the TAM3 (Venkatesh & Bala, 2008), as well as studies in e-learning in Saudi Arabia (Al-Gahtani, 2016; Al-Mushasha, 2013; Alenezi, 2012; Almarashdeh & Alsmadi, 2016; Muniasamy, Eljailani, & Anandhavalli, 2014), and other countries (Hwa, Hwei, & Peck, 2015; Majdalawi, Almarabeh, & Mohammad, 2014; Al-Adwan, Al- Adwan, & Smedley, 2013; Park, 2009; Mohammadi, 2015; Baharin, Lateh , Nathan, & Nawawi, 2015; Abdullah & Toycan, 2017; Lee, Hsiao, & Purnomo, 2014; Hsu & Chang, 2013; Tanduklangi, 2017).

Furthermore, it was assumed that BI is directly affected by PEOU of LMS (H18). This study provides evidence that PEOU positively impacts BI ($\beta = 0.239$, $p < 0.001$), and, thus, H18 is accepted. This result demonstrates that without an obvious PEOU of LMS, the students' BI to use LMS is reduced, which impacts their AU of LMS. One possible justification for this result is that e-learning is relatively new in Saudi Arabi; therefore, ease of use is very important for students' intention to use LMS. Although some researchers (Amin, Afrin Azhar, & Akter, 2016; Baharin, Lateh , Nathan, & Nawawi, 2015; Mohammadi, 2015; Park, 2009) found the opposite, these studies were conducted in different contexts than this study (i.e. not in Saudi Arabia). The findings of this study confirm previous literature on information systems models, such as the TAM, the TAM2, the model of PEOU determinants, and the TAM3, as well as many studies on e-learning (Abdullah & Toycan, 2017; Al-Azawei, Parslow, & Lundqvist, 2017; Tarhini, Hone, Liu, & Tarhini, 2017; Tanduklangi, 2017; Abdullah, Ward, & Ahmed, 2016; Hwa, Hwei, & Peck, 2015; Lee, Hsiao, & Purnomo, 2014; Tarhini, Hone, & Liu, 2014a; Shah, Bhatti, Iftikhar, Qureshi, & Zaman, 2013) and particularly in Saudi Arabia (Al-Aulamie, 2013; Al-Gahtani, 2016; Alenezi, Abdul Karim, & Veloo, 2011; Almazroi, Shen, Teoh, & Babar, 2016). Furthermore, Venkatesh et al. (2003) revealed that effort expectancy in the UTAUT, such as PEOU, influences BI. Therefore, this study supports the presence of a strong and positive effect of PEOU on students' intention to use LMS in Saudi Arabia.

7.2.10 Perceived Usefulness

For this current study, PU is defined as the extent to which students in Saudi universities believe that utilising LMS is useful for their education (Davis, 1986). In this study, it was hypothesised that PU has a direct positive influence on students' BI of LMS (H19). The results reveal that PU positively affects BI ($\beta = 0.595$, $p < 0.001$), and, thus, H19 is accepted. This result indicates that the relationship between PU and BI is the strongest between the direct relationships. This result is in accordance with previous literature (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Morris, 2000), in which users were primarily driven by the usefulness and functions provided by the system. Many studies on e-learning systems (Al-Gahtani, 2016; Tarhini, Hone, Liu, & Tarhini, 2017; Almazroi, Shen, Teoh, & Babar, 2016; Ramírez Anormaliza, Sabate, & Audet Llinàs, 2016; Ma, Chao, & Cheng, 2013) indicate that the path PU → BI is the strongest. Consequently, if the usefulness of LMS is not established, students simply ignore the system and search for another, more useful LMS. One possible justification of this result is that most participants (N = 509) had a low level of experience with LMS, and the relationship between PU and BI is usually stronger for less-experienced users. This argument is in line with Davis et al. (1989) and Taylor and Todd (1995a). In contrast, Park (2009) did not find a relationship between PU and BI of e-learning, and attributed this result to the usefulness of e-learning being well-known to university students in Korea, as they use it in high school, which is not the case in Saudi Arabia. The findings of this study agree with technology models such as the TAM, the A-TAM, the TAM2, the model of PEOU determinants, and the TAM3, as well as studies in e-learning in Saudi Arabia (Al-Aulamie, 2013; Almazroi, Shen, Teoh, & Babar, 2016; Al-Gahtani, 2016; Muniasamy, Eljailani, & Anandhavalli, 2014; Al-Mushasha, 2013; Alenezi, Abdul Karim, & Veloo, 2011; Alenezi, Abdul Karim, & Veloo, 2010), and other countries (Abdullah & Toycan, 2017; Tanduklangi, 2017; Al-Azawei, Parslow, & Lundqvist, 2017; Tarhini, Hone, Liu, & Tarhini, 2017; Amin, Afrin Azhar, & Akter, 2016; Abdullah, Ward, & Ahmed, 2016; Hwa, Hwei, & Peck, 2015; Mohammadi, 2015; Baharin, Lateh , Nathan, & Nawawi, 2015; Lee, Hsiao, & Purnomo, 2014; Majdalawi, Almarabeh, & Mohammad, 2014; Tarhini, Hone, & Liu, 2014a; Al-Adwan, Al- Adwan, & Smedley, 2013). Furthermore, Venkatesh et al. (2003), in the UTAUT, and Venkatesh et al. (2012), in the UTAUT2, reveal that performance expectancy, such as PU, influences BI. Therefore, this study supports the presence of a strong and positive effect of PU on students' intention to use LMS in Saudi Arabia.

7.2.11 Behavioural Intention

In the context of this study, BI is defined as higher-educational students' aims or plans to use LMS in Saudi Arabia (Fishbein & Ajzen, 1975). In this model, it was hypothesised that BI has a direct positive influence on students' AU of LMS (H20). The results reveal that AU is positively affected by BI ($\beta = 0.590$, $p < 0.001$), and, thus, H20 is accepted. This result confirms that when students are strongly willing to use LMS, they are more likely to use it. This finding is consistent with technology models, such as the TRA, the TPB, the TAM, the A-TAM, the TAM2, the model of PEOU determinants, the UTAUT, the TAM3, and the UTAUT2, as well as studies on e-learning (Alenezi, 2012; Alenezi, Abdul Karim, & Veloo, 2011; Baleghi-Zadeh, Ayub, Mahmud, & Daud, 2017; Mohammadi, 2015; Tarhini, 2013). Therefore, this study provides evidence of the existence of a strong and positive effect of BI on students' use of LMS in Saudi Arabia.

In this section, the direct relationships between the independent variables (CQ, LS, VD, SN, EOA, SI, IA, and SL) and the dependent variables (PEOU, PU, BI, and AU) were discussed in detail. The following section discusses the differences between the demographic groups and how they impact the model's results.

7.3 Differences in the Acceptance of Learning Management Systems

In this research, the second question is concerned with the differences in the proposed model to accommodate the students' demographic characteristics, namely gender, age, level of education, and LMS experience. An awareness of the differences in the students' acceptance of LMS might provide a more profound understanding of the decision to use LMS among different groups of students. This understanding, in turn, helps to design strategies for each students' segment; thus, increasing the chance of them using LMS. Section 6.5 presents the results obtained from the analysis of the differences in the acceptance of LMS based on the students' demographic characteristics. The following subsections discuss these results and provide answers for the second question in this study.

7.3.1 Gender

The findings of the testing of the hypotheses for male and female students are depicted in Figure 7.2 and Figure 7.3, respectively. The results demonstrate that the explained variance was 78.2% for PEOU, 67.7% for PU, 61.4% for BI, and 33.8% for AU in the male student sample; whereas, in the female student sample, the shared variance was 70.8% for PEOU, 65.3% for PU, 61.8% for BI, and 35% for AU. These results suggest a good model fit for the dependent variables PEOU, PU, BI, and AU in both genders. In accordance with previous studies in e-learning (e.g. Smeda, 2017; Tarhini, 2013), the explained variance of BI and AU is higher in female students.

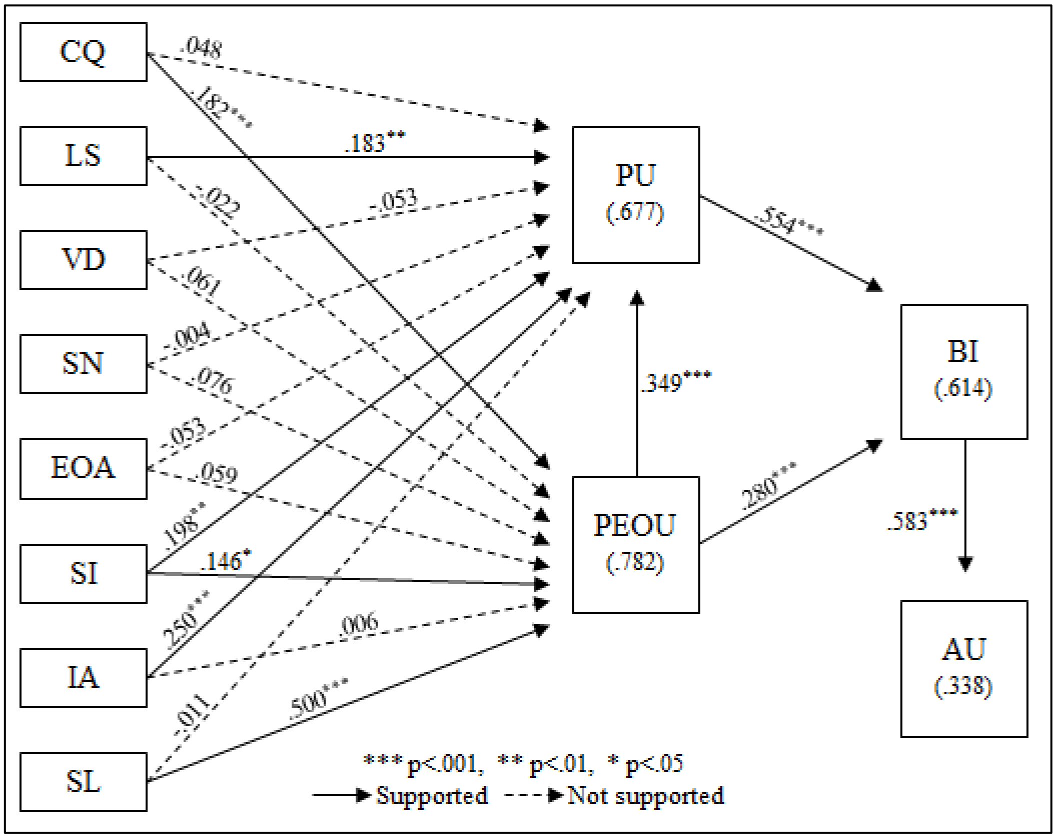

Figure 7.2 Results of Hypotheses Testing for Male Students

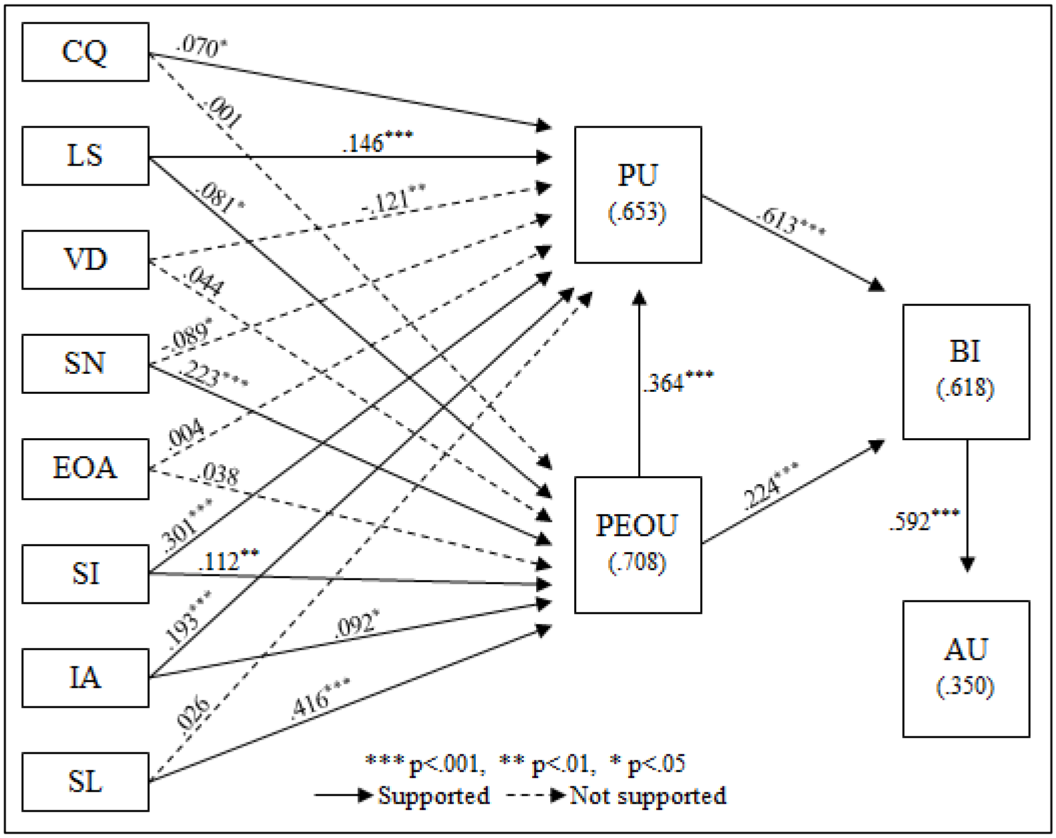

Figure 7.3 Results of Hypotheses Testing for Female Students

Compared with males, females have more statistically significant relationships in the model, indicating that responding to findings might have more significance for women. In another Saudi study (Al-Aulamie, 2013), it was found that male students have more statistically significant relationships in the model (9 out of 18). This might be attributed to the fact that Al-Aulamie (2013) targeted only undergraduate students. In this current model for male students, the effect of PU → BI is stronger than PEOU → BI. This result is in line with the argument of Venkatesh and Morris (2000) and Venkatesh et al. (2003), who theorised that men are more motivated by PU, as men are more task-orientated than women. Among the independent variables, the highest significant path for male students is SL → PEOU (β = 0.500), and the lowest significant path is SI → PEOU (β = 0.146). These results imply that although interactions with other students, teachers, and content exist to support the PEOU of LMS, their importance is weak compared with the other independent factors. In the model for male students, the strongest determinant of PEOU is SL ($\beta = 0.500$), and strongest determinant of PU is IA ($\beta = 0.250$). However, Al-Aulamie (2013) found that the strongest determinant of PEOU is accessibility ($\beta = 0.450$), and strongest determinant of PU is information quality ($\beta = 0.366$). In this current model for female students, the relationship between PU and BI is stronger than the other relationships, which is consistent with previous literature (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Morris, 2000; Taylor & Todd, 1995a). This result means that females' intention to use LMS is driven, to a large extent, by the usefulness and functionality provided by the system. This finding is consistent with Al-Aulamie (2013), who revealed that functionality is imperative in LMS acceptance by female students in Saudi higher education. Therefore, more consideration should be dedicated to the functionality provided by the system when dealing with female students. Furthermore, follow-up qualitative research should be conducted asking women in more depth about the features they categorise as useful. Such research would help direct impactful development efforts. Among the external variables of the female model, the strongest significant path is SL → PEOU ($\beta = 0.416$), and the weakest significant path is CQ → PU ($\beta = 0.070$). One possible interpretation of these results is that, regardless of the importance of easy to reach, updated, sufficient, and well-organised content, its effect on the females' PU of LMS is limited compared with the other independent factors. Further, the strongest determinant of PEOU is SL ($\beta = 0.416$), and strongest determinant of PU is IA ($\beta = 0.301$). However, Al-Aulamie (2013) found that the strongest determinant of PEOU is user interface design ($\beta = 0.550$), and strongest determinant of PU is functionality ($\beta = 0.602$).

7.3.2 Age

The findings of the hypotheses testing for younger and older students are depicted in Figure 7.4 and Figure 7.5, respectively. The results demonstrate that the shared variance is 76.2% for PEOU, 69% for PU, 64.3% for BI, and 36.5% for AU in the younger student sample (age <= 21); whereas, in the older student sample (age > 21), the explained variance is 69.2% for PEOU, 63.7% for PU, 57.4% for BI, and 31.7% for AU. These results indicate that the proposed model explains more variance in the younger student sample than in the older student sample, meaning a better model fit for younger students in the dependent variables PEOU, PU, BI, and AU.

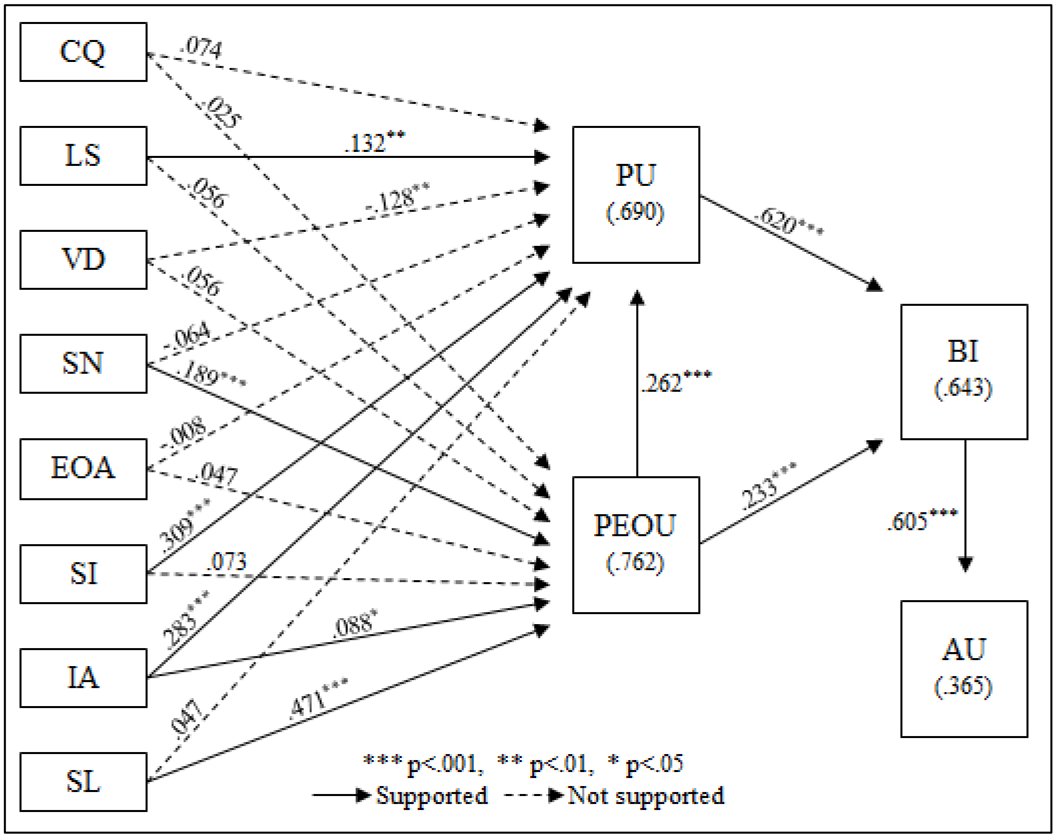

Figure 7.4 Results of Hypotheses Testing for Younger Students

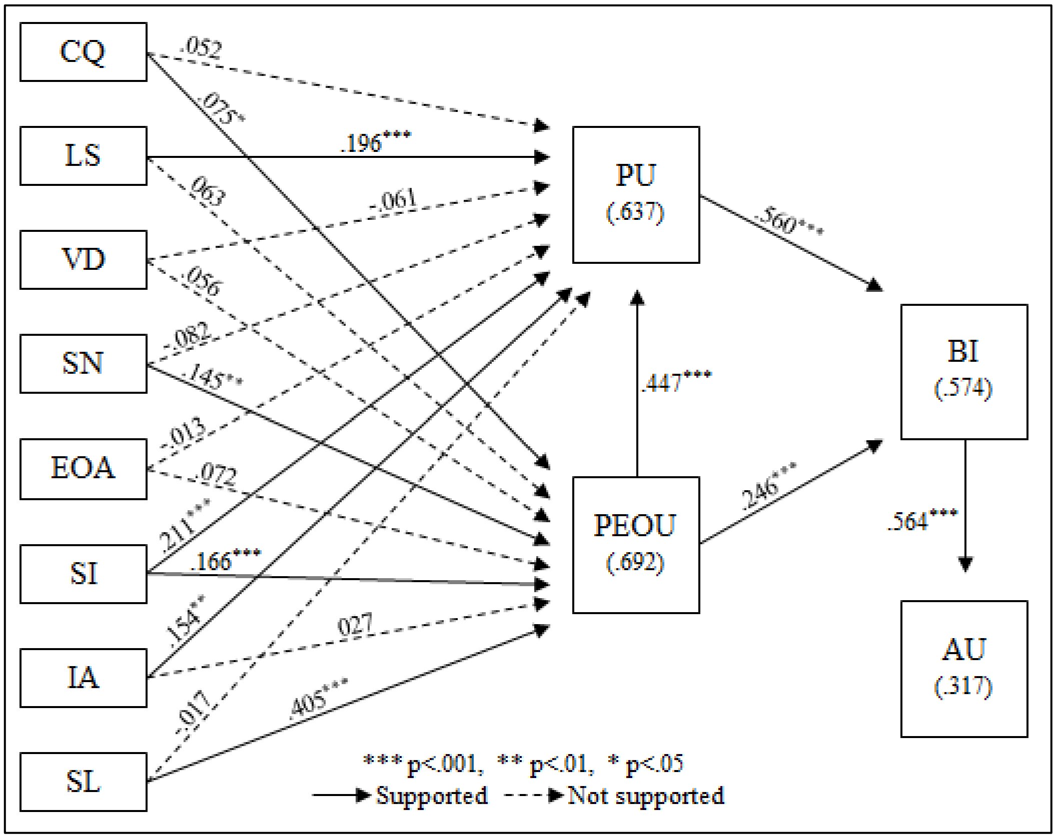

Figure 7.5 Results of Hypotheses Testing for Older Students

Regarding the number of statistically significant relationships, younger and older students have similar results, indicating that the model is reflective for younger and older students alike. Among the independent variables, the highest significant path for both groups is SL → PEOU, implying that the use of LMS strongly relies on the students' perceived learnability. Regarding the model of the younger student model, the relationship between PU and BI is the stronger than any other relationships, in accordance with the TAM (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989). This result means that younger students are significantly motivated by the usefulness of the system, indicating special attention should be paid to the functions of LMS when targeting younger students. The lowest significant path for younger students is IA → PEOU ($\beta = 0.088$). This result implies that although providing good assessment tools is necessary in the students' use of LMS, its importance is weak compared with the other independent factors. For older students, the weakest significant path is CQ →

PEOU (β = 0.075). A plausible interpretation of this result is that, regardless of the importance of easy to reach, updated, sufficient, and well-organised content, its effect on the PEOU of LMS of older students is limited compared with the other independent factors.

7.3.3 Level of Education

The findings of the undergraduate and postgraduate students' model testing are depicted in Figure 7.6 and Figure 7.7, respectively. The results demonstrate that the explained variance is 73.4% for PEOU, 67.8% for PU, 62.5% for BI, and 37.9% for AU in the undergraduate student sample; whereas, in the postgraduate student sample, the shared variance is 75.6% for PEOU, 62.6% for PU, 53.6% for BI, and 19% for AU. These results indicate that the proposed model explains more variance in the undergraduate student model compared with postgraduate student model, meaning a better model fit for undergraduate students in the dependent variables, especially for AU. This result is consistent with the findings of Tarhini (2013), who examined the factors affecting student use of LMS in Lebanon and England and found that his model explained more variance in the undergraduate student sample in both countries.

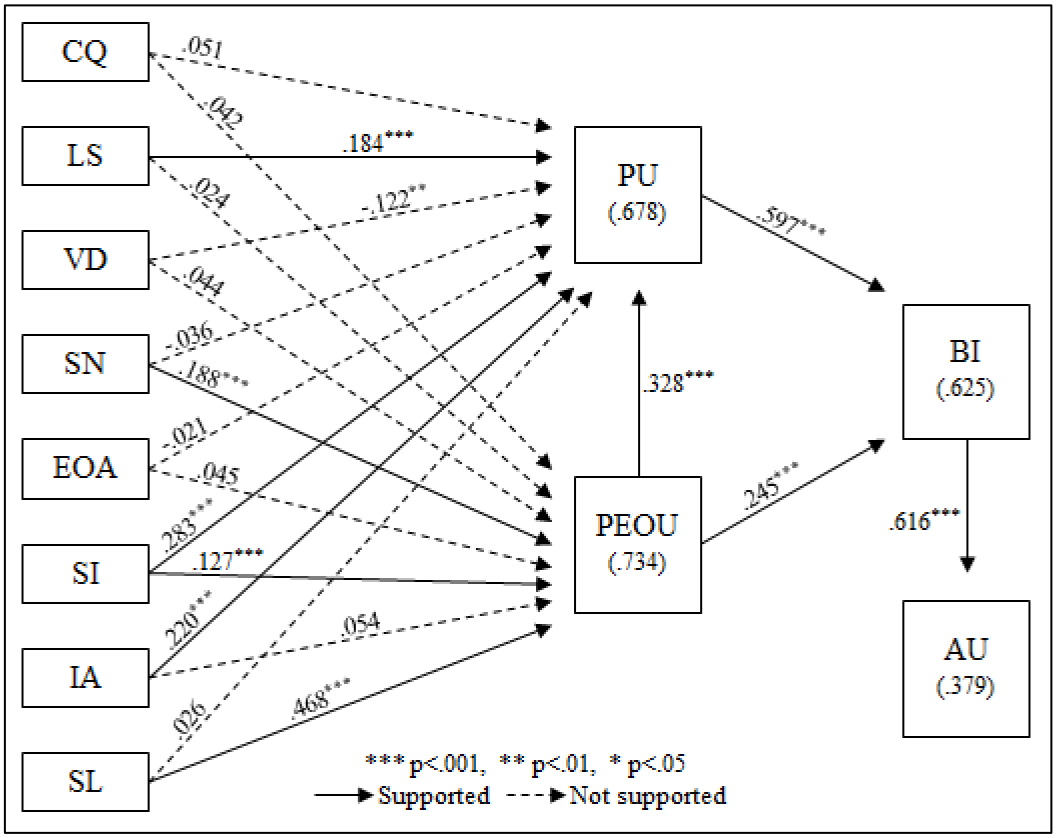

Figure 7.6 Results of Hypotheses Testing for Undergraduate Students

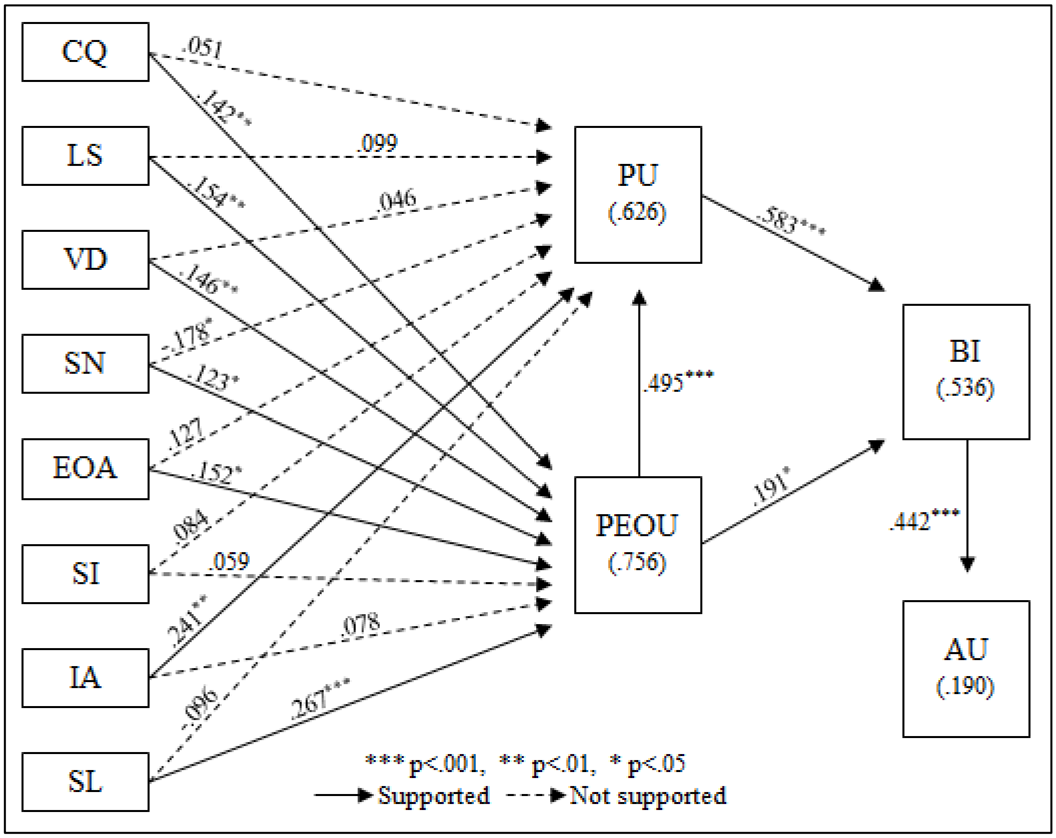

Figure 7.7 Results of Hypotheses Testing for Postgraduate Students

Compared with the undergraduate students (10 paths), the postgraduate students (12 paths) had more statistically significant relationships, indicating that responding to findings might have more significance for postgraduates. Among the independent variables, the highest significant path in the two models is between SL and PEOU, meaning that when LMS are easy to learn, students are more likely to use the system, regardless of their educational level. Therefore, universities should ensure that the adopted LMS have a high degree of learnability to motive students to use them. The lowest significant path for undergraduates is SI → PEOU ($\beta = 0.127$). This result implies that although interactions with other students, teachers, and content exist to support the PEOU of LMS, their importance is weak compared with the other independent factors. Regarding postgraduate students, the relationship between PU and BI is the strongest of the relationships, which is consistent with previous literature (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Morris, 2000; Taylor

& Todd, 1995a). This result means that postgraduates' intentions to use LMS are driven, to a large extent, by the usefulness and functions provided by the system. Therefore, more consideration should be dedicated to the functions provided by the system when dealing with postgraduate students. Among the external variables of the postgraduate model, the weakest significant path is SN → PEOU ($\beta = 0.123$). One interpretation of this result is that, regardless of the importance of enabling students to find information, predict links, and leave and return easily, SN's effect on the postgraduates' PEOU of LMS is limited compared with the other independent factors.

7.3.4 Experience

Following Venkatesh and Morris (2000), experience, in the context of this study, refers to the number of years students have been using LMS. The findings of the hypotheses testing for less-experienced and more-experienced students are displayed in Figure 7.8 and Figure 7.9, respectively. The results demonstrate that the shared variance is 76.8% for PEOU, 70.7% for PU, 65.6% for BI, and 37% for AU in the less-experienced sample of students (experience <= 2.0); whereas, in the more-experienced sample of students (experience > 2.0), the explained variance is 66.3% for PEOU, 59.6% for PU, 54.2% for BI, and 27.5% for AU. These results highlight that the proposed model explains more variance in the less-experienced sample of students than for the more-experienced sample of students, meaning that the LMS usage of less-experienced students is better predicted using the independent variables. This result is in accordance with previous literature on information systems (Taylor & Todd, 1995a; Venkatesh & Bala, 2008).

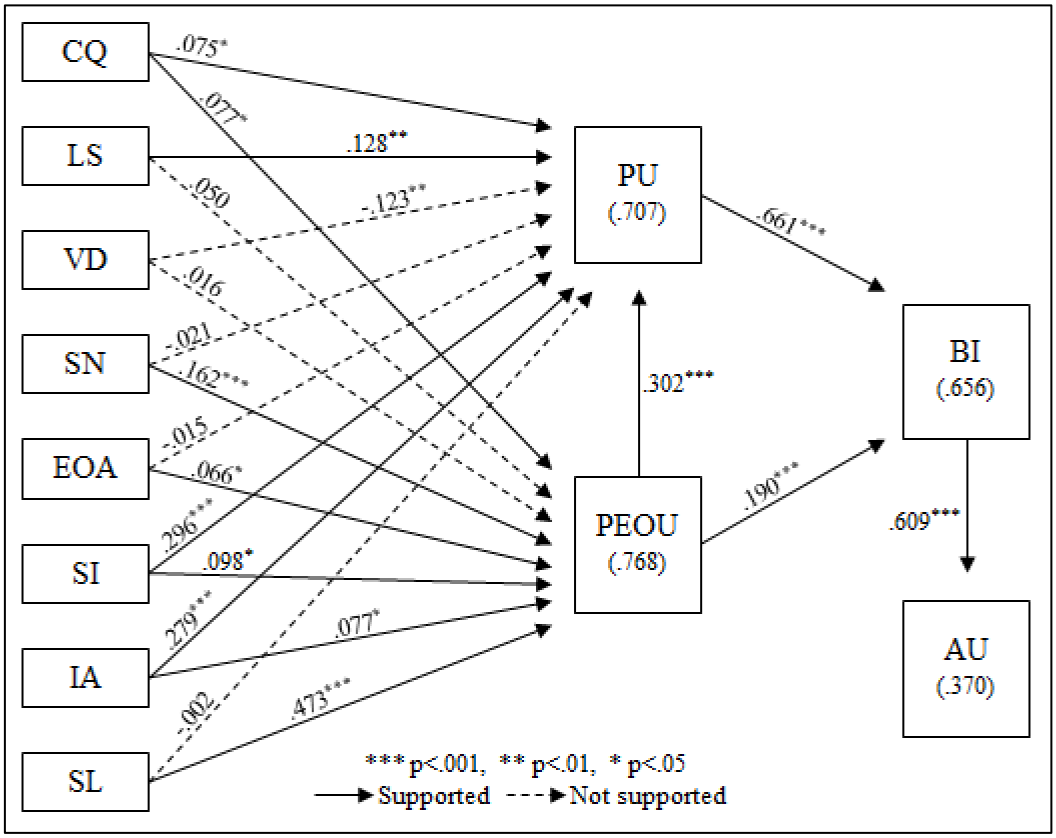

Figure 7.8 Results of Hypotheses Testing for Less-Experienced Students

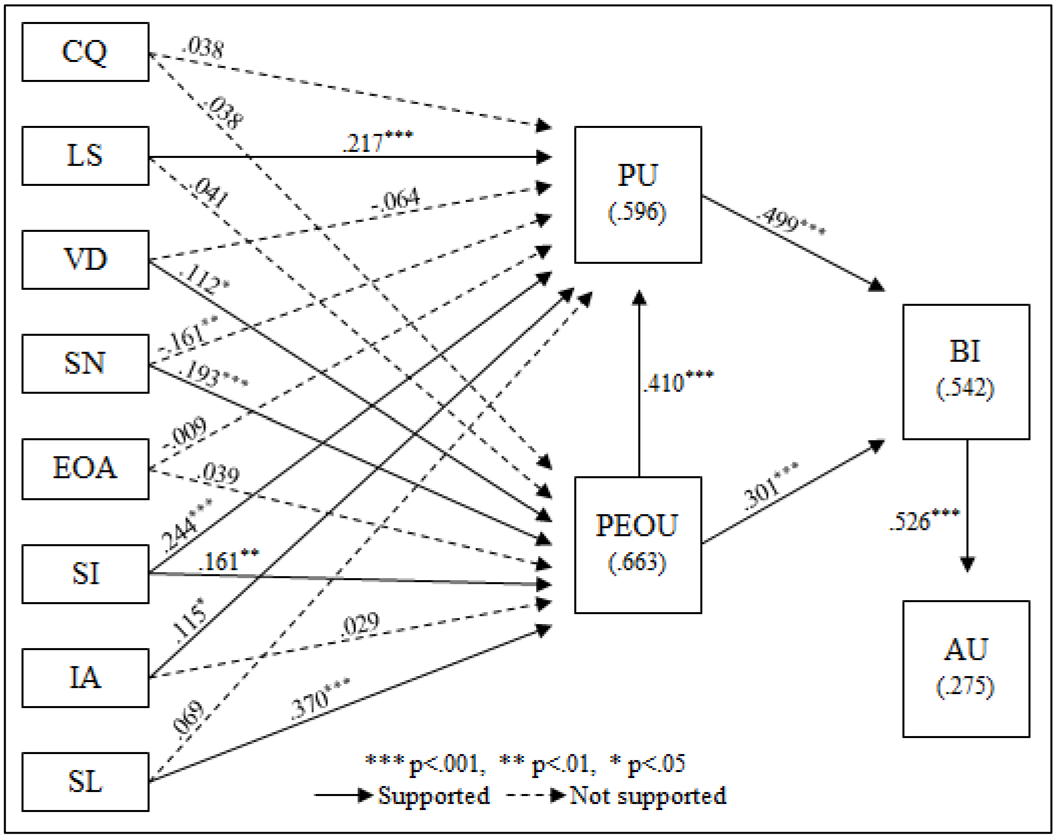

Figure 7.9 Results of Hypotheses Testing for Higher-Experienced Students

Concerning the proposed paths, less-experienced students had more statistically significant relationships than students with higher experience with LMS, indicating that responding to findings might have more significance for less-experienced students. Among the independent variables, the highest significant path for both groups is SL → PEOU, followed by SI → PU, implying that PEOU is strongly driven by SL and PU by SI, which, in turn, contribute to the students' use of LMS. Similar to findings for the TAM (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989), PU → BI is the strongest relationship for less-experienced students. This means that students with lower experience were significantly motivated by the usefulness of LMS, indicating that special attention should be paid to the expected performance of LMS when working with less-experienced students. The least significant paths are EOA → PEOU ($\beta = 0.066$) for less-experienced students, and VD → PEOU ($\beta = 0.112$) for higher-experienced students. These results imply that, although providing LMS with an attractive VD and making it easy to access is necessary for the students' use of LMS, the effects of these variables on the students' PEOU of LMS are limited compared with the other independent factors.

Having explained the differences between students regarding the acceptance of LMS, the results related to the statistically significant differences and four personal moderators are discussed in the following section.

7.4 Moderating Effect

In this research, the third question concerns the moderating effect of the four demographic characteristics on the relationships in the proposed model. This study hypothesised that the students' demographic characteristics could indirectly influence the students' AU of LMS by moderating the relationships between the independent and dependent variables. Section 6.6 presents the results obtained from the analysis of the moderating effect of the students' demographic characteristics. The following subsections discuss these results and provide answers for the third question in this study.

7.4.1 Gender

The MGA revealed that both the male and the female student groups are affected similarly in most relationships (19 out of 20). Such a result is a little surprising in the context of Saudi Arabia due to the cultural influence of gender segregation, in which males and females are physically separated in work and education (see Chapter 1). Nevertheless, this finding is compatible with studies in e-learning systems (Arenas-Gaitán, Rondan-Cataluña, & Ramirez-Correa, 2010; Ramírez-Correa, Arenas-Gaitán, & Rondán-Cataluña, 2015; Wong, Teo, & Russo, 2012; Dečman, 2015; Raman, Don, Khalid, & Rizuan, 2014) that argue that males and females are equally motivated to use LMS. Consequently, decision-makers can utilise similar policies to prompt male and female students toward using LMS. This finding can be attributed to the way that technology has penetrated the regular day-to-day life of students. Also, differences in utilisation among male and female students have been limited to the point that they are no longer critical (Smeda, 2017; Wong, Teo, & Russo, 2012). This result indicates that gender moderated only one path in the proposed model; in addition, little research has examined the moderating effect of gender on e-learning acceptance in Saudi universities (Al-Aulamie, 2013). Thus, further examination is required to confirm the differences between the two sexes in the context of higher education in Saudi Arabia.

Only one relationship is statistically different between male and female students in the developed model. The path between CQ → PEOU is moderated by the gender variable, meaning hypothesis H21a is supported. More specifically, the effect between CQ and PEOU is stronger for male students than female students. The path between CQ and PEOU is significant in the model for male students and insignificant in the model for female students. This result implies that males are more affected when LMS have easy to reach, updated, sufficient, and well-organised content, which, in turn, leads them to perceive their access as somewhat effortless and influences their usage of LMS. Reviewing previous literature revealed that this result is consistent with another study (Al-Aulamie, 2013) conducted on Saudi higher education. Al-Aulamie (2013) extended the TAM to investigate students' acceptance of LMS at three universities in Saudi Arabia. He justified this result by stating that men are more interested in the system CQ, particularly the textual data (e.g. accurate, well-organised, updated content). This interest is different from female students, who find non-textual data more attractive (Cyr, Head, & Ivanov, 2006). Therefore, the findings suggest accepting hypothesis H21a; that is, gender moderates the effect of CQ on students' PEOU of LMS. In Saudi Arabia, this result has an implication for university staff when implementing LMS, and for individual lecturers when designing content.

7.4.2 Age

The MGA disclosed that the age variable does not moderate the relationships in the proposed model. In other words, no matter what age group a student belongs to, those with a positive attitude toward LMS are more likely to use them than those with a negative attitude. Therefore, universities can utilise similar policies to prompt younger and older students toward using LMS. This finding is compatible with e-learning studies (Abbasi, 2011; Altawallbeh, Thiam, Alshourah, & Fong, 2015) that investigated the acceptance of e-learning systems in developing countries (Pakistan and Jordan, respectively). These studies demonstrated that age is not a moderator variable in the domain of e-learning systems. Similar results were achieved in other domains, such as decision support systems (Jaradat, Imlawi, & Mashaqba, 2012), e-library (Rahman, Jamaludin, & Mahmud, 2011), information technologies (Alkhasawneh & Alanazy, 2015), and internet marketing (Isa & Wong, 2015). This result can be attributed to an increasing awareness of technology among users no matter the age group (Jaradat, Imlawi, & Mashaqba, 2012). Thus, the hypotheses that age has a significant effect on the relationships in the proposed model (H27, H28, H29, H30, H31 and H32) could not be confirmed.

7.4.3 Level of Education

Incompatible with the proposed hypotheses and previous studies (e.g. Abu-Shanab, 2011; Sun & Zhang, 2006; Tarhini, 2013; Tarhini, Hone, & Liu, 2014b), examining the significant differences between undergraduates and postgraduates using the MGA revealed that 18 out of 20 relationships were not moderated by the students' level of education. This result means that the proposed model (18 hypotheses) is appropriate to be utilised no matter the students' education level. This influence might be explained by the fact that the population of this study had very similar levels of education, as they were all university students (Tarhini, Hone, & Liu, 2014b). This result is consistent with the conclusion of Dečman (2015), who found that education does not moderate student acceptance of e-learning systems. Dečman (2015) attributes his findings to the usage of LMS becoming straightforward and similar to other technologies that students use in their daily life.

Using the MGA analysis, it was found that undergraduate and postgraduate students are significantly different in two paths: SL → PEOU and BI → AU. Furthermore, the two moderated relationships were stronger for undergraduate students. Our results indicate that the two paths have less influence on postgraduates than on undergraduates. These findings are unsurprising, because people with less education could perceive new technologies to be arduous and difficult to learn; therefore, their decision to adopt and use e-learning systems depends on the ease of use of the technology (Abbasi, 2011; Claar, Dias, & Shields, 2014). Compared with less-educated people, Sun and Zhang (2006) argue that those with a higher education possess a greater ability to understand the value of a new technology, to accept it, and to use it. Previous studies (Abbasi, 2011; Agarwal & Prasad, 1999; Lymperopoulos & Chaniotakis, 2005) suggest that users with less education are associated with computer anxiety, which causes low-levels of computer self-efficacy, which could contribute to lowering ease of use perceptions. Supporting this argument, Powell (2013) reviewed 276 articles and revealed that educational level and computer self-efficacy are negatively correlated with computer anxiety. Furthermore, a meta-analysis study by Maricutoiu (2014) found that computer anxiety is negatively associated with computer ease of use. Similarly, Agarwal and Prasad (1999), Claar et al. (2014), and Calisir, Gumussoy, and Bayram (2009) conclude that education has a positive significant effect on PEOU. Therefore, the hypotheses that level of education has a significant effect on SL → PEOU (H37h) and BI → AU (H36) are accepted.

7.4.4 Experience

In contrast to Venkatesh et al. (2003) and Tarhini (2013) in Lebanon, the test of the moderating effect disclosed that student experience with LMS moderates the relationship between PU and BI, meaning that hypothesis H43 is supported. Although Tarhini et al. (2014b) demonstrated that the effect of PU and BI is stronger for more-experienced students in Lebanon, the path PU → BI in this study is stronger for less-experienced students, which is consistent with previous literature regarding information systems (Davis, Bagozzi, & Warshaw, 1989; Taylor & Todd, 1995a), LMS (Abbasi, 2011), and VLE (Zhang, Liu, Yan, & Zhang, 2017). Davis et al. (1989) and Taylor and Todd (1995a) assumed that more-experienced users have greater concerns about enjoyment, which, consequently, reduces the effect of PU (Abbasi, Irani, & Chandio, 2010). The result of this present study indicates that less-experienced students are more influenced when LMS enable them to achieve tasks more quickly and learn effectively, which, in turn, increases their intention to use LMS. Thus, the usefulness of the system should be treated carefully when dealing with less-experienced students. In addition, the relationship PU → BI is stronger in less-experienced students than in more-experienced students, which might have led to this moderating effect.

Regarding IA → PU, the MGA reveals that this relationship is statistically different between low-experience and high-experience students. The path between IA → PU is moderated by the LMS experience variable, meaning that hypothesis H40g is supported. More specifically, the effect between IA and PU is stronger for less-experienced students than high-experienced students. Furthermore, how IA impacts PU is significant in both groups, but higher in the model of less-experienced students. This result implies that students with less experience are more influenced when LMS have good self-assessment tools that help them understand the content of courses, which, in turn, makes them regard LMS useful in their education. Moreover, the effect of IA is extended to affect the less-experienced students' intentions to use LMS, as the relationship between PU and BI is stronger for these students. One plausible justification for this result is that inexperienced learners accept self-assessment (Ibrahim-Gonzalez & Noordin, 2012). Therefore, the findings suggest supporting hypotheses H43 – that experience moderates the effect of PU on BI to use LMS – and H40g – that experience moderates the effect of IA on students' PU of LMS.

7.5 Summary

This chapter discussed the results found regarding answering the research questions in Section 1.4. The first section considered the factors that affect the students' use of the LMS at public universities in Saudi Arabia. This section included a discussion of the findings of the 12 constructs that were examined by the 20 hypotheses. The acceptance and rejection of the direct relationships in the structural model were explained to help understand the influence of the independent variables on the students' use of LMS in Saudi higher education.

The second and third sections of this chapter discussed the evidence for the second and third research questions, respectively. Question 2 concerns the differences in the proposed model between the students' demographic characteristics (gender, age, level of education, and LMS experience). Question 3 concerns the moderating effect of the four demographic characteristics on the relationships between the factors impacting the students' use of LMS in Saudi public universities. This effect is important because understanding the use of LMS among male, female, younger, older, undergraduate, postgraduate, less-experienced, and more-experienced students in Saudi higher education helps direct appropriate resources toward improving educational experiences.

The next chapter (Chapter 8) draws the conclusion of this study, which 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

This chapter presents an overall conclusion based on the results obtained in this research. The chapter begins with a summary of the research objectives, proposed model, key findings, the research questions, and how they were answered. This section is followed by the research recommendations to and implications for decision-makers and practitioners in Section 8.3. Section 8.4 discusses the contributions to theory, methodology, and domain achieved by this research. In Section 8.5, future research directions are offered based on the limitations drawn in this study. Finally, Section 8.6 concludes the chapter.

8.2 Research Overview and Key Findings

This study was primarily conducted to investigate the effects of usability attributes and demographic characteristics on students' use of LMS in Saudi public universities. Learning management systems have been introduced across all universities in Saudi at the request of the Government. However, previous literature related to student use of LMS in Saudi higher education (Al-Aulamie, 2013; Al-Jarf, 2007; Alenezi, 2012) reveals that LMS continue to be underutilised. As LMS represent a significant investment, including the cost of licences, staff development, and new roles as learning technologists, exploring student perceptions toward LMS is an important topic. The TAM (Davis, Bagozzi, & Warshaw, 1989) was selected from the other technology-acceptance theories (see Section 2.4) as the theoretical framework for this study due to its popularity, flexibility, and effectiveness in examining student use of e-learning systems (see Section 3.3). Reviewing previous literature regarding usability in educational technologies (see Section 2.3) led to the selection of appropriate usability attributes for the evaluation of LMS. This study builds on established theory to consider technology acceptance in a new context; thus, it incorporates perceptions of usability to extend the TAM through usability research. It is important to understand the effects of perceived usability on student acceptance of LMS, as the usability of modern, flexible LMS can be enhanced. Based on the TAM and the identified usability attributes, the proposed research model comprises 12 independent and dependent variables, namely CQ, LS, VD, SN, EOA, SI, IA, SL, PEOU, PU, BI, and AU, as well as four personal moderating variables, namely gender, age, level of education, and experience. More explanation about each variable is provided in Chapter 3. Figure 8.1 depicts the proposed research model.

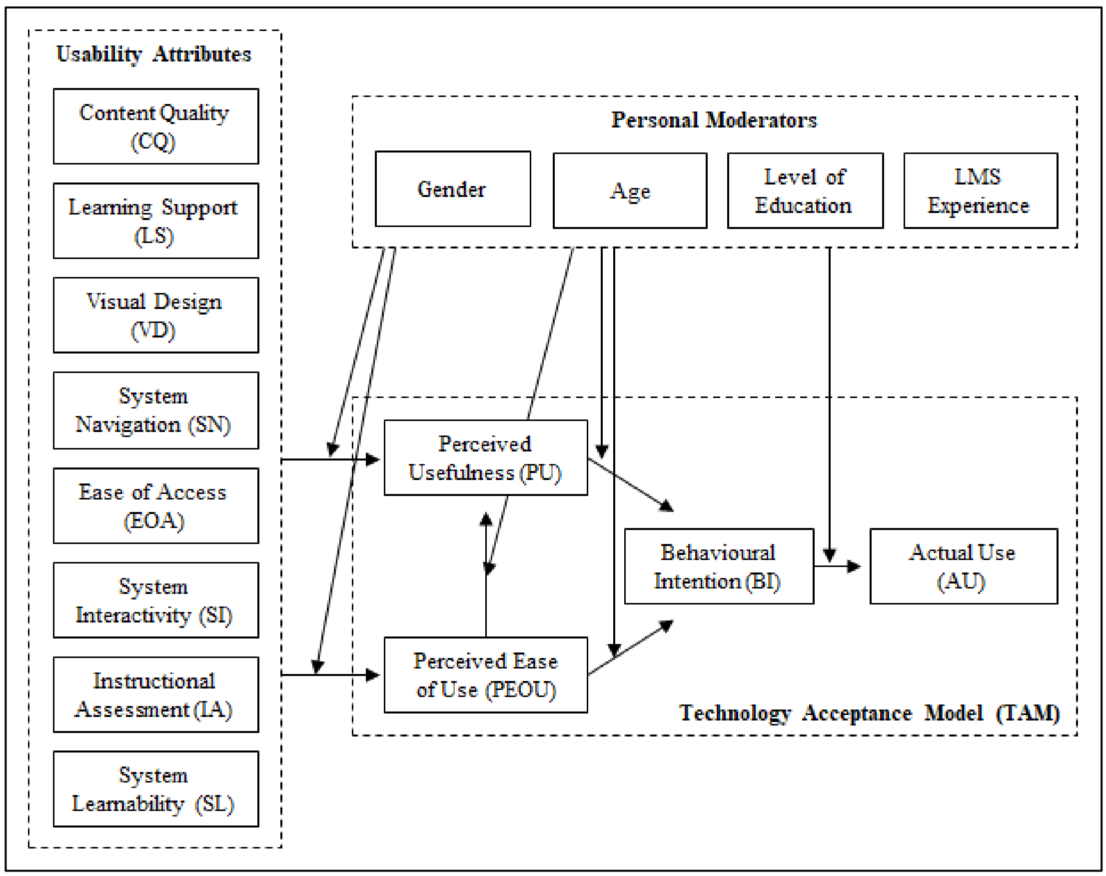

Figure 8.1 The Proposed Conceptual Model

Table 8.1 provides a summary of the research questions and the methods employed to address each question and analyse the data collected. The selection of the data-collection method and data analysis technique were justified in Chapter 4.

Table 8.1 Methods Used to Answer Research Questions

	Research Questions	Method	Analysis	Location
RQ1	What are the usability attributes that have significant and positive effects on student acceptance and use of learning management systems in Saudi public universities?	Online survey used to collect data about the students' attitude toward LMS.	Run the path analysis using the SmartPLS software for the entire dataset	Path analysis in Section 6.3.2
RQ2	To what extent do the effects of the usability attributes on student acceptance and use of learning management systems in Saudi public universities differ between students based on their demographic characteristics of gender, age, level of education, and experience?	Online survey used to collect data about the students' demographic information and attitude toward LMS.	Run the path analysis using the SmartPLS software for each group	Path analysis for each group in Section 6.5
RQ3	To what extent do the demographic characteristics of gender, age, level of education, and experience significantly moderate the effects of the usability attributes on student acceptance and use of learning management systems in Saudi public universities?	Online survey used to collect data about the students' demographic information and attitude toward LMS.	Run the MGA using the SmartPLS software	Permutation test for each group in Section 6.6

The analysis of the quantitative data in Chapter 5 and Chapter 6 produced many results. The key findings obtained from this analysis are summarised as follows:

- Six usability attributes were found to have significant and positive effects on the students' PEOU of LMS. The attributes are arranged from the most significant to the least significant as follows: SL, SN, SI, IA, CQ, and EOA. The relationship between EOA and PEOU is the least significant relationship.
- Five usability attributes were revealed to have significant and positive effects on the students' PU of LMS. The attributes are arranged from the most significant to the least significant as follows: PEOU, SI, IA, LS, and CQ.
- Two factors were demonstrated to have significant and positive influences on the students' BI to use LMS, which are PEOU and PU. The relationship between PU and BI is the most significant relationship.

- The students' AU of LMS is significantly and positively affected by their BI to use LMS.
- For the group of male students, three usability attributes were found to have significant and positive effects on the students' PEOU of LMS. The attributes are arranged from the most significant to the least significant as follows: SL, CQ, and IA. Four usability attributes were revealed to have significant and positive influences on the students' PU of LMS. The attributes are arranged from the most significant to the least significant as follows: PEOU, IA, SI, and LS.
- For females, five usability attributes were found to have significant and positive effects on the students' PEOU of LMS. The attributes are arranged from the most significant to the least significant as follows: SL, SN, SI, IA, and VD. Five usability attributes were revealed to have significant and positive influences on the students' PU of LMS. The attributes are arranged from the most significant to the least significant as follows: PEOU, SI, IA, LS, and CQ.
- For the group of younger students, three usability attributes were found to have significant and positive effects on the students' PEOU of LMS. The attributes are arranged from the most significant to the least significant as follows: SL, SN, and IA. Four usability attributes were revealed to have significant and positive influences on the students' PU of LMS. The attributes are arranged from the most significant to the least significant as follows: SI, IA, PEOU, and LS.
- For older students, four usability attributes were found to have significant and positive effects on the students' PEOU of LMS. The attributes are arranged from the most significant to the least significant as follows: SL, SI, SN, and CQ. Four usability attributes were revealed to have significant and positive influences on the students' PU of LMS. The attributes are arranged from the most significant to the least significant as follows: PEOU, SI, LS, and IA.

- Regarding the group of undergraduate students, three usability attributes were found to have significant and positive effects on the students' PEOU of LMS. The attributes are arranged from the most significant to the least significant as follows: SL, SN, and SI. Four usability attributes were revealed to have significant and positive influences on the students' PU of LMS. The attributes are arranged from the most significant to the least significant as follows: PEOU, SI, IA, and LS.
- For postgraduates, six usability attributes were found to have significant and positive effects on the students' PEOU of LMS. The attributes are arranged from the most significant to the least significant as follows: SL, LS, EOA, VD, CQ, and SN. Two usability attributes were revealed to have significant and positive influences on the students' PU of LMS. The attributes are arranged from the most significant to the least significant as follows: PEOU and IA.
- Regarding less-experienced students, six usability attributes were found to have significant and positive effects on the students' PEOU of LMS. The attributes are arranged from the most significant to the least significant as follows: SL, SN, SI, CQ, IA, and EOA. Five usability attributes were revealed to have significant and positive influences on the students' PU of LMS. The attributes are arranged from the most significant to the least significant as follows: PEOU, SI, IA, LS, and CQ.
- For more-experienced students, four usability attributes were found to have significant and positive effects on the students' PEOU of LMS. The attributes are arranged from the most significant to the least significant as follows: SL, SN, SI, and VD. Four usability attributes were revealed to have significant and positive influences on the students' PU of LMS. The attributes are arranged from the most significant to the least significant as follows: PEOU, SI, LS, and IA.
- One relationship was moderated by the students' gender. More specifically, the effect of CQ on PEOU was stronger for male students than for female students.

- The age variable did not moderate any relationships in the proposed model.
- Two relationships were moderated by the students' education levels. More specifically, the effect of SL on PEOU and the effect of BI on AU were stronger for undergraduate students.
- Two relationships were moderated by the students' experience, which are the effect of IA on PU and the effect of PU on BI. More specifically, the less-experienced students are, the more significant those relationships become.

The practical implications and recommendations for practitioners are now presented.

8.3 Research Implications

Based on the research results, this section presents guidelines for leaders, decisions makers, system developers and educators in higher-educational institutions in Saudi Arabia to improve the use and quality of LMS.

8.3.1 Content Quality

It is evident that CQ is a determinant of the students' acceptance and use of LMS at public universities in Saudi Arabia. System-designers should enhance the quality of LMS content by including easy to reach, updated, sufficient, and well-organised content. Universities could promote CQ guidelines, offer training for academic staff regarding increasing CQ, and conduct audits designed to enhance quality. These efforts will improve the chance of students in Saudi higher education adopting and using LMS. System quality will lead to an increase in the students' PEOU and PU, which, in turn, increases the utilisation level of LMS. As CQ is more noticeable with students who are male, older, postgraduate, and/or less-experienced, more consideration should be dedicated to CQ when dealing with these demographic groups. Furthermore, the moderating effects suggest that the influence of CQ on PEOU is stronger for male students.

8.3.2 Learning Support

Learning support was identified as an important factor that influences the acceptance and use of LMS by students at higher-educational institutions in Saudi Arabia. University leaders are responsible for providing LMS that have appropriate and sufficient tools to support the students' education with help. Effective LS will augment the students' PU, which, in turn, attracts more students to use LMS. This effect is observed more with students who are male, younger, undergraduates, and less-experienced; therefore, more attention should be paid to LS when dealing with these demographic groups.

8.3.3 Visual Design

Visual design is not a significant precursor of the acceptance and use of LMS by students at public universities in Saudi Arabia. More specifically, the system design does not affect the students' PEOU or PU, which, in turn, has no influence on their intention to use LMS. This result is due to the participants' experience with LMS and self-declared moderate and high levels of computer and Internet skills. Thus, VD is not crucial when users possess high ICT skills. Nevertheless, VD is more relevant for postgraduate and experienced students regarding affecting their PEOU. Hence, more consideration should be dedicated to VD when dealing with these two groups.

8.3.4 System Navigation

System navigation is a determinant of the students' acceptance and use of LMS at higher-educational institutions in Saudi Arabia. To attract more students to use LMS and to save time finding appropriate resources, system-developers should ensure that LMS enable students to find information, predict links, and leave and return easily. More accurately, good SN drives students to perceive the system to be easy to use, which, in turn, enhances their intention to use and their AU of LMS. This finding is more relevant for students who are female, younger, and undergraduates; therefore, practitioners should consider SN when dealing with these demographic groups.

8.3.5 Ease of Access

The results indicate that EOA is a precursor of the students' acceptance and use of LMS at public universities in Saudi Arabia. The system-designers should enhance the accessibility of LMS by easing the login process, supporting different Internet browsers, enhancing the downloading and uploading of pages, and solving technical problems. These efforts will improve the chance of adopting and using LMS by students in Saudi higher education. The attribute EOA leads to an increase in the students' PEOU, which, in turn, increases the utilisation level of LMS. The impact of EOA is noticeable with postgraduate students and less-experienced students; therefore, more consideration should be dedicated to EOA when dealing with these two groups. Nevertheless, EOA is the weakest determinant of PEOU.

8.3.6 System Interactivity

System interactivity was identified as an important factor that influences the acceptance and use of LMS by students at higher-educational institutions in Saudi Arabia. Decision-makers in universities are responsible for providing students with LMS that are rich with asynchronous and synchronous tools that facilitate the students' communication with each other and with teachers. System interactivity augments students' PEOU and PU, which, in turn, attracts more students to use LMS. More specifically, SI is the strongest determinant of the students' PU among the external variables. The effects of this construct are observed more with students who are female, older, undergraduates, and/or less-experienced; therefore, more attention should be paid to SI when dealing with these demographic groups. However, SI is considered not very important for postgraduate students.

8.3.7 Instructional Assessment

According to the results, IA is a determinant of the students' acceptance and use of LMS at public universities in Saudi Arabia. Educators should ensure that LMS have easy-to-use self-assessment tools enabling students to understand the course content and measure their achievement of the learning objectives. To improve the students' use of LMS, the system should include good self-assessment tools, which contribute to an increase in the students' PEOU and PU. The influence of the IA construct is more relevant to students who are female, younger, and less-experienced; therefore, educators should consider IA when dealing with these demographic groups. Furthermore, the moderating effects suggest that the influence of IA on PU is stronger for less-experienced students than for more-experienced students.

8.3.8 System Learnability

As e-learning has only recently been adopted in Saudi Arabia, SL was identified as a significant condition for the students' acceptance and use of LMS at higher-educational institutions in Saudi Arabia. Hence, learning technologists should ensure that the system is easy to learn by providing online help, predictable links or buttons, and consistency across different courses. Moreover, officials at Saudi universities should ensure that it is clear to students what they should do when they have questions regarding how to use the system. Good SL encourages students to perceive the system as easy to use, which, in turn, enhances their intention to use and the AU of LMS. More specifically, SL is the strongest determinant of students' PEOU. Furthermore, the impact of SL is considered important for all demographic groups. The moderating effects suggest that the influence of SL on PEOU is stronger for undergraduates than for postgraduates. Therefore, decision-makers in Saudi public universities are recommended to significantly consider SL, as most students in Saudi higher education are undergraduates.

Having discussed the practical research implications, the following section provides the theoretical and methodological research contributions.

8.4 Research Contributions

Based on the results obtained and the methodology used to conduct this study, the following research contributions to theory and methodology are outlined in this section.

8.4.1 Contribution to Theory

The main outcome of this thesis is the development of a new conceptual model that helps to uncover the effects of perceived usability, and thereby BI and AU, on the students' use of LMS in Saudi public universities while considering the moderating effect of the four personal characteristics. This research contributes to the following findings:

- *Perceived usability and technology acceptance:* The literature review (see Sections 3.2 and 3.5) revealed that this present study is one of the few studies that primarily aims to use the TAM to investigate the effects of perceived usability on student use of LMS in Saudi higher education. This thesis has extended the work of previous researchers and achieved new results. Hence, this work might prove a useful guide for future research and guide explanations regarding the effects of perceived usability in the domain of educational technologies.
- *Developing a novel model:* A second contribution is that this study has advanced the theory by extending the TAM theory (Davis, Bagozzi, & Warshaw, 1989) and developing a novel model to explain student acceptance and use of LMS. Eight usability factors were added the TAM, namely CQ, LS, VD, SN, EOA, SI, IA, and SL, as well as four personal moderating variables, namely gender, age, level of education, and experience. This thesis has used

previous literature on usability, technology acceptance, and e-learning to develop the proposed conceptual model. Therefore, the developed model can be employed to examine student acceptance and use of e-learning systems in different cultural contexts. Furthermore, this thesis provided an extensive literature review about the proposed relationships in the developed model within the context of e-learning systems from the perspective of higher-education students. This content helps to understand the relationships between factors in the domain in educational technologies worldwide.

- *Adapting the instructional assessment construct:* Another considerable contribution to knowledge by this research was revealing that the IA variable is a predictor of student acceptance and use of technology in education. The IA factor has previously been suggested as being important in e-learning systems by Zaharias and Poylymenakou (2009). Nevertheless, IA has never been adopted into the TAM, nor has it been empirically examined within the context of e-learning systems. Therefore, this present study contributes to the theory by adopting the IA variable into the TAM to examine student use of LMS. This adoption will provide useful information to universities when designing course content.
- *High explained variance:* A fourth significant contribution of this research is that the findings demonstrate the significance of the usability factors as antecedents to technology use in the domain of e-learning systems. The proposed model is capable of explaining a high percentage of the variance in the dependent variables. The model explained 76.4% of the variance in PEOU, 66.7% in PU, 61.5% in BI, and 34.7 in AU. Furthermore, the developed model advances the theory by achieving the highest percentage of explained variance in PEOU, PU, BI, and AU when compared with similar studies on Saudi higher education (see Table 8.2).

Table 8.2 Explained Variance of LMS Acceptance Studies in Saudi Arabia

Study	Additional Factors	Moderators	Explained Variance (R^2)			
			PEOU	PU	BI	AU
This current study	Content quality Learning support Visual design System navigation Ease of access System interactivity Instructional assessment System learnability	Gender Age Education Experience	0.734	0.667	0.615	0.347
(Abdel-Maksoud, 2018)	Satisfaction	N/A	N/A	N/A	N/A	N/A
(Almarashdeh & Alsmadi, 2016)	N/A	N/A	N/A	N/A	N/A	N/A
(Muniasamy, Eljailani, & Anandhavalli, 2014)	N/A	N/A	N/A	0.544	0.395	N/A
(Al-Aulamie, 2013)	Information quality Functionality Accessibility User interface design Computer playfulness Enjoyment Learning goal	Gender	0.480	0.590	0.560	N/A
(Al-Mushasha, 2013)	University support Computer self-efficacy	N/A	0.200	0.250	0.220	N/A
(Alenezi, 2012)	System performance System functionality System response System interactivity	N/A	N/A	N/A	0.110	0.211
(Al-Harbi, 2011)	University support Computer self-efficacy Accessibility	N/A	0.230	0.560	0.430	N/A
(Alenezi, Abdul Karim, & Veloo, 2011)	Training Technical support Facilitating conditions	N/A	N/A	N/A	0.110	0.211
(Alenezi, Abdul Karim, & Veloo, 2010)	Perceived enjoyment Computer self-efficacy Computer anxiety Internet experience	N/A	N/A	N/A	0.610	N/A

- *National and individual level:* A fifth contribution is that this study is considered one of the few studies that analysed the acceptance of LMS by students at a national and individual level based on their personal characteristics, namely gender, age, level of education, and experience (see Table 3.1). This thesis has extended the work of previous researchers to examine the students' acceptance of LMS at an individual level based on four personal characteristics in Saudi higher education. Hence, this research provides useful guidelines for future research investigating the acceptance of technology by users at a more individual level in Saudi Arabia. Moreover, researchers usually analyse the full set of collected data while assuming that the data were derived from a homogenous population; however, this assumption is not always correct (Hair, Hult, Ringle, & Sarstedt, 2017; Sarstedt, Henseler, & Ringle, 2011). Not considering the heterogeneity between observations might affect the validity of the analysis and lead to incorrect interpretations (Hair, Sarstedt, Ringle, & Mena, 2012). For example, when the relationship between two constructs is negatively significant for male participants and positively significant for female participants, the analysis of the full dataset might not find any significance.

- *Moderating effect:* The final contribution of this thesis to theory concerns the investigation of the moderating effect of the personal characteristics on the relationships in the proposed model. Previous researchers (Morris, Venkatesh, & Ackerman, 2005; Sun & Zhang, 2006) reported that the moderating effect of the personal characteristics on technology acceptance and use has not been well understood. Furthermore, although the TAM (Davis, Bagozzi, & Warshaw, 1989) is the most cited model, it has been criticised by researchers (Al-Gahtani, 2008; Venkatesh & Morris, 2000; Venkatesh, Morris, Davis, & Davis, 2003) for a lack of moderating variables. This study has extended the work of previous researchers to measure the moderating effect of four personal characteristics, namely gender, age, level of education and experience, on the students' use of LMS in Saudi higher education. Therefore, this study advances the theory by extending the TAM (Davis, Bagozzi, & Warshaw, 1989) and using four personal moderators.

8.4.2 Contribution to Methodology

Although this study employed a quantitative survey approach, which is common for technology acceptance research, the aim and objectives of this work were achieved while making several methodological contributions to knowledge. The methodology employed in this research contributed to the following:

- *Sampling technique:* This study is one of the few on technology acceptance that benefits from utilising the multi-stage cluster-sampling technique to take a representative sample from the target population. While the non-probability convenience-sampling technique is the most popular technique in technology acceptance (Tarhini, 2013), the multi-stage cluster-sampling technique is useful for generalising findings (Cohen, Manion, & Morrison, 2013) and for targeting large and distributed populations (Bryman, 2016), which is the case in this study. Therefore, future research on technology acceptance, in Saudi Arabia in particular, could use the sampling technique and procedures followed in this work as a guide.
- *Instrument development:* Another considerable methodological contribution of this thesis was to develop and validate a novel survey instrument. This research adapted survey items from various fields in Western culture and modified it to fit the context of LMS in Saudi Arabia, such as the IA construct, which has never been validated for use with LMS. The survey was validated several times (during the face validity with five academic experts, the pilot study with 58 students, and the main study with 833 students). The survey items demonstrated an acceptable level of indicator reliability, construct reliability, convergent validity, and discriminant validity. Furthermore, the developed instrument was translated into the language of the target population (Arabic). Hence, two versions, Arabic and English, of this instrument are available to be used by other studies (see Appendices A and B). Therefore, the developed

survey can be replicated by future studies and validated with different technologies, users, and cultural contexts.

- *Using the PLS-SEM and MGA analysis:* The final contribution to methodology is that this study employed the PLS-SEM technique using the SmartPLS software to assess the measurement and structural models. The PLS-SEM technique is the less popular SEM technique compared with CB-SEM (Ringle, Sarstedt, & Straub, 2012; Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016). Furthermore, researchers have rarely used the PLS-SEM technique to explain the effects of perceived usability on technology acceptance (Aziz & Kamaludin, 2014). Moreover, this study contributes to methodology by using the MGA to assess the moderating effect of the four personal characteristics on the proposed relationships between the independent and dependent variables. As the MGA analysis using the PLS-SEM technique has been limited in previous research (Sarstedt, Henseler, & Ringle, 2011; Matthews, 2017), this study is among only a few that have used MGA to assess the moderating effect. Therefore, this study provides a clear example of how to use the PLS-SEM technique and the MGA analysis using the SmartPLS software, which could be used for alternative contexts.

8.5 Research Limitations and Future Work

This study extended the TAM with eight usability attributes and four personal moderators to explain their effects on the students' use of LMS within the context of higher-educational institutions in Saudi Arabia. However, as with any study, this research is not free of potential limitations. These are discussed in this section, below.

- *The TAM:* This study proposed a novel model based on the TAM to explain the acceptance of LMS. Using another TAM (e.g. the UTAUT or the UTAUT2) might improve the explained variance of the BI and AU constructs.

Therefore, future researchers should consider the adoption of the usability factors into another pre-developed model, such as the UTAUT2.

- *Quantitative survey approach:* Another significant limitation of this research concerns the methodology. This study relied solely on a quantitative survey approach to collect data from the target population due to time and resource limitations. A survey is considered the most widely used tool to collect data in the domain of technology acceptance. This method helps to measure the participants' beliefs and attitude toward technology. Nevertheless, future work could consider the utilisation of qualitative methods (e.g. interviews and focus groups) to obtain an in-depth understanding of the investigated problem and the participants' attitude.
- *Self-reported data:* This study employed self-reported data to measure the students' AU of LMS, rather than analysing log files from the back-end of the system. Self-reported data were used because of the large and distributed population and the difficulty of obtaining access to public universities in Saudi Arabia. Furthermore, utilising the self-reported data to explain AU is supported by previous literature in e-learning acceptance (see Table 3.1). However, a future study could access data analytics supported by LMS to obtain a measure of AU.
- *Cross-sectional design:* A fourth limitation of this research was to use a cross-sectional design due to the available time and budget for this research. However, longitudinal studies can be conducted more than once to measure user intention and AU over a period of time, which is associated with high cost and time (Bryman & Bell, 2015; Cohen, Manion, & Morrison, 2013). Considering that user behaviour changes over time (Venkatesh, Morris, Davis, & Davis, 2003), future studies are recommended to use a longitudinal design that provides a better understanding of the relationship between student intention and AU of LMS, as recommended by Al-Aulamie (2013).
- *Mandatory use:* This research investigated the influence of usability attributes and demographic characteristics on the use of LMS in mandatory use. Previous

literature (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh, Morris, Davis, & Davis, 2003) demonstrated that voluntariness has a significant effect on user perception toward technology. Hence, it would probably be inappropriate to generalise the findings of this study to voluntary settings. Other studies could examine the proposed hypotheses between independent and dependent variables in a voluntary environment.

- *Target public universities:* This study targeted the students' acceptance and use of LMS at Saudi public universities. The perception of students at private universities in Saudi Arabia toward LMS might be different from students at Saudi public universities. Hence, it may be incorrect to generalise the findings of this study to private universities. Consequently, a further study could be conducted to extend the scope of this research to target students at both public and private higher-educational institutions in Saudi Arabia.
- *Adopt additional variables:* Kattoua et al. (2016) reported that the implementation of e-learning systems does not rely solely on the technical solution, but also on factors such as social, individual, and organisational variables. Another limitation of this research was investigating the influence of eight usability attributes and four personal moderators on the students' use of LMS. Other usability attributes (e.g. consistency) and/or personal factors (e.g. academic major) that might be more salient to the students' acceptance and use regarding LMS could be adopted. Thus, future researchers should consider other usability attributes, personal moderators, and/or different users (e.g. educators and employees).
- *Focus on e-learning system:* This research exclusively examined student use of a particular type of e-learning system (the LMS). Individuals have different determinants for accepting and using different types of technology (Hakami, 2018). Furthermore, the students' perceptions might be different when presented with another e-learning technology, such as a content management system, mobile learning, or social media (e.g. Facebook or WhatsApp). Hence, this study could be replicated with a different e-learning system.

8.6 Conclusion

This study demonstrated the significance of usability attributes for student acceptance and use of LMS in the context of Saudi higher education. Despite the research limitations (see Section 8.5), the findings of this research have made many contributions to theory, methodology, and practice. Regarding the direct determinants, this study revealed that SI is the most salient factor among the usability attributes regarding improving the students' PU. Furthermore, SL is the strongest driver for PEOU, indicating that an easy-to-learn system leads students to perceive it as easy to use.

Considering the personal differences between students (gender, age, level of education, and experience), this research revealed that each demographic group (e.g. postgraduate versus undergraduate students) is motivated by different usability factors. Hence, decision-makers at Saudi universities should consider the suggested drivers in this study when dealing with each demographic group. For example, a women-only university (e.g. Princess Nourah bint Abdulrahman University) should consider more relevant drivers for female students, such as system organisation and navigation. For a men-only university (e.g. King Fahd University of Petroleum & Minerals), consideration should be given to IA.

Regarding the moderating effects, this research examined the four personal moderators, namely gender, age, level of education, and experience, on 80 parameter relationships. Only five relationships in the proposed model were significantly moderated by the four variables. Therefore, these demographic moderators have very little moderating effect on the students' use of LMS in Saudi public universities. Thus, it is suggested that university leaders in Saudi Arabia should, in general, utilise similar policies to prompt students toward using LMS. In so doing, students can obtain the maximum benefit of their educational experience.

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APPENDIX A: QUESTIONNAIRE (ENGLISH)

Dear Participant,

I am a PhD student in Edinburgh Napier University in the United Kingdom. The title of my research is ‘The Influence of Usability Attributes on the Utilisation of Learning Management Systems in the Kingdom of Saudi Arabia: The Perceptions of Students’.

The main objective of this study is to investigate the used Blackboard in Saudi Arabia, and it should take no longer than 10 minutes to complete. This study is exclusive for students who use the Blackboard system at the university. Please, do not complete the survey if you do not use the Blackboard system.

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 to what it says.

1. Your participation in this research conducted by Mr. Sami Binyamin, a PhD student in the Edinburgh Napier School of Computing, is completely voluntary.
2. If you feel unable or unwilling to continue at any time during the survey, you are free to leave. Your participation in this study is completely voluntary, and you may withdraw from it at any time without negative consequences.
3. Should you not wish to answer any particular question or questions, you are free to decline.
4. You understand the broad goal of this research study.
5. Your responses will be anonymised, and identifying information such as your name, email address or IP address will not be collected. You will not be identified or identifiable in any report subsequently produced by the researcher even though these data may be submitted for publication.
6. Your agreement is not a waiver of any legal rights.

If you have any questions or concerns about the study or the online survey procedures, please contact me [redacted] or my supervisor [redacted]

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

Demographic Information:

1. What is your gender?
    - o Male
    - o Female

2. What is your university?
    - o King Abdulaziz University
    - o King Saud University
    - o Imam Abdulrahman Bin Faisal University

3. What is your education level?
    - o Undergraduate
    - o Graduate

4. What is your field of study?
    - o Science
    - o Art

5. How do you rate your computer skills?
    - o Novice
    - o Moderate
    - o Expert

6. How do you rate your Internet skills?
    - o Novice
    - o Moderate
    - o Expert

7. How old are you?

    [ ] Years

8. How long have you been using Blackboard?

    [ ] Years

9. What is your GPA? (Out of 5)

    [ ] / 5

Usability Factors:

Content Quality

10. The vocabularies used in Blackboard are appropriate for me (e.g. discussion board, content, assignments… etc.).

11. Overall, the content of Blackboard is up-to-date.
12. Overall, the content is organised in an appropriate sequence.
13. Overall, there is sufficient content to support my learning.

Learning Support

14. Blackboard provides tools that support my learning.
15. Blackboard supports individual and group learning.
16. The online help of Blackboard is always available.
17. The Blackboard manual is written clearly.
18. The Blackboard manual provides the information I need.

Visual Design

19. Text, colours, and layout used in Blackboard are consistent.
20. The interface design of Blackboard is attractive to me.
21. Text and graphics of Blackboard are readable.
22. Important information is placed in areas most likely to attract my attention.

System Navigation

23. I always know where I am in Blackboard.
24. The navigational structure of Blackboard is convenient for me.
25. It is easy for me to find the information I need in Blackboard.
26. Links in Blackboard are working satisfactorily.
27. I can leave Blackboard at any time and easily return.

Ease of Access

28. It is easy for me to login to Blackboard.
29. I can access Blackboard from different browsers.
30. The pages and other elements of Blackboard download quickly.
31. Blackboard is free from technical problems.

System Interactivity

32. In general, Blackboard provides me with good synchronous and asynchronous communication tools (e.g. email, chat, forum).
33. Blackboard promotes my communication with teachers.
34. Blackboard facilitates my communication with students.
35. Blackboard helps me engage more with my learning.

Instructional Assessment

36. Blackboard provides good self-assessment tools (e.g. exams, quizzes, case studies).
37. It is easy for me to use the self-assessment tools in Blackboard.
38. The self-assessment tools in Blackboard help me to understand the content of course.

39. The self-assessment tools in Blackboard measure my achievements of learning objectives.

System Learnability
40. It is easy for me to learn how to use Blackboard.
41. The results of clicking on buttons are predictable.
42. I do not need to read a lot to learn how to use Blackboard.
43. I can start using Blackboard with only online help.

TAM's Factors:

Perceived Ease of Use
44. I find Blackboard flexible to interact with.
45. It is easy for me to get Blackboard to do what I want it to do.
46. It is easy for me to become skillful at using Blackboard.
47. Overall, Blackboard is easy to use.

Perceived Usefulness
48. Blackboard enables me to achieve tasks more quickly.
49. Blackboard improves my learning performance.
50. Blackboard helps me to learn effectively.
51. Blackboard makes it easier for me to learn course content.
52. Overall, Blackboard is useful in my learning.

Behavioural Intention to Use
53. I would like to use Blackboard in all future courses.
54. I would recommend using Blackboard to others.
55. I would encourage my teachers to use Blackboard in courses.
56. I will continue using Blackboard in the future.

Actual Use
57. I use Blackboard frequently.
58. I tend to use Blackboard for as long as is necessary.
59. I have been using Blackboard regularly.
60. I usually get involved with Blackboard.

Usage of Blackboard:

How do you rate your usage frequency of the Blackboard features below?

	Features	**Never**	**Rarely**	**Sometimes**	**Very Often**	**Always**
61	Course materials					
62	Announcements					

	Features	Never	Rarely	Sometimes	Very Often	Always
63	Assignments					
64	Discussion board					
65	Messages and email					
66	Grades					
67	Exams and Quizzes					
68	Virtual classrooms					

APPENDIX B: QUESTIONNAIRE (ARABIC)

عزيزي المشارك/عزيزتي المشاركة

يقوم الباحث بإعداد رسالة الدكتوراة في كلية الحاسبات بجامعة أدنبره نابيير بالمملكة المتحدة بعنوان "تأثير خصائص قابلية الاستخدام على استعمال نظم إدارة التعلم في الجامعات السعودية من وجهة نظر الطلاب". تهدف هذه الدراسة إلى تقييم نظم إدارة التعلم (بلاكبورد) من وجهة نظر طلاب وطالبات الجامعات السعودية العامة. حيث تعتبر هذه الدراسة حصرية لمستخدمي نظام بلاكبورد من الطلاب والطالبات، علماً بأن المشاركة في هذه الدراسة لا تتطلب أكثر من 10 دقائق لإكمالها. شاكراً ومقدراً حسن تعاونكم وإهتمامكم سلفاً

يتطلب من جميع المشاركين في هذه الدراسة البحثية إعطاء موافقتهم على ذلك. لذا يرجى قراءة ما يلي والنقر على أيقونة "التالي" في حال الموافقة:

1. المشاركة في هذه الدراسة التي سيجريها الأستاذ/ سامي بن يمين (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. مشاركتك في هذه الدراسة تطوعية تماماً، ويمكنك الانسحاب منها في أي وقت دون أي عواقب سلبية
3. إذا كنت لا ترغب في الإجابة على أي سؤال أو أسئلة معينة بإمكانك التحفظ عن الإجابة
4. المشاركة في هذه الدراسة ستكون سرية، ولن يتم جمع المعلومات المتعلقة بتحديد هوية المشارك/المشاركة (مثل الاسم والبريد الإلكتروني)، ولن يتم تحديد هوية المشارك/المشاركة في أي تقرير سيتم عمله في وقت لاحق من قبل الباحث، مع العلم بأنه سيتم استخدام بيانات الاستبانة بغرض النشر العلمي
5. موافقتك لا تعني التنازل عن أي حقوق قانونية

إذا كان لديك أي أسئلة أو استفسارات حول الدراسة، يرجى التواصل مع الباحث من خلال البريد الإلكتروني [redacted]

إذا كنت قد قرأت وفهمت ما ورد أعلاه وتوافق على المشاركة في هذه الدراسة، يرجى النقر على أيقونة "التالي" أدناه

البيانات الشخصية:

1. ماهو جنسك؟
   - ذكر
   - أنثى

2. ماهي الجامعة التي تدرس بها؟
   - جامعة الملك عبد العزيز
   - جامعة الملك سعود
   - جامعة الإمام عبد الرحمن بن فيصل

3. ماهو مستواك التعليمي؟
   - دبلوم أو بكالوريوس
   - دراسات عليا

4. ماهو تخصصك الدراسي
   - علمي
   - أدبي

5. كيف تقييم مهارات استخدام الحاسب الآلي لديك؟
   - مبتدئ
   - متوسط
   - خبير

6. كيف تقييم مهارات استخدام الإنترنت لديك؟
   - مبتدئ
   - متوسط
   - خبير

7. كم عمرك؟

8. كم عدد سنوات استخدامك لنظام بلاكبورد؟

9. كم معدلك التراكمي؟ (من 5)

العوامل المتعلقة بقابلية استخدام النظام:

جودة المحتوى:

10. المفردات المستخدمة في نظام بلاكبورد (مثل: لوحة النقاش، المحتوى، الواجبات ... إلخ) مناسبة لي.
11. بشكل عام، محتوى نظام بلاكبورد يعتبر حديث.
12. بشكل عام، يتم تنظيم المحتوى في تسلسل مناسب.
13. بشكل عام، يوفر نظام بلاكبورد محتوى كافٍ يساعدني في تعليمي.

دعم التعلم:

14. يوفر نظام بلاكبورد الأدوات التي تدعم تعليمي.
15. يدعم نظام بلاكبورد التعلم الفردي والجماعي.
16. المساعدة عبر الإنترنت دائماً متاحة في نظام بلاكبورد.
17. كتيب دليل نظام بلاكبورد مكتوب بشكل واضح.
18. يوفر كتيب دليل نظام بلاكبورد المعلومات التي احتاجها.

تصميم النظام:

19. النصوص والألوان وتخطيط الصفحات في نظام بلاكبورد متناسقة مع بعضها البعض.
20. يعتبر تصميم صفحات نظام بلاكبورد جذاب.
21. النصوص والرسومات في نظام بلاكبورد سهلة القراءة.
22. يتم وضع المعلومات المهمة في الأماكن التي من المرجح أن تجذب إنتباهي.

التنقل في النظام:

23. دائماً أعرف الصفحة التي أتواجد بها في نظام بلاكبورد.
24. يعتبر تنظيم وترتيب قوائم التنقل في نظام بلاكبورد مناسب.
25. من السهل بالنسبة لي الوصول للمعلومات التي أحتاجها في نظام بلاكبورد.
26. الروابط في نظام بلاكبورد تعمل بشكل صحيح.
27. يمكنني مغادرة نظام بلاكبورد متى ما أريد والعودة إليه بسهولة.

الدخول إلى النظام:

28. من السهل بالنسبة لي الدخول لنظام بلاكبورد.
29. يمكنني الدخول لنظام بلاكبورد من متصفحات مختلفة.
30. تظهر الصفحات والعناصر الأخرى في نظام بلاكبورد بشكل سريع.
31. نظام بلاكبورد يخلو من المشاكل التقنية.

التفاعل في النظام:

32. بشكل عام، يوفر نظام بلاكبورد أدوات إتصال متزامنة وغير متزامنة ملائمة (مثل: البريد الإلكتروني ولوحة النقاش).
33. نظام بلاكبورد يعزز تواصلي مع المعلمين.
34. نظام بلاكبورد يسهل تواصلي مع الطلاب.
35. نظام بلاكبورد يجعل العملية التعلمية أكثر جذاباً بالنسبة لي.

التقييم التعليمي:

36. يوفر نظام بلاكبورد أدوات تقييم ذاتي ملائمة (مثل: الإختبارات و الواجبات).
37. من السهل علي إستخدام أدوات التقييم الذاتي في نظام بلاكبورد.
38. أدوات التقييم الذاتي في نظام بلاكبورد تساعدني على فهم محتوى المواد.
39. أدوات التقييم الذاتي في نظام بلاكبورد تقيس أدائي الدراسي بناءاً على الأهداف التعليمية.

تعلم استخدام النظام:

40. من السهل علي تعلم استخدام نظام بلاكبورد.
41. نتائج النقر على الروابط والأيقونات متوقعة.
42. لا أحتاج قراءاة الكثير لمعرفة كيفية استخدام نظام بلاكبورد.

43. كل ما أحتاجه للبدء في استخدام نظام بلاكبورد هو المساعدة عبر الإنترنت فقط.

<u>العوامل المتعلقة بنموذج قبول التقنية:</u>

سهولة استخدام النظام:

44. يتمتع نظام بلاكبورد بالمرونة.
45. من السهل علي جعل نظام بلاكبورد يقوم بما أريد أن أفعله.
46. من السهل علي أن أصبح ماهراً في استخدام نظام بلاكبورد.
47. بشكل عام، يعتبر نظام بلاكبورد سهل الاستخدام.

فائدة النظام:

48. استخدام نظام بلاكبورد يمكنني من إنجاز مهامي التعليمية بشكل أسرع.
49. استخدام نظام بلاكبورد يطور من أدائي الدراسي.
50. استخدام نظام بلاكبورد يساعدني على التعلم بشكل فعال.
51. استخدام نظام بلاكبورد يسهل علي فهم محتوى المواد.
52. بشكل عام، يعتبر نظام بلاكبورد مفيد في دراستي.

النية السلوكية لاستخدام النظام:

53. أرغب في استخدام نظام بلاكبورد في جميع المقررات الدراسية المستقبلية.
54. أوصي الأخرين باستخدام نظام بلاكبورد.
55. أشجع أساتذتي على استخدام نظام بلاكبورد.
56. سوف استمر في استخدام نظام بلاكبورد في المستقبل.

الاستخدام الفعلي للنظام:

57. استخدم نظام بلاكبورد بشكل متكرر.
58. استخدم نظام بلاكبورد كلما استدعت الحاجة لذلك.
59. استخدم نظام بلاكبورد بشكل منتظم.
60. عادة استخدم نظام بلاكبورد.

<u>استخدام نظام بلاكبورد:</u>

كيف تقييم مستوى استخدامك لأدوات نظام بلاكبورد

	الأدوات	**لا استخدمها**	**نادراً**	**أحياناً**	**غالباً**	**دائماً**
61	محتوى المادة					
62	الإعلانات					
63	الواجبات					
64	لوحة المناقشة					
65	الرسائل والإيميل					
66	الدرجات					
67	الإختبارات					
68	الفصول الإفتراضية					

APPENDIX C: ETHICAL APPROVAL

Application for Cross-University Ethical Approval

1. Research Details

Name:	Mr. Sami Binyamin
School or Professional service department:	School of Computing
Email:	[redacted]
Contact number:	[redacted]
Project Title:	The Influence of Usability Attributes on the Utilization of Learning Management Systems in the Kingdom of Saudi Arabia: The Perceptions of Students
Start Date:	01/02/2016
Duration of Project:	4 years
Type of Research: UG/Taught PG/Masters/Doctoral Student/ Staff: PhD student	

2. Screening Questions

Please answer the following questions to identify the level of risk in the proposed project:
If you answer 'No' to all questions, please complete Section 3a only.
If you have answered 'Yes' to any of the questions 5-14 please complete Section 3a and 3b.
If you have answered 'Yes to any of the questions 1-4, complete all of Section 3.

	You Must Answer All Questions	Yes	No
1.	Is the research clinical in nature?	☐	☒
2.	Is the research investigating socially or culturally 'controversial' topics (for example pornography, extremist politics, or illegal activities)?	☐	☒
3.	Will any covert research method be used?	☐	☒
4.	Will the research involve deliberately misleading participants (deception) in any way?	☐	☒
5.	Does the Research involve staff or students within the University?	☒	☐
6.	Does the Research involve vulnerable people? (For example people under 18 or over 70 years of age, disabled (either physically or mentally), those with learning difficulties, people in custody, migrants etc).	☐	☒
7.	Is the information gathered from participants of a sensitive or personal nature?	☐	☒
8.	Is there any realistic risk of any participants experiencing either physical or psychological distress or discomfort?	☐	☒
9.	Have you identified any potential risks to the researcher in carrying out the research? (for example physical/emotional/social/economic risks?)	☐	☒
10.	Are there implications from a current or previous professional relationship i.e. staff/student/line manager/managerial position that would affect the voluntary nature of the participation?	☐	☒
11.	Will the research require the use of assumed consent rather than informed consent? (For example when it may be impossible to obtain informed consent due to the setting for the research – e.g. observational studies/videoing/photography within a public space)	☐	☒
12.	Is there any risk to respondents' anonymity in any report/thesis/publication from the research, even if real names are not used?	☐	☒
13.	Will any payment or reward be made to participants, beyond reimbursement or out-of-pocket expenses?	☐	☒
14.	Does the research require external ethics clearance? (For example from the NHS or another institution)	☒	☐
15.	Does the research involve the use of secondary data?	☐	☒

3A. Details of Project

In this section please provide details of your project and outline data collection methods, how participant consent will be given as well as details of storage and dissemination.

Please give a 300 word overview of the research project
Despite the wide adoption of learning management systems (LMS) by higher educational institutions worldwide, the usability and utilization of such systems are still not within the acceptable levels. Saudi Arabia is no exception. Therefore, this study will be conducted to investigate the perceived usability and the influence of usability attributes on the use of LMS in Saudi Arabia from the perceptions of students. Other objectives include, but not limited to: 1. Develop, propose, validate and examine a conceptual model to investigate the effect of usability attributes on the students' actual use of LMS. 2. Investigate the students' acceptance of LMS in Saudi Arabia. 3. Identify the most critical usability issues from students' perception. 4. Determine the appropriate usability attributes for evaluating the usability of LMS. 5. Identify the students' utilization level and most used features of LMS in Saudi Arabia. 6. Address the usability factors influencing the utilization of LMS from Saudi students' perception. 7. Investigate the statistical significant differences between the perceived usability and students' actual use of LMS and different variables such as gender, age, experience with LMS, education level and field of study. This study aims to answer "To what extent do usability attributes influence the students' use of learning management systems in Saudi Arabia?" In order to obtain the answer, the primary question is divided into sub-questions as the following: RQ1. What are the critical usability issues of LMS from the perception of Saudi students? RQ2. What is the students' utilization level of LMS? RQ3. What are the usability attributes that influence the use of LMS? RQ4. Are there any significant differences in the perceived usability and the actual use of LMS between demographic characteristic groups: gender, age, experience with LMS, education level and field of study?

Data Collection	
1.	**Who will be the participants in the research?**
	This study is exclusive for higher education students at governmental universities in Saudi Arabia who use Blackboard as a learning management system.
2.	**How will you collect and analyse the research data? (please outline all methods e.g. questionnaires/focus groups/internet searches/literature searches/interviews/observation)**
	As this study is quantitative in nature, the decision was made to use online and paper-based questionnaires for data collection. Based on Partial Least Square Structural Equation Modelling technique (PLS-SEM), the collected data will be analysed using Statistical Package for the Social Sciences (SPSS) and SmartPLS software.
3.	**Where will the data will be gathered (e.g. in the classroom/on the street/telephone/on-line)**
	For paper-based questionnaires, data will be collected on the campuses of the Saudi universities i.e. classrooms, lectures and venues. The data will also be collected on-line using Novi Survey.
4.	**Please describe your selection criteria for inclusion of participants in the study**

	This study targets higher education students at governmental universities in Saudi Arabia who use Blackboard as a learning management system regardless their demographic characteristics: gender, age, experience with LMS, ICT skills, education level and field of study.
5.	**If your research is based on secondary data, please outline the source, validity and reliability of the data set**
	The research is not based on secondary data.
Consent and Participant Information	
7.	**How will you invite research participants to take part in the study? (e.g. letter/email/asked in lecture)**
	For online questionnaires, participants will be invited via several ways i.e. email, social media, university websites, forums and LMS. For paper-based questionnaires, students in classrooms and lectures will be asked to participate in the study.
8.	**How will you explain the nature and purpose of the research to participants?**
	The nature and purpose of the research will be explained to participants through the cover letter of the questionnaires.
9.	**How will you record obtaining informed consent from your participants?**
	For online questionnaires, informed consent will be recorded online using Novi Survey. For paper-based questionnaires, participants will read and sign the informed consent.
Data storage and Dissemination	
10.	**How and in what format will data be stored? And what steps will be taken to ensure data is stored securely?**
	Online questionnaires will be stored using Novi Survey, that is provided and hosted on the resources of Edinburgh Napier University. Novi Survey is characterized with its high security and reliability. Importantly, it supports Arabic language, the participants' first language. Paper-based questionnaires will be kept in the researcher's office in the Edinburgh Napier School of Computing in a locked cabinet. The collected data will be entered and stored on the researcher's space on the university servers for further analysis using statistical software i.e. SPSS and SmartPLS. The researcher's computer is secured with a password and only used by the researcher, and the data files will be password-protected for further security.
11.	**Who will have access to the data?**
	The researcher
12.	**Will the data be anonymised so that files contain no information that could be linked to any participant?**
	Data will be completely anonymised. Participants will not be linked with the research materials and will not be identified or identifiable in any report subsequently produced by the researcher.
13.	**How long will the data be kept?**
	The data will be kept until the project is complete. The expected date of completion is 01/02/2020.
14.	**What will be done with the data at the end of the project?**
	As parts of the findings might be submitted for publication, the data will be kept for at least 10 years after the project is complete. This can be done by long time archiving in the repository of Edinburgh Napier University. The repository staff will be able to assist with this

	matter.
15.	**How will the findings be disseminated?**
	The collected data will be presented in the data analysis and results chapters of the researcher's PhD dissertation. In addition, parts of the findings might be submitted for publication in academic journals and scientific conferences.
16.	**Will any individual be identifiable in the findings?**
	Individuals will not be identifiable in the findings.

3B. Identification and Mitigation of Potential risks

This section is designed to identify any realistic risks to the participants and how you propose to deal with it.

1. **Does this research project involve working with potentially vulnerable individuals?**

Group	Yes	NO	Details (for example programme student enrolled on, or details of children's age/care situation, disability)
Students at Napier	☐	☒	
Staff at ENU	☐	☒	
Children under 18	☐	☒	
Elderly (over 70)	☐	☒	
Disabled	☐	☒	
Migrant workers	☐	☒	
Prisoners / people in custody	☐	☒	
Learning difficulties	☐	☒	

2. **If you are recruiting children (under 18 years) or people who are otherwise unable to give informed consent, please give full details of how you will obtain consent from parents, guardians, carers etc.**

Not applicable

3. **Please describe any identified risks to participants or the researcher as a result of this research being carried out**

There are no potential risks (physical/emotional/social/economic) to the researcher or participants in carrying out this research.

4. **Please describe what steps have been taken to reduce these identified risks? (for example providing contact details for appropriate support services (e.g. University Counselling, Samaritans), reminding participants of their right to withdraw and/or not answering questions, or providing a full debriefing to participants)**

Not applicable

5. **If you plan to use assumed consent rather than informed consent please outline why this is necessary**

Not applicable

6. **If payment or reward will be made to participants please justify that the amount and type are appropriate (for example the amount should not be so high that participants would be financially coerced into taking part, or that the type of reward is appropriate to the research topic).**

Not applicable

3C. Justification of High Risk Projects

If you answered 'Yes' to the screening questions 1-4, this section asks for justification on the choice of research topic and methodology.

1. **If you have answered yes to question 1 please give a full description of all medical procedures to be used within the research and provide evidence that the project has obtained NHS ethical approval.**

2. **If you have answered yes to questions 2 (research into a controversial topic) please provide a justification for your choice of research topic, and describe how you would deal with any potential issues arising from researching that topic.**

3. **If you have answered yes to questions 3 or 4 (use of deception or covert research methods) please provide a justification for your choice of methodology, and state how you will mitigate the risks associated with these approaches.**

Declaration	
☒	I consider that this project has no significant ethical implications to be brought to the attention of Research Integrity Committee
☐	I consider that this project may have significant ethical implications to be brought to the

	attention of the Research Integrity Committee

Researcher Signature: [redacted]	Date: 24/05/2017
Director of Studies/Supervisor/Principal Investigator Signature: [redacted]	Date: 29.5.2017

Checklist

All applications require the following to be submitted with the application form

Participant Information Sheet	☒
Informed Consent Form	☒
Interview/Survey Questions	☒

APPENDIX D: APPROVALS FROM SAUDI UNIVERSITIES

King Abdulaziz University:

KINGDOM OF SAUDI ARABIA
Ministry of Higher Education
KING ABDULAZIZ UNIVERSITY

المملكة العربية السعودية
وزارة التعليم العالي
جامعة الملك عبدالعزيز

كلية المجتمع بجدة
Jeddah Community College

Ref. :
Date :
Encl. :

الرقم : ٣٤٤٩/غ/٢٨
التاريخ : ٣٠/٨/١٤٣٨ هـ
المرفقات : ١ لف

السادة الأعزاء في الملحقية الثقافية بالمملكة المتحدة المحترمين

السلام عليكم ورحمة الله وبركاته

بناءاً على طلب منسوبنا المحاضر والمبتعث/ سامي سعيد صالح بن يمين، صاحب رقم (KAU1641) على القيام برحلة علمية للمملكة العربية السعودية لمدة (90) يوماً ابتداءاً من 2017/10/01 بغرض جمع البيانات المطلوبة لبحث الدكتوراة.

عليه نفيدكم بموافقة القسم للمبتعث على القيام بالرحلة العلمية والاشراف المباشر على هذه الرحلة لمدة (90) يوماً ابتداءاً من 2017/10/01 ليتمكن من جمع البيانات اللازمة لبحثه.

شاكرين حسن تعاونكم ،،،،

رئيس قسم الحاسب وتقنية المعلومات

[redacted]

د. بسام بن عبدالوهاب ظفر

ص.ب ٨٠٢٨٣ جـدة ٢١٥٨٩ — فاكس ٢٨٧٠٠٢٤ — ☎ ٢٨٧٠٠٢٦

King Saud University:

KINGDOM OF SAUDI ARABIA
Ministry of Education
KING ABDULAZIZ UNIVERSITY
(035)
: 80200 Jaddah 21589
: (+966) 12 6952015
Fax.: (+966) 12 6952441
http://gssr.kau.edu.sa

٢٢٢٠٥
١٤٣٨/١٠/١٤

المملكة العربية السعودية
وزارة التعليم
جامعة الملك عبد العزيز
(٠٣٥)
: ٨٠٢٠٠ جدة : ٢١٥٨٩
: ٦٩٥٢٠١٥ ١٢ (+٩٦٦)
فاكس : ٦٩٥٢٤٤١ ١٢ (+٩٦٦)
E-mail: research@kau.edu.sa

مكتب وكيل الجامعة للدراسات العليا والبحث العلمي
Office of the Vice President for Graduate Studies and Research

سعادة وكيل جامعة الملك سعود للدراسات العليا والبحث العلمي حفظه الله

السلام عليكم ورحمة الله وبركاته

وكالة جامعة الملك عبدالعزيز للدراسات العليا والبحث العلمي تهدي سعادتكم أطيب تحياتها وتقديرها، وتشير الى الطلب المقدم من المحاضر/ سامي بن سعيد صالح يمين، المبتعث بجامعة ادمبره نابير في بريطانيا، بشأن اعداد بحث درجة الدكتوراه في مجال علوم الحاسب الالي بعنوان: تأثير خواص سهولة الاستعمال على استخدام نظم ادارة التعلم في الجامعات السعودية من وجهة نظر الطلاب.

وانطلاقاً من مبدأ التعاون بين الجامعات السعودية لدعم البحث العلمي، آمل التكرم بالموافقة على قيامه بجمع البيانات، وتسهيل مهمته العلمية.

وتقبلوا سعادتكم خالص تحياتي وتقديري ...

وكيل الجامعة
للدراسات العليا والبحث العلمي
[redacted]
أ.د/ يوسف بن عبدالعزيز عبدالله التركي

١ بتوجيه سعادته
سعادة الدكتور/ [illegible] وكيل الشؤون يحفظه الله
[illegible]
[redacted]

٢ بتوجيه سعادته مع الموافقة
[redacted]

العريضي

الرقم: ١٠٧٥٨٣/٢٨/د Ref.: التاريخ: ١٥/١٠/١٤٣٨ Date: المرفقات: كامل بيانه Encl.:

Imam Abdulrahman Bin Faisal University:

المملكة العربية السعودية
وزارة التعليم
وكالة الجامعة للدراسات
العليا والبحث العلمي

جامعة الإمام عبدالرحمن بن فيصل
IMAM ABDULRAHMAN BIN FAISAL UNIVERSITY

رقم المعاملة : ٧٤٦٢٨
التاريخ : ١٤٣٨/١١/١٤هـ

إحالة داخلية

من سعادة وكيل الجامعة للدراسات العليا والبحث العلمي — مع خالص تحياتي

☐ معالي الدكتور مدير الجامعة	حفظه الله
☐ سعادة وكيل الجامعة للشؤون الأكاديمية	سلمه الله
☐ سعادة وكيل الجامعة	سلمه الله
☐ سعادة وكيل الجامعة لشؤون الفروع	سلمه الله
☐ سعادة وكيل الجامعة للدراسات والتطوير	سلمه الله

إلى : (..)

الكليات

☐ عميد كلية الطب	☐ عميد كلية العمارة والتخطيط	☐ عميدة كلية العلوم
☐ عميد كلية طب الأسنان	☐ عميد كلية التصاميم	☐ عميدة كلية الآداب
☐ عميد كلية العلوم الطبية التطبيقية	☐ عميد كلية الهندسة	☐ عميد الدراسات التطبيقية وخدمة المجتمع
☐ عميد كلية التمريض	☐ عميد كلية إدارة الأعمال	☐ عميد علوم الحاسب وتقنية المعلومات
☐ عميد كلية الصيدلة الإكلينيكية	☐ عميدة كلية التربية	☐ عميدة كلية المجتمع
☐ عميد كلية الصحة العامة	☐ عميدة كلية التربية بالجبيل	☐

العمادات والمراكز والمعاهد

☐ عميد الدراسات العليا	☐ عميدة الدراسات الجامعية للطالبات	☐ عميد أعضاء هيئة التدريس والموظفين
☑ عميد البحث العلمي	☐ عميد السنة التحضيرية والدراسات المساندة	☐ مديرة مركز النشر العلمي
☐ عميدة معهد الأبحاث والاستشارات الطبية	☐ عميد عمادة التعليم الإلكتروني	☐ ممثل نظام المؤتمرات والندوات
☐ عميد شؤون المكتبات	☐ عميد عمادة تطوير التعليم الجامعي	☐ مدير إدارة التعاون والتبادل المعرفي
☐ عميد القبول والتسجيل	☐ عميد الإتصالات وتقنية المعلومات	☐ وحدة العلوم والتقنية {KACST}
☐ عميد شؤون الطلاب	☐ وكيلة التطوير الإداري	☐ مديرة مكتب براءة الاختراع ونقل التقانة

(ص ع)

الإدارات .. اللجان الدائمة

☐ مدير عام أعضاء هيئة التدريس والموظفين	☐ المشرف على إدارة المدينة الجامعية	☐ أمين المجلس العلمي
☐ مدير عام الشئون الإدارية والمالية	☐ مدير إدارة المشاريع والخدمات العامة	☐ سكرتير المجلس العلمي
☐ المشرف العام لإدارة التخطيط والميزانية	☐ مدير إدارة التطوير الإداري	☑ مدير المكتب
☐ مدير الإدارة القانونية	☐ مدير إدارة المشتريات	☐ سكرتير أبحاث مدينه الملك عبدالعزيز
☐ مدير عام إدارة العلاقات العامة والإعلام	☐ مدير المطابع (مطبعة الجامعة)	☐ سكرتير لجنة المعيدين والمحاضرين
☐ المشرف على الجودة والاعتماد الأكاديمي	☐ سكرتير لجنة اخلاقيات البحث العلمي	☐ سكرتير اللجنة الدائمة لمكافأة التميز

إشارة الى خطاب وكيل جامعة الملك عبدالعزيز للدراسات العليا والبحث العلمي رقم ١٠٩٢٩٣ بتاريخ ١٤٣٨/١٠/١٥هـ بشأن طلب الباحث طالب الدراسات العليا/ سامي بن سعيد يمين ، الموافقة على تطبيق أداة بحثيه من قبل طلاب وطالبات الجامعة .

☐ للتوجيه بما ترونه	☐ للدراسة وإبداء الرأي	☐ المفاهمة هاتفياً	☐ للاعتذار
☑ فضلاً لاستكمال اللازم	☐ للمتابعة	☐ للعلم	☐ للحفظ
☐ تزويدنا بتقرير	☐ المفاهمة شخصياً	☐ للإفادة	☐ للاعتماد

وتقبلوا خالص تحيتي وتقديري

[redacted]

أ. د/ عبدالسلام بن عبدالله السليمان

ح.الوديعي

APPENDIX E: NORMALITY TEST

Indicators	Skewness		Kurtosis	
	Statistic	Standard Error	Statistic	Standard Error
AU01	-.304	.085	-1.085	.169
AU02	-1.056	.085	.325	.169
AU03	-.150	.085	-1.152	.169
AU04	-.213	.085	-1.126	.169
BI01	-.572	.085	-.848	.169
BI02	-.595	.085	-.744	.169
BI03	-.713	.085	-.704	.169
BI04	-.603	.085	-.734	.169
CQ01	-.581	.085	-.225	.169
CQ02	-.535	.085	-.501	.169
CQ03	-.397	.085	-.835	.169
CQ04	-.221	.085	-.888	.169
EOA01	-1.217	.085	.716	.169
EOA02	-.652	.085	-.531	.169
EOA03	-.325	.085	-.796	.169
EOA04	.030	.085	-.993	.169
IA01	-.607	.085	-.458	.169
IA02	-.315	.085	-.733	.169
IA03	-.247	.085	-.684	.169
IA04	-.202	.085	-.759	.169
LS01	-.363	.085	-.561	.169
LS02	-.330	.085	-.832	.169
LS03	-.119	.085	-.806	.169
LS04	-.105	.085	-.726	.169
LS05	-.097	.085	-.689	.169
PEOU01	-.354	.085	-.696	.169
PEOU02	-.188	.085	-.813	.169
PEOU03	-.655	.085	-.367	.169
PEOU04	-.641	.085	-.484	.169
PU01	-.507	.085	-.745	.169
PU02	-.271	.085	-.857	.169
PU03	-.340	.085	-.801	.169
PU04	-.314	.085	-.814	.169
PU05	-.626	.085	-.575	.169
SI01	-.547	.085	-.440	.169
SI02	-.287	.085	-1.008	.169
SI03	.029	.085	-1.148	.169
SI04	-.248	.085	-.964	.169
SL01	-.755	.085	-.288	.169
SL02	-.396	.085	-.670	.169
SL03	-.605	.085	-.609	.169
SL04	-.482	.085	-.628	.169
SN01	-.254	.085	-1.040	.169
SN02	-.253	.085	-.984	.169
SN03	-.291	.085	-.952	.169
SN04	-.461	.085	-.717	.169

Indicators	Skewness		Kurtosis	
	Statistic	Standard Error	Statistic	Standard Error
SN05	-.962	.085	.012	.169
VD01	-.438	.085	-.837	.169
VD02	.081	.085	-1.144	.169
VD03	-.582	.085	-.575	.169
VD04	-.254	.085	-.996	.169