JISTaP http://www.jistap.org
Journal of Information Science Theory and Practice

RESEARCH PAPER
J Inf Sci Theory Pract 10(3): 24-39, 2022

eISSN : 2287-4577 pISSN : 2287-9099

https://doi.org/10.1633/JISTaP.2022.10.3.3

Predicting Online Learning Adoption: The Role of Compatibility, Self-Efficacy, Knowledge Sharing, and Knowledge Acquisition

Haider Mshali
Ministry of Higher Education and Scientific Research, Baghdad, Iraq
E-mail: haidermshali@gmail.com

Ahmed Al-Azawei*
Software Department, College of Information Technology, University of Babylon, Babylon, Iraq
E-mail: ahmedhabeeb@itnet.uobabylon.edu.iq

ABSTRACT

Online learning is becoming ubiquitous worldwide because of its accessibility anytime and from anywhere. However, it cannot be successfully implemented without understanding constructs that may affect its adoption. Unlike previous literature, this research extends the Unified Theory of Acceptance and Use of Technology with three well-known theories, namely compatibility, online self-efficacy, and knowledge sharing and acquisition to examine online learning adoption. A total of 264 higher education students took part in this research. Partial Least Squares-Structural Equation Modeling was used to evaluate the proposed theoretical model. The findings suggested that performance expectancy and compatibility were significant predictors of behavioral intention, whereas behavioral intention, facilitating conditions, and compatibility had a significant and direct effect on online learning's actual use. The results also showed that knowledge acquisition, knowledge sharing, and online self-efficacy were determinates of performance expectancy. Finally, online self-efficacy was a predictor of effort expectancy. The proposed model achieved a high fit and explained 47.7%, 75.1%, 76.1%, and 71.8% of the variance of effort expectancy, performance expectancy, behavioral intention, and online learning actual use, respectively. This study has many theoretical and practical implications that have been discussed for further research.

Keywords: online learning adoption, Unified Theory of Acceptance and Use of Technology, compatibility, knowledge acquisition, knowledge sharing, self-efficacy

Received: April 22, 2022
Revised: May 24, 2022
Accepted: July 7, 2022
Published: September 30, 2022

***Corresponding Author:** Ahmed Al-Azawei
https://orcid.org/0000-0002-4121-2531
E-mail: ahmedhabeeb@itnet.uobabylon.edu.iq

1. INTRODUCTION

The rapid development of information technology (IT) helps provide rich educational content over the Internet, which is known as online learning. This refers to the integration of education and the learning process with modern technologies. Flexibility and accessibility are the main advantages of this learning technology (Wu et al., 2010). Moreover, online learning facilitates the learning process, reduces costs, and provides accessible education (Mahande & Malago, 2019). Besides these advantages, several issues and challenges need more effort to achieve the desired goals of online learning. In its early application, limited access and communication represented its key drawbacks (Chin, 1999). With time, this was replaced with other issues such as isolation, lack of motivation and direct guidance, and lack of experience (Abbad, 2021; Bouhnik & Marcus, 2006; Dutton et al., 2001).

Despite the spreading use of online learning technologies around the world, developing countries still face many challenges. This is due to the low rate of technology acceptance, the unavailability of adequate technical and human infrastructure, and the lack of information sharing and institutional cooperation (Kim & Park, 2018). Accordingly, online learning systems are not gaining popularity in developing countries (Farid et al., 2015). In Iraq, for example, after the partial and full shutdown due to the COVID-19 pandemic, all educational institutions adopted distance and blended education. However, many obstacles still prevent the successful application of this technology in Iraq (Al-Azawei et al., 2016; Al-Radhi, 2008). To address such issues, it is necessary to understand what can affect users' acceptance and adoption of online learning technology (Ashraf et al., 2016). Thus, identifying factors that may affect online learning adoption can help educational institutions apply specific strategies to attract students towards this technology (Park, 2009).

Consequently, it is necessary to make further efforts to expose the common factors that may influence learners' decisions in adopting online learning technology, particularly in developing countries. This present study, therefore, aims to (1) investigate learners' adoption of online learning in Iraq as a case of developing nations, (2) extend the Unified Theory of Acceptance and Use of Technology (UTAUT) model to understand the influence of other theories on technology acceptance, (3) improve the predictability of UTAUT by integrating new variables, and (4) highlight constructs that can help predict effort expectancy and performance expectancy, as this has been neglected in the original UTAUT. The research draws upon UTAUT (Venkatesh et al., 2003). However, it proposes an integrated model based on four theories, namely UTAUT, compatibility, online self-efficacy, and knowledge sharing and knowledge acquisition. Two motivations are behind this extension. First, this can address the deficit of UTAUT by investigating the influence of the integrated theories on online learning adoption. Second, these theories can complement each other, as they look towards technology acceptance from different angles, particularly in online learning systems.

2. PREVIOUS WORK AND THE PROPOSED MODEL

Implementing IT relies on user acceptance (Davis, 1989). The acceptance may refer to user satisfaction with this particular technology to accomplish the activities and tasks for which the technology was intended (Al-Azawei, 2019; Walldén et al., 2016; Wixom & Todd, 2005). Ignoring learners' perceptions, on the other hand, can negatively affect the acceptance of educational technologies (Alowayr & Al-Azawei, 2021).

To reach the desired acceptance, many efforts have been made in several domains including psychology, sociology, and information system (IS), to develop theoretical models for predicting and explaining user acceptance of IT or IS (Chao, 2019). The technology acceptance model (TAM) of Davis (1986) is a widely cited theory in this field. However, some studies have pointed out many disadvantages of TAM related to external variables of its perceived usefulness and perceived ease of use (Chao, 2019; Tsai et al., 2018). Therefore, Venkatesh et al. (2003) proposed another theory which is the so-called UTAUT. It has attracted considerable attention in online learning acceptance research (Abbad, 2021; Alowayr & Al-Azawei, 2021; Mahande & Malago, 2019).

Although UTAUT has been widely used and adopted, there is controversy and doubt about its capability to explain users' technology acceptance. This may indicate that the factors and variables used in UTAUT may not be sufficient to determine the required level of technology adoption. Accordingly, previous research modified and extended UTAUT (Chao, 2019; Cimperman et al., 2016; Khalilzadeh et al., 2017; Mtebe et al., 2016). Such literature suggested that adding several different external variables could improve the model's predictability. In online learning, Alowayr and Al-Azawei (2021) extended the model based on the self-determination and expectation-confirmation theories. Based on UTAUT, Kim and Lee (2020) built a conceptual framework of effective information communication technologies-based instruction.

To address some of UTAUT's limitations, this present study extends it by constructing an integrated framework based on four well-known theories. Here, four external variables are integrated with UTAUT, which are compatibility, online self-efficacy, knowledge sharing, and knowledge acquisition. This study, therefore, investigates the effect of these four external constructs as depicted in the proposed research model (see Fig. 1).

2.1. Unified Theory of Acceptance and Use of Technology

UTAUT is a research theory based on psychology and sociology, developed from previous models (Venkatesh et al., 2003). Practically, UTAUT is used for the explanation of user perception and acceptance behavior. The original UTAUT model consists of four essential variables and four moderators. Performance expectancy is the belief of users that the system (specific technology) can help to improve job performance, while effort expectancy refers to users' beliefs that technology does not need a high mental effort. Social influence means the social pressure on users' decisions and their perceptions when other parties important to them believe that they should use the technology. Finally, facilitating conditions refer to users' beliefs that technical and organizational infrastructures are available to support the use of technology (Venkatesh et al., 2012). Moreover, UTAUT proposed four key moderators, namely the voluntariness of use, experience, gender, and age.

Aliaño et al. (2019) highlighted that effort expectancy, performance expectancy, and social influence were determinants of behavioral intention to use online learning. Furthermore, Davis (1986) confirmed that effort expectancy is a predictor of performance expectancy. In UTAUT, Venkatesh et al. (2003) found that behavioral intention and facilitating conditions were predictors of actual use. Accordingly, the hypotheses proposed in this study are:

H1: Effort expectancy significantly affects behavioral intention

H2: Effort expectancy significantly affects performance expectancy

H3: Performance expectancy significantly affects behavioral intention

H4: Social influence significantly affects behavioral intention

H5: Facilitating conditions significantly affect the actual use

H6: Behavioral intention significantly affects the actual use

2.2. Compatibility

Compatibility refers to the degree to which innovations are perceived as in agreement with the current values, needs, and past experiences of probable adopters (Rogers, 1995). In online learning technology adoption, the compatibility theory has emerged as one of the important factors that may affect the behavioral intention of users to adopt modern technology (Cheng, 2015; Isaac et al., 2019;

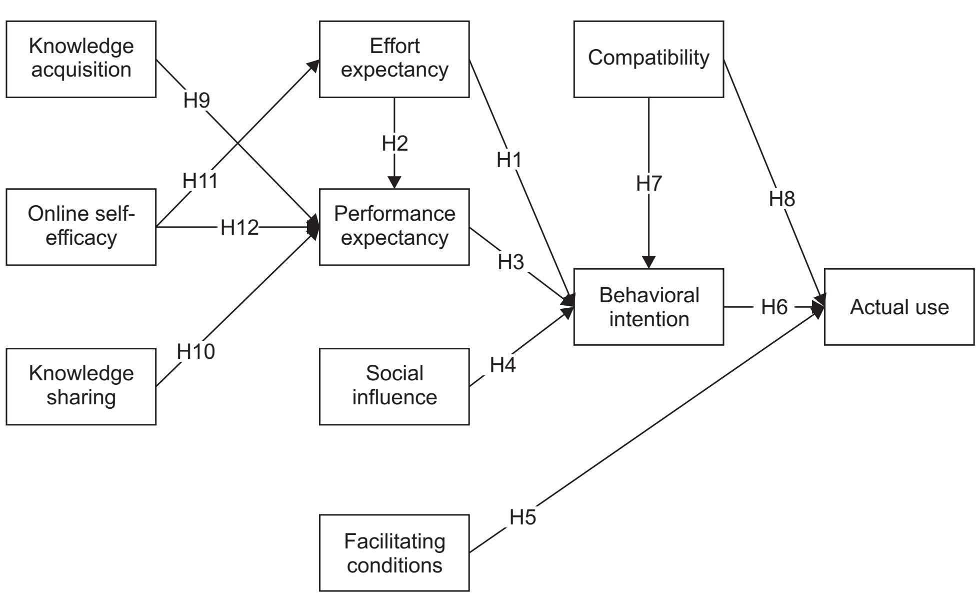

Fig. 1. Proposed research model.

Ozturk et al., 2016). Chang et al. (2005) showed that there is a need for more effort to demonstrate the importance of this factor in e-learning systems. Moreover, a significant relationship between real usage of mobile learning adoption and compatibility was found (Cheng, 2015). In this research, we assume that the compatibility factor positively affects both behavioral intention and actual use.

H7: Compatibility significantly affects behavioral intention

H8: Compatibility significantly affects actual use

2.3. Knowledge Acquisition and Knowledge Sharing

A large number of enrolled students in educational institutions could raise challenges and issues related to knowledge acquisition and knowledge sharing (Al-Emran et al., 2019). Such issues could be addressed by online learning systems (Al-Emran & Teo, 2020). Nevertheless, a few efforts demonstrate the impact of these two factors on the adoption of online learning. In this context, knowledge acquisition and knowledge sharing might have an influential effect on learners' intention to adopt online learning technology and/or performance expectancy (Al-Emran & Teo, 2020; Lau & Tsui, 2009).

Knowledge acquisition means how a learner gains new knowledge by extracting, structuring, and organizing knowledge from one source (Al-Emran & Teo, 2020; Huang, 2020). Al-Emran et al. (2018) revealed that knowledge acquisition was a determinant of performance expectancy and effort expectancy. Knowledge sharing means the spread of diverse resources among individuals involved in particular activities. Previous studies indicated a positive relationship between knowledge sharing and performance expectancy (Al-Emran et al., 2018; Cheung & Vogel, 2013). According to this discussion, the current study suggested the following hypotheses:

H9: Knowledge acquisition significantly affects performance expectancy

H10: Knowledge sharing significantly affects performance expectancy

2.4. Online Self-efficacy

Self-efficacy is another widely used cognitive factor that is related to users' motivational beliefs. It refers to users' evaluation of their personal ability to complete tasks and goals well (Bandura, 1986). In an online learning context, self-efficacy is "a student's self-confidence in his or her ability to perform certain learning tasks using the e-learning system" (Tarhini et al., 2014).

In line with the above, self-efficacy shows a significant effect on adopting online learning (Qiao et al., 2021; Zhang & Liu, 2019). Thus, the motivation of students to use online learning systems is highly related to their successful adoption (Wang & Newlin, 2002). Earlier literature showed that self-efficacy was a determinant of both performance expectancy and effort expectancy (Wu, 2017; Yilmaz, 2016; Zhang & Liu, 2019). According to this discussion, we assumed that

H11: Online self-efficacy significantly affects effort expectancy

H12: Online self-efficacy significantly affects performance expectancy

3. RESEARCH METHODOLOGY

This study adopts a survey research design to examine the cause and effect relationships among the proposed research model. One of the advantages of this research is that the subjectivity issues are not found, as researchers rely solely on the statistical findings to understand the possible causality associations between different constructs.

3.1. The Research Instrument

The distributed online questionnaire included the main page that presented the key aims of the questionnaire, its filling out time, ethical considerations, and a few instructions to answer its questions correctly. This was followed by general questions to collect demographic information from the research participants. The third part consisted of items that were designed to measure students' perceptions and intention to use online learning. Overall, 38 questions were designed based on previous literature to cover the ten constructs of the proposed research model, namely behavioral intention, actual use, knowledge acquisition, knowledge sharing, performance expectancy, online self-efficacy, effort expectancy, facilitating conditions, social influence, and compatibility (see Appendix). A five-point Likert scale was adopted, ranging from one which means 'strongly disagree,' whereas five refers to 'strongly agree.'

3.2. The Research Participants

This study recruited undergraduate and postgraduate students from a public university in one of the center governorates in Iraq. Of about 400 students, 264 responded voluntarily to the online questionnaire with a response rate of 66%. The research subjects agreed to take part in this study based on submitting the questionnaire as an indicator of their consent. It was also illustrated in the questionnaire that all collected data would be used for research purposes only and would not be shared with a third party.

Out of the 264 participants, 93 (35.2%) were man and 171 (64.8%) were woman. Regarding the age class, 202 (76.5%) were aged from 18 to 22, while only 62 (23.5%) were 23 years old or over. In terms of the study type, 182 (68.9%) were from the morning study, whereas 82 (31.1%) were from the evening study. Table 1 shows the key features of the research participants.

3.3. Data Collection

The research data were collected in the second semester of 2020-2021. The participation was voluntary, and the authors provided a general view of the purpose of the study before filling out the research questionnaire. The questionnaire was distributed online via Google Classroom, as it was the online learning platform used by the university. All received responses were valid because all questions were required to prevent submitting incomplete answers. The filling procedure of the research questionnaire took from 10 to 15 minutes. Here, the convenience sampling approach was adopted. The research data were analyzed using SmartPLS software package version 3.0 (Ringle et al., 2015). The *p*-value was set to 0.05.

Table 1. Participants' information

Variable	Value (n=264)
Year	
First	107 (40.5)
Second	44 (16.7)
Third	31 (11.7)
Fourth	80 (30.3)
Postgraduate	2 (0.8)
Gender	
Man	93 (35.2)
Woman	171 (64.8)
Age (yr)	
18-22	202 (76.5)
23 or more	62 (23.5)
Study type	
Morning	182 (68.9)
Evening	82 (31.1)

Values are presented as number (%).

4. RESULTS

The proposed theoretical model was investigated using partial least squares (PLS). In comparison to traditional statistics, such as regression, this method has many advantages. First, it can be used to examine the association among a series of constructs (Al-Azawei, 2017). Moreover, according to Chin (1998), structural equation modeling (SEM) is a superior method for theory development and prediction. Finally, previous research on predicting users' behavior has widely adopted this technique (Al-Azawei & Alowayr, 2020; Ameen et al., 2019; Shin & Kang, 2015). The collected data were analyzed in two steps. The first was validating the research survey, whereas the second was examining the predictability of the independent variables to the dependent constructs.

4.1. Validating the Research Questionnaire

The significance of confirming reliability and validity comes from the influence of both measurements on the quality of the gathered data (Pallant, 2013). Moreover, the impact of reliability and validity cannot be about the quality of data only, as those characteristics can also affect the research findings and recommendations (Al-Sabawy, 2013). In SEM, examining reliability and validity is a step prior to investigating the structural model. This is to confirm the questionnaire's validity. In this research, convergent, construct, and discriminant validities were validated.

The reliability can be evaluated based on measuring the unidimensionality of each factor in the research model. Based on the threshold proposed by Hulland (1999), the unidimensionality of the research questionnaire was supported because the outer loadings of all indicators used to measure the research constructs were greater than 0.7. Moreover, Cronbach's alpha and composite reliability (CR) were all greater than 0.7 as assumed by Pallant (2013). Based on Tables 2 and 3, it is clear that the outer loadings of all indicators used to measure a particular variable are greater than 0.7; as well, Cronbach's alpha (internal consistency) and CR are more than the threshold of 0.7. Thus, the research questionnaire has confronted all thresholds recommended and this, in turn, clearly supports its reliability and validity. The Cronbach's alpha and CR of all constructs ranged from 0.824 to 0.940 and from 0.896 to 0.957 for both measurements respectively.

 https://doi.org/10.1633/JISTaP.2022.10.3.3

Table 2. Outer loading

Item	AU	BI	Comp	EE	FC	KA	KS	OSE	PE	SI
BI1		0.935								
BI2		0.897								
BI3		0.946								
BI4		0.904								
COMP1			0.913							
COMP2			0.948							
COMP3			0.915							
EE1				0.879						
EE2				0.890						
EE3				0.887						
EE4				0.895						
FC1					0.888					
FC2					0.885					
FC3					0.808					
KA1						0.892				
KA2						0.905				
KA3						0.876				
KA4						0.895				
KA5						0.836				
KS1							0.752			
KS2							0.822			
KS3							0.860			
KS4							0.900			
KS5							0.858			
OSE1								0.873		
OSE2								0.917		
OSE3								0.910		
PE1									0.878	
PE2									0.910	
PE3									0.861	
PE4									0.873	
SI1										0.923
SI2										0.926
SI3										0.926
USE1	0.910									
USE2	0.912									
USE3	0.910									
USE4	0.746									

AU, actual use; BI, behavioral intention; Comp, compatibility; EE, effort expectancy; FC, facilitating conditions; KA, knowledge acquisition; KS, knowledge sharing; OSE, online self-efficacy; PE, performance expectancy; SI, social influence.

Table 3. Construct reliability and validity

Factor	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted
Actual use	0.893	0.908	0.927	0.761
Behavioral intention	0.940	0.940	0.957	0.848
Compatibility	0.916	0.917	0.947	0.857
Effort expectancy	0.910	0.911	0.937	0.788
Facilitating conditions	0.824	0.826	0.896	0.741
Knowledge acquisition	0.928	0.928	0.946	0.777
Knowledge sharing	0.895	0.897	0.923	0.705
Online self-efficacy	0.883	0.888	0.928	0.810
Performance expectancy	0.904	0.905	0.933	0.776
Social influence	0.916	0.916	0.947	0.856

Table 4. Discriminant validity

Factor	AU	BI	Comp	EE	FC	KA	KS	OSE	PE	SI
AU	0.872									
BI	0.797	0.921								
Comp	0.812	0.832	0.926							
EE	0.673	0.666	0.716	0.888						
FC	0.695	0.702	0.723	0.727	0.861					
KA	0.759	0.772	0.752	0.719	0.679	0.881				
KS	0.673	0.715	0.653	0.691	0.735	0.815	0.840			
OSE	0.735	0.737	0.755	0.691	0.764	0.696	0.679	0.900		
PE	0.782	0.793	0.750	0.739	0.746	0.819	0.773	0.730	0.881	
SI	0.647	0.688	0.707	0.677	0.692	0.697	0.656	0.677	0.687	0.925

AU, actual use; BI, behavioral intention; Comp, compatibility; EE, effort expectancy; FC, facilitating conditions; KA, knowledge acquisition; KS, knowledge sharing; OSE, online self-efficacy; PE, performance expectancy; SI, social influence.

Convergent validity refers to a type of measurement validity for multiple indicators according to the notion that indicators of one construct will act alike or converge, whereas construct validity means how well the indicators of one variable converge or how well the indicators of different variables diverge (Bernard, 2012). Average variance extracted (AVE) between 0.5 and 1 is a good indicator to confirm the convergent validity (Fornell & Larcker, 1981). Table 3 confirms the convergent validity of the research questionnaire. On the other hand, the discriminant validity of a research measurement was also proved as discussed by Alowayr and Al-Azawei (2021). Based on Table 4, the discriminant validity has also been supported. Finally, construct validity can be evaluated based on the goodness of fit (Al-Sabawy, 2013) as indicated in Table 5.

4.2. Findings of the Proposed Model

Table 6 shows that ten out of twelve hypotheses were supported based on the path association among the proposed variables, whereas Fig. 2 illustrates R^2 and β values of the model after performing the PLS. According to this analysis, the results indicate that performance expectancy

 https://doi.org/10.1633/JISTaP.2022.10.3.3

($\beta_{PE \to BI}$=0.371, p<0.001) and compatibility ($\beta_{Comp \to BI}$=0.514, p<0.001) were significant predictors of behavioral intention to explain 76.1% (R^2=0.761) of the variance of this construct, supporting hypotheses H3 and H7. On the other hand, effort expectancy ($\beta_{EE \to BI}$=-0.043, p=0.428) and social influence ($\beta_{SI \to BI}$=0.100, p=0.055) were not determinants of behavioral intention, and so hypotheses H1 and H4 were rejected.

Regarding the predictors of actual online learning use, the findings show that facilitating conditions ($\beta_{FC \to AU}$=0.152, p=0.007), behavioral intention ($\beta_{BI \to AU}$=0.345, p<0.001), and compatibility ($\beta_{Comp \to AU}$=0.416, p<0.001) were determinants of this construct to explain 71.8% (R^2=0.718) of its overall variance. Such results supported hypotheses H5, H6, and H8.

The results also confirm that four constructs were predictors of performance expectancy, namely effort expectancy ($\beta_{EE \to PE}$=0.193, p=0.002), knowledge acquisition ($\beta_{KA \to PE}$=0.392, p<0.001), knowledge sharing ($\beta_{KS \to PE}$=0.186, p=0.008), and online self-efficacy ($\beta_{OSE \to PE}$=0.198, p=0.003). These variables explained 75.1% (R^2=0.751). Thus, hypotheses H2, H9, H10, and H12 were confirmed. Finally, online self-efficacy ($\beta_{OSE \to EE}$=0.691, p<0.001) was also a significant predictor of effort expectancy to explain 47.7% of its variance. This confirms hypothesis H11.

Table 5. Model fit

The goodness of fit	Saturated model	Estimated model
SRMR	0.046	0.084
d_ULS	1.581	5.288
d_G	1.150	1.298
Chi-square	1,666.087	1,746.200
NFI	0.843	0.835

5. DISCUSSION

This research extends UTAUT to investigate the accep-

Table 6. Research findings

Hypothesis	β	Mean	SD	T-value	*p*-value	Findings
H1: Effort expectancy -> Behavioral intention	-0.043	-0.043	0.055	0.793	0.428	Rejected
H2: Effort expectancy -> Performance expectancy	0.193	0.193	0.062	3.117	0.002	Supported
H3: Performance expectancy -> Behavioral intention	0.371	0.371	0.067	5.547	0.000	Supported
H4: Social Influence -> behavioral intention	0.100	0.100	0.052	1.923	0.055	Rejected
H5: Facilitating conditions -> Actual use	0.152	0.156	0.057	2.683	0.007	Supported
H6: Behavioral intention -> Actual use	0.345	0.341	0.067	5.147	0.000	Supported
H7: Compatibility -> Behavioral intention	0.514	0.513	0.054	9.538	0.000	Supported
H8: Compatibility -> Actual use	0.416	0.416	0.070	5.951	0.000	Supported
H9: Knowledge acquisition -> Performance expectancy	0.392	0.393	0.074	5.321	0.000	Supported
H10: Knowledge sharing -> Performance expectancy	0.186	0.185	0.070	2.661	0.008	Supported
H11: Online self-efficacy -> Effort expectancy	0.691	0.692	0.040	17.358	0.000	Supported
H12: Online self-efficacy -> Performance expectancy	0.198	0.197	0.068	2.922	0.003	Supported

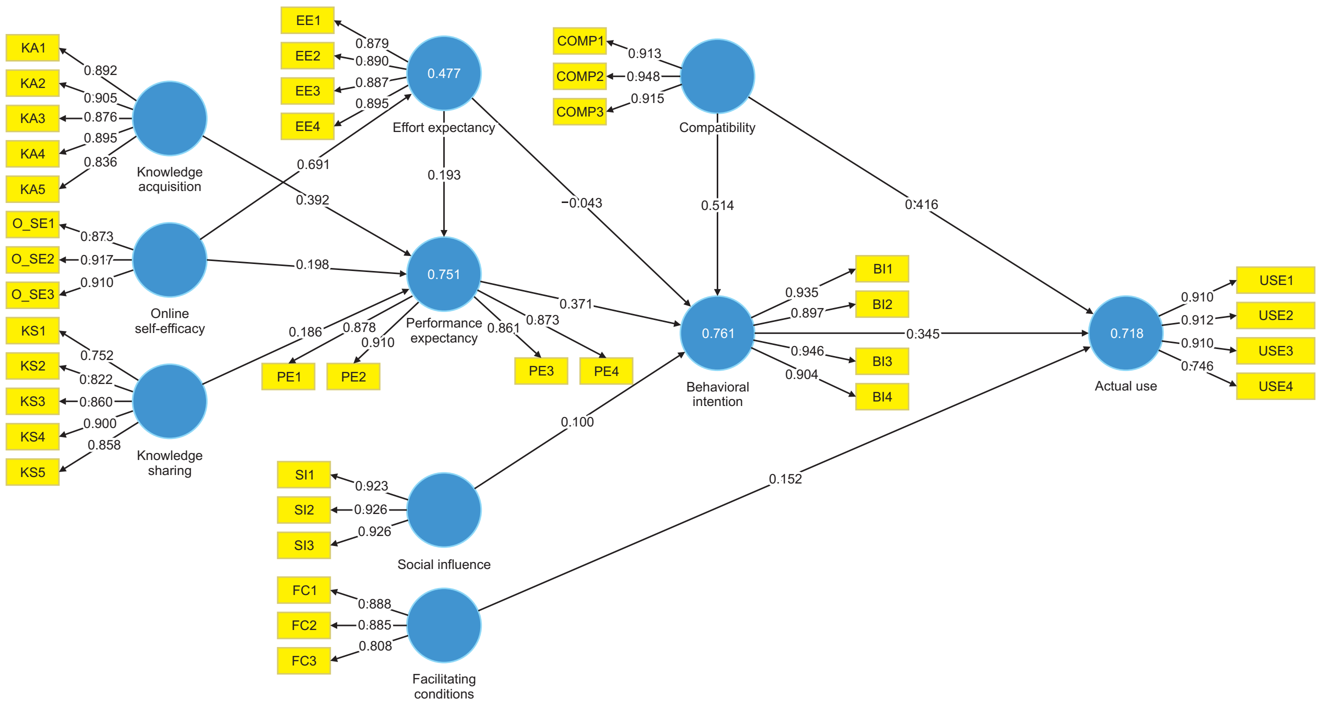

Fig. 2. Findings of the proposed model.

tance of online learning. It takes into account compatibility as a direct predictor of behavioral intention. The study also assumes that knowledge acquisition and knowledge sharing are determinants of performance expectancy, whereas online self-efficacy is proposed as a predictor of effort expectancy and performance expectancy. Thus, this research addresses some of the weaknesses in the original UTAUT, as it did not explain what can affect effort and performance expectancies. It also ignored the role of compatibility in examining online learning adoption. Table 7 summarizes the key findings of the proposed hypotheses. From Fig. 2, it is clear that knowledge acquisition was the strongest predictor of performance expectancy ($\beta_{KA \rightarrow PE}$=0.392). Compatibility, on the other hand, was the best predictor of both behavioral intention ($\beta_{Comp \rightarrow BI}$=0.514) and actual use ($\beta_{Comp \rightarrow AU}$=0.416). This reveals that extending UTAUT with the new constructs such as knowledge acquisition and compatibility has a significant influence on improving its predictability.

As for the predictors of performance expectancy, all proposed variables, namely effort expectancy, knowledge acquisition, knowledge sharing, and online self-efficacy, were determinants of this construct, supporting hypotheses H2, H9, H10, and H12. These four constructs explained 75.1% of the variance of performance expectancy. In agreement with our results, earlier research revealed that effort expectancy is a predictor of performance expectancy (Al-Emran et al., 2020; Davis, 1989), indicating that users can perceive the usefulness of technology if its use does not require a high mental effort. Moreover, other studies also found that both knowledge acquisition and knowledge sharing were predictors of performance expectancy (Al-Emran & Teo, 2020). This means that online courses should be designed in a way that allows participants to share knowledge and improve its acquisition. Thus, when students are capable of sharing and acquiring knowledge through online learning technology, their perceptions about technology usefulness in improving their overall performance can be enhanced as well. The research analysis also shows that online self-efficacy had a direct and positive relationship with performance expectancy. This may indicate that when learners are self-confident about their personal abilities in using online learning technology, their perceptions regarding its usefulness will be increased accordingly.

Online self-efficacy as a reference of learners' self-expectation was a predictor of effort expectancy to explain 47.7% of its variance, confirming hypothesis H11. Bandura (1986) assumes that people's expectations of efficacy can determine subsequent behavior in terms of the beginning and continuous coping behavior. According to Lin (2021), the self-efficacy of people may reveal

Table 7. Summary of the research hypotheses and findings

Hypothesis	Findings
Hypotheses for predicting performance expectancy	
H2: Effort expectancy -> Performance expectancy	Supported
H9: Knowledge acquisition -> Performance expectancy	Supported
H10: Knowledge sharing -> Performance expectancy	Supported
H12: Online self-efficacy -> Performance expectancy	Supported
Hypotheses for predicting behavioral intention	
H1: Effort expectancy -> Behavioral intention	Rejected
H3: Performance expectancy -> Behavioral intention	Supported
H4: Social influence -> Behavioral intention	Rejected
H7: Compatibility -> Behavioral intention	Supported
Hypotheses for predicting actual use	
H5: Facilitating conditions -> Actual use	Supported
H6: Behavioral intention -> Actual use	Supported
H8: Compatibility -> Actual use	Supported
Hypotheses for predicting effort expectancy	
H11: Online self-efficacy -> Effort expectancy	Supported

the motivational level of effort invested in an endeavor and this, in turn, could indicate that an individual with a low self-efficacy level will not persist in adopting or using technology. Based on our analysis, it is obvious that when students have a high level of self-efficacy, a low effort will be required to perform a particular action.

It was also found that two constructs out of four were determinants of behavioral intention, namely performance expectancy and compatibility, confirming hypotheses H3 and H7 to explain 76.1% of the variance of behavioral intention towards online learning use. On the other hand, this analysis rejects hypotheses H1 and H4. Overall, our findings are in agreement with earlier research that performance expectancy is a determinant of behavioral intention (Alowayr & Al-Azawei, 2021; Wang & Lin, 2021). This means that students are willing to continue using online learning because of its usefulness in improving their performance. The research analysis also shows that compatibility had a significant effect on intention to use. Such a finding is consistent with the outcomes of Wang and Lin (2021). This may indicate that students had a high level of compatibility in online learning settings and this, in turn, reflected their positive attitudes towards online classes. On the contrary, social influence and effort expectancy had no significant influence on behavioral intention. This may indicate that students had positive perceptions of the advantages of online learning regardless of the effort that is required to adopt it or the perspectives of other people who are important to the students. In an earlier research study (Al-Azawei & Alowayr, 2020), it was also found that both effort expectancy and social influence did not affect students' decision or perception to use mobile learning technology in the Iraqi context. A possible explanation for the weak influence of effort expectancy is that as students are part of the youth, they use online technologies daily, so their experience in dealing with them is great. Moreover, Ameen and Willis (2018) also revealed that the social influence of Iraqi students did not affect behavioral intention.

The research findings suggest that facilitating conditions, behavioral intention, and compatibility were determinants of online learning's actual use, which explained 71.8% of the variance of this construct and supported hypotheses H5, H6, and H8. In UTAUT, Venkatesh et al. (2003) assume that facilitating conditions could be a predictor of technology's actual use. This assumption was confirmed in our research to indicate that educational institutions have to provide reliable information and communication technologies infrastructure, and support all users to ensure the successful application of online learning. Furthermore, based on previous literature, behavioral intention towards a particular action can indicate that people will actually perform it (Ajzen & Fishbein, 1980). Finally, in this research, compatibility was the strongest predictor of online learning usage. This means that students might perceive the consistency of this technology with their individual needs, particularly after the spread of the COVID-19 pandemic worldwide. It also suggests that when learning technology is compatible with learners' individual needs and practice styles, their actual use will increase accordingly. Such an outcome is in line with the findings of earlier literature that real usage of mobile learning can be predicted by compatibility (Cheng, 2015). In agreement with the UTAUT hypotheses (Venkatesh et al., 2003), technology's actual use can be positively enhanced if users feel that there is direct organizational support for technical issues that they may face.

Based on the research findings and analysis, many theoretical and practical implications can be drawn. Theoretically, this research extends previous work on online learning adoption, particularly in the case of developing countries. Furthermore, it extends current technology acceptance theories according to the integration of UTAUT with variables from the social cognitive theory (self-efficacy), compatibility theory (compatibility), and knowledge management topic (knowledge sharing and knowledge acquisition). Accordingly, this research is among the early literature that investigates the extension of UTAUT in an online learning context. From the practical view, this research provides clear guidance for decision-makers, teachers, and online technology designers to apply innovative means in online learning to enhance knowledge sharing and acquisition among learners. Moreover, educational institutions should ensure that both academic staff and students have high confidence in their personal abilities to use the technology, as this could affect their decision to adopt it. Finally, as compatibility was a predictor of behavioral intention and actual use, online learning courses should be designed in a manner that responds to learners' individual expectations and preferences.

6. CONCLUSION

This research aimed at extending UTAUT to understand online learning acceptance. To achieve this aim, four constructs were integrated with UTAUT, namely compatibility, knowledge acquisition, knowledge sharing, and online self-efficacy. Although UTAUT suggested that effort expectancy and performance expectancy are determinants of adoption behavior, it does not explain what can affect these factors. Accordingly, the present study confirmed that knowledge acquisition and/or sharing as well as online self-efficacy had a significant role in predicting such constructs. Moreover, this research supports the necessity of considering compatibility in predicting both behavioral intention and actual behavior.

In regard to future research directions, it is recommended to carry out a longitudinal research design to understand the phenomenon under investigation over a longer period. Furthermore, choosing a sample from different disciplines and cultures should be another aim of future research. Finally, researchers also need to analyze the role of knowledge sharing and knowledge acquisition in other contexts of the learning process.

CONFLICTS OF INTEREST

No potential conflict of interest relevant to this article was reported.

REFERENCES

Abbad, M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and information technologies,* 26(6), 7205-7224. https://doi.org/10.1007/s10639-021-10573-5.

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior.* Prentice-Hall.

Al-Azawei, A. (2019). What drives successful social media in education and e-learning? A comparative study on Facebook and Moodle. *Journal of Information Technology Education: Research,* 18, 253-274. https://doi.org/10.28945/4360.

Al-Azawei, A., & Alowayr, A. (2020). Predicting the intention to use and hedonic motivation for mobile learning: A comparative study in two Middle Eastern countries. *Technology in Society,* 62, 101325. https://doi.org/10.1016/j.techsoc.2020.101325.

Al-Azawei, A., Parslow, P., & Lundqvist, K. (2016). Barriers and opportunities of e-learning implementation in Iraq: A case of public universities. *The International Review of Research in Open and Distributed Learning,* 17(5), 126-146. https://doi.org/10.19173/irrodl.v17i5.2501.

Al-Azawei, A. H. S. (2017). *Modelling e-learning adoption: The influence of learning style and universal learning theories.* (Doctoral dissertation). https://centaur.reading.

ac.uk/77921/.

Al-Emran, M., Arpaci, I., & Salloum, S. A. (2020). An empirical examination of continuous intention to use m-learning: An integrated model. *Education and Information Technologies,* 25(4), 2899-2918. https://doi.org/10.1007/s10639-019-10094-2.

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Students' perceptions towards the integration of knowledge management processes in m-learning systems: A preliminary study. *International Journal of Engineering Education,* 34(2A), 371-380. https://scholar.google.com/citations?view_op=view_citation&hl=da&user=J-p9z_gAAAAJ&citation_for_view=J-p9z_gAAAAJ:VaXvl8Fpj5cC.

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2019). An innovative approach of applying knowledge management in m-learning application development: A pilot study. *International Journal of Information and Communication Technology Education,* 15(4), 94-112. https://doi.org/10.4018/IJICTE.2019100107.

Al-Emran, M., & Teo, T. (2020). Do knowledge acquisition and knowledge sharing really affect e-learning adoption? An empirical study. *Education and Information Technologies,* 25(3), 1983-1998. https://doi.org/10.1007/s10639-019-10062-w.

Al-Radhi, A. A. D. J. K. (2008). Information professionals in a globalized world: Distance learning/e-learning for Iraq: Concept and road map. *Bulletin of the American Society for Information Science and Technology,* 34(3), 34-37. https://doi.org/10.1002/bult.2008.1720340311.

Al-Sabawy, A. Y. (2013). *Measuring e-learning systems success*. (Doctoral dissertation). https://eprints.usq.edu.au/27422/.

Aliaño, Á. M., Hueros, A. M. D., Franco, M. D. G., & Aguaded, I. (2019). Mobile learning in university contexts based on the unified theory of acceptance and use of technology (UTAUT). *Journal of New Approaches in Educational Research,* 8(1), 7-17. https://doi.org/10.7821/naer.2019.1.317.

Alowayr, A., & Al-Azawei, A. (2021). Predicting mobile learning acceptance: An integrated model and empirical study based on higher education students' perceptions. *Australasian Journal of Educational Technology,* 37(3), 38-55. https://doi.org/10.14742/ajet.6154.

Ameen, N., & Willis, R. (2018). Towards closing the gender gap in Iraq: Understanding gender differences in smartphone adoption and use. *Information Technology for Development,* 25(4), 660-685. https://doi.org/10.1080/02681102.2018.1454877.

Ameen, N., Willis, R., Abdullah, M. N., & Shah, M. (2019). Towards the successful integration of e-learning systems in higher education in Iraq: A student perspective. *British Journal of Educational Technology,* 50(3), 1434-1446. https://doi.org/10.1111/bjet.12651.

Ashraf, S., Khan, T. A., & ur Rehman, I. (2016). E-learning for secondary and higher education sectors: A survey. *International Journal of Advanced Computer Science and Applications,* 7(9), 275-283. https://doi.org/10.14569/IJACSA.2016.070939.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bernard, H. R. (2012). *Social research methods: Qualitative and quantitative approaches.* 2nd ed. Sage.

Bouhnik, D., & Marcus, T. (2006). Interaction in distance-learning courses. *Journal of the American Society for Information Science and Technology,* 57(3), 299-305. https://doi.org/10.1002/asi.20277.

Chang, M. K., Cheung, W., & Lai, V. S. (2005). Literature derived reference models for the adoption of online shopping. *Information & Management,* 42(4), 543-559. https://doi.org/10.1016/j.im.2004.02.006.

Chao, C. M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in Psychology,* 10, 1652. https://doi.org/10.3389/fpsyg.2019.01652.

Cheng, Y. M. (2015). Towards an understanding of the factors affecting m-learning acceptance: Roles of technological characteristics and compatibility. *Asia Pacific Management Review,* 20(3), 109-119. https://doi.org/10.1016/j.apmrv.2014.12.011.

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education,* 63, 160-175. https://doi.org/10.1016/j.compedu.2012.12.003.

Chin, K. L. (1999, July 12-15). A study into students' perceptions of web-based learning environment. *Proceedings of the 1999 HERDSA Annual International Conference. Cornerstones: What do we value in higher education?* (pp. 12-15). Higher Education Research and Development Society of Australasia.

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly,* 22(1), vii-xvi. https://www.jstor.org/stable/249674.

Cimperman, M., Makovec Brenčič, M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior-applying an Extended UTAUT model. *International Journal of Medical Informatics,* 90, 22-31. https://doi.org/10.1016/j.ijmedinf.2016.03.002.

Davis, F. D. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. (Doctoral dissertation). http://hdl.handle.

net/1721.1/15192.
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly,* 13(3), 319-340. https://doi.org/10.2307/249008.
Dutton, J., Dutton, M., & Perry, J. (2001). Do online students perform as well as lecture students? *Journal of Engineering Education,* 90(1), 131-136. https://doi.org/10.1002/j.2168-9830.2001.tb00580.x.
Farid, S., Ahmad, R., Niaz, I. A., Arif, M., Shamshirband, S., & Khattak, M. D. (2015). Identification and prioritization of critical issues for the promotion of e-learning in Pakistan. *Computers in Human Behavior,* 51(Pt A), 161-171. https://doi.org/10.1016/j.chb.2015.04.037.
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research,* 18(1), 39-50. https://doi.org/10.2307/3151312.
Huang, C. E. (2020). Discovering the creative processes of students: Multi-way interactions among knowledge acquisition, sharing and learning environment. *Journal of Hospitality, Leisure, Sport & Tourism Education,* 26, 100237. https://doi.org/10.1016/j.jhlste.2019.100237.
Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic Management Journal,* 20(2), 195-204. https://doi.org/10.1002/(SICI)1097-0266(199902)20:2%3C195::AID-SMJ13%3E3.0.CO;2-7.
Isaac, O., Aldholay, A., Abdullah, Z., & Ramayah, T. (2019). Online learning usage within Yemeni higher education: The role of compatibility and task-technology fit as mediating variables in the IS success model. *Computers & Education,* 136, 113-129. https://doi.org/10.1016/j.compedu.2019.02.012.
Khalilzadeh, J., Ozturk, A. B., & Bilgihan, A. (2017). Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry. *Computers in Human Behavior,* 70, 460-474. https://doi.org/10.1016/j.chb.2017.01.001.
Kim, B., & Park, M. J. (2018). Effect of personal factors to use ICTs on e-learning adoption: Comparison between learner and instructor in developing countries. *Information Technology for Development,* 24(4), 706-732.
Kim, J., & Lee, K. S. S. (2020). Conceptual model to predict Filipino teachers' adoption of ICT-based instruction in class: Using the UTAUT model. *Asia Pacific Journal of Education*. https://doi.org/10.1080/02188791.2020.1776213.
Lau, A., & Tsui, E. (2009). Knowledge management perspective on e-learning effectiveness. *Knowledge-Based Systems,* 22(4), 324-325. https://doi.org/10.1016/j.knosys.2009.02.014.
Lin, T. J. (2021). Exploring the differences in Taiwanese university students' online learning task value, goal orientation, and self-efficacy before and after the COVID-19 outbreak. *The Asia-Pacific Education Researcher,* 30(3), 191-203. https://doi.org/10.1007/s40299-021-00553-1.
Mahande, R. D., & Malago, J. D. (2019). An e-learning acceptance evaluation through UTAUT model in a postgraduate program. *Journal of Educators Online,* 16(2). https://eric.ed.gov/?id=EJ1223779.
Mtebe, J. S., Mbwilo, B., & Kissaka, M. M. (2016). Factors influencing teachers' use of multimedia enhanced content in secondary schools in Tanzania. *International Review of Research in Open and Distributed Learning,* 17(2), 65-84.
Ozturk, A. B., Bilgihan, A., Nusair, K., & Okumus, F. (2016). What keeps the mobile hotel booking users loyal? Investigating the roles of self-efficacy, compatibility, perceived ease of use, and perceived convenience. *International Journal of Information Management,* 36(6 Pt B), 1350-1359. https://doi.org/10.1016/j.ijinfomgt.2016.04.005.
Pallant, J. (2013). *SPSS survival manual: A step by step guide to data analysis using IBM SPSS.* 5th ed. McGraw Hill.
Park, S. Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning. *Educational Technology & Society,* 12(3), 150-162. https://www.jstor.org/stable/jeductechsoci.12.3.150.
Qiao, P., Zhu, X., Guo, Y., Sun, Y., & Qin, C. (2021). The development and adoption of online learning in pre- and post-COVID-19: Combination of technological system evolution theory and unified theory of acceptance and use of technology. *Journal of Risk and Financial Management,* 14(4), 162. https://doi.org/10.3390/jrfm14040162.
Ringle, C. M., Wende, S., & Becker, J. M. (2015). *SmartPLS 3*. http://www.smartpls.com.
Rogers, E. M. (1995). Diffusion of innovations: Modifications of a model for telecommunications. In M. W. Stoetzer, & A. Mahler (Eds.), *Die diffusion von innovationen in der telekommunikation. Schriftenreihe des wissenschaftlichen instituts für kommunikationsdienste* (pp. 25-38). Springer. German. https://doi.org/10.1007/978-3-642-79868-9_2.
Shin, W. S., & Kang, M. (2015). The use of a mobile learning management system at an online university and its effect on learning satisfaction and achievement. *International Review of Research in Open and Distributed Learning,* 16(3), 110-130. https://doi.org/10.19173/irrodl.v16i3.1984.
Tarhini, A., Hone, K., & Liu, X. (2014). Measuring the moderating effect of gender and age on e-learning acceptance in England: A structural equation modeling approach for an extended technology acceptance model. *Journal of Educational Computing Research,* 51(2), 163-184. https://doi.

org/10.2190/EC.51.2.b.

Tsai, Y. Y., Chao, C. M., Lin, H. M., & Cheng, B. W. (2018). Nursing staff intentions to continuously use a blended e-learning system from an integrative perspective. *Quality & Quantity,* 52(6), 2495-2513. https://doi.org/10.1007/s11135-017-0540-5.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly,* 27(3), 425-478. https://doi.org/10.2307/30036540.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly,* 36(1), 157-178. https://doi.org/10.2307/41410412.

Walldén, S., Mäkinen, E., & Raisamo, R. (2016). A review on objective measurement of usage in technology acceptance studies. *Universal Access in the Information Society,* 15(4), 713-726. https://doi.org/10.1007/s10209-015-0443-y.

Wang, A. Y., & Newlin, M. H. (2002). Predictors of web-student performance: The role of self-efficacy and reasons for taking an on-line class. *Computers in Human Behavior,* 18(2), 151-163. https://doi.org/10.1016/S0747-5632(01)00042-5.

Wang, W. T., & Lin, Y. L. (2021). The relationships among students' personal innovativeness, compatibility, and learning performance: A social cognitive theory perspective. *Educational Technology & Society,* 24(2), 14-27. https://www.jstor.org/stable/27004928.

Wixom, B. H., & Todd, P. A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research,* 16(1), 85-102. https://doi.org/10.1287/isre.1050.0042.

Wu, J. H., Tennyson, R. D., & Hsia, T. L. (2010). A study of student satisfaction in a blended e-learning system environment. *Computers & Education,* 55(1), 155-164. https://doi.org/10.1016/j.compedu.2009.12.012.

Wu, J. Y. (2017). The indirect relationship of media multitasking self-efficacy on learning performance within the personal learning environment: Implications from the mechanism of perceived attention problems and self-regulation strategies. *Computers & Education,* 106, 56-72. https://doi.org/10.1016/j.compedu.2016.10.010.

Yilmaz, R. (2016). Knowledge sharing behaviors in e-learning community: Exploring the role of academic self-efficacy and sense of community. *Computers in Human Behavior,* 63, 373-382. https://doi.org/10.1016/j.chb.2016.05.055.

Zhang, S., & Liu, Q. (2019). Investigating the relationships among teachers' motivational beliefs, motivational regulation, and their learning engagement in online professional learning communities. *Computers & Education,* 134, 145-155. https://doi.org/10.1016/j.compedu.2019.02.013.

Appendix. The research questionnaire

Factor	Reference
Knowledge acquisition	Al-Emran and Teo (2020)
KA1. Online learning facilitates the process of acquiring knowledge.	
KA2. Online learning allows me to generate new knowledge based on my existing knowledge.	
KA3. Online learning enables me to acquire knowledge through various resources.	
KA4. Online learning assists me to acquire the knowledge that suits my needs.	
KA5. Online learning can assist our university with better knowledge acquisition.	
Knowledge sharing	
KS1. Online learning facilitates the process of knowledge sharing in anytime anywhere settings.	Al-Emran and Teo (2020)
KS2. Online learning supports discussions with my instructor and classmates.	
KS3. Sharing my knowledge through online learning strengthens my relationships with my instructor and classmates.	
KS4. Online learning enables me to share different types of resources with my class instructor and classmates.	
KS5. Online learning facilitates collaboration among the students.	
Performance expectancy	
PE1: I find online learning useful in my daily study.	Venkatesh et al. (2012)
PE2: Using online learning increases my chances of achieving tasks that are important to me in my study.	
PE3: Using online learning helps me accomplish tasks more quickly.	
PE4: Using online learning increases my productivity in my study.	
Effort expectancy	
EE1: Learning how to use an online learning system is easy for me.	Venkatesh et al. (2012)
EE2: My interaction with the online learning system is clear and understandable.	
EE3: I find the online learning system easy to use.	
EE4: It is easy for me to become skillful at using the online learning system.	
Social influence	
SI1: People who are important to me think that I should use online learning	Venkatesh et al. (2012)
SI2: People who influence my behavior think that I should use online learning.	
SI3: People whose opinions that I value prefer that I use online learning.	
Facilitating conditions	
FC1: I have the resources necessary to use an online learning system.	Venkatesh et al. (2012)
FC2: Online learning system is compatible with other technologies I use.	
FC3: I can get help from others when I have difficulties using an online learning system.	

 https://doi.org/10.1633/JISTaP.2022.10.3.3

Appendix. Continued

Factor	Reference
Behavioral intention	
BI1: I intend to use online learning in the future.	Venkatesh et al. (2012)
BI2: I will always try to use online learning in my daily study.	
BI3: I plan to use online learning in the future.	
BI4: I will recommend other students use online learning.	
Actual use	
AU1: I frequently use online learning system in my study.	Al-Azawei (2019)
AU2: I depend upon an online learning system in my study.	
AU3: I use an online learning system daily.	
AU4: I use an online learning system often.	
Compatibility	
Comp1: Online learning is compatible with my values.	Isaac et al. (2019)
Comp2: Online learning is compatible with my lifestyle.	
Comp3: Online learning is compatible with my needs.	