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Online Learning Apps Adoption in the Saudi Context: A Perspective on the Unified Theory of Acceptance and Use of Technology

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ABSTRACT

The aim of this study is to determine the behavioural intentions and actual usage of online learning apps through the lens of the unified theory of acceptance and use of technology, which is a synthesis of numerous theories and models and is most commonly used to examine technology adoption behaviours. The study has utilised an exploratory research design, and data were collected using a questionnaire survey. The items used for establishing the questionnaire to measure the study constructs are adopted from different valid studies conducted previously. The current study examines the role of various factors, including performance expectancy, effort expectancy, social influence, hedonic motivations, price value, and habits on the behavioural intentions of Saudi students using online learning apps. The data were collected from 245 Saudi university students and then analysed using structural equational modelling. The results highlight that an emphasis on all the theory elements, including performance expectancy, effort expectancy, social influence, hedonic motivations, price value, and habits, can positively lead to behavioural intention to use online learning apps, leading in turn to actual usage. Although these results can be put into the context of future studies, the study encourages practitioners, policymakers, and educational designers to focus on performance expectancy, effort expectancy, social influence, habit, price value, and hedonic motivation when designing and adopting online learning apps for Saudi university students.

KEYWORDS

educational technology, m-learning, higher education, technology acceptance, Saudi Arabia

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1. Introduction

Currently, the term 'information technology' (IT) is used to describe the digital processing and transfer of data. IT requires infrastructure design, installation, configuration, training, and maintenance. IT enhances the efficiency and effectiveness of information management and is increasingly acknowledged as a significant enabler of economic and technological advancement, as well as a force and driver of modern technological development and globalisation (Ejiaku, 2014). Adoption of IT has been proven to increase national economic output and generate new jobs (Macharia and Gituru, 2006). The infrastructure of IT and telecommunications, which currently acts as a foundation for regional and global development, is the foundation of the modern global economy. IT has enormous potential to enhance business operations, education, technology, and economic growth. If utilised to meet domestic and national needs, this technology has the potential to contribute to the reduction of poverty in developing economies; however, developed and developing countries have unequal access to information and communication technologies (Macharia and Gituru, 2006). The emergence of innovative technologies in any sector can improve the quality of outputs, as in the case of the education sector, where the adoption of new or advanced technologies can not only improve the quality of educational products but also help students get better knowledge (Ansari and Tripathi, 2017). Many studies have highlighted the educational impacts of information technologies and particularly their adoption, such as computers (Brusilovsky *et al.*, 2014), internet availability/access, computer-aided instructions, and mobile devices (Sung *et al.*, 2016). Now, however, researchers are keen to know more about online learning apps and their adoption among students (Pugalendhi and Mary, 2022).

Numerous educational institutions have made substantial investments to improve the quality of teaching and learning procedures; however, if students do not utilise the learning system, the investment of substantial resources is ineffective (Pituch and Lee, 2006). As a result, understanding the factors that influence students' intentions towards online learning apps and their actual use is critical for their successful adoption. In 2014, smartphone learning apps became the fastest-growing app category, while in 2019, about 6.3 billion smartphone users downloaded learning apps, making it a billion-dollar industry (Khalil *et al.*, 2021). Even though the adoption of online learning apps is increasing, there is still a need to study the behaviour of people adopting these apps (Ansari and Tripathi, 2017). To learn about adoption behaviour and usage intention, there are many theories and models; among them, the unified theory of acceptance and use of technology (UTAUT) and its advanced version (UTAUT 2) are the most detailed (Tseng *et al.*, 2022).

Theoretical models for understanding online learning app adoption include the technological acceptance model (TAM), UTAUT (Venkatesh *et al.*, 2003), TAM2 (Venkatesh and Davis, 2000), and UTAUT 2 (Venkatesh *et al.*, 2012). Venkatesh *et al.* (2003) incorporated eight IT acceptance models into UTAUT. The original UTAUT has four key constructs, namely performance expectancy, social influence, effort expectancy, and facilitating conditions, which impact behavioural intention to adopt a technology and user behaviour. According to UTAUT, performance expectations, effort expectations, and social influence are key aspects that drive behavioural intention to use technology; however, behavioural intention and facilitating conditions help in determining technology use. Additionally, individual variations such as gender, age, and experience are regarded as moderators of the UTAUT model's four constructs. Based on their findings, Venkatesh *et al.* (2012) recently improved the UTAUT model, adding three new constructs to it. The first construct is hedonic motivation (intrinsic motivation). The second construct is price, which is an essential consideration when consumers face the cost of purchasing devices as well as services but will be disregarded in this paper, as no direct cost is imposed (and thus is less significant). The third construct is habit. The researchers Venkatesh *et al.* (2012) asserted that the proposed additions to UTAUT 2 contribute to major changes in the variance discussed in behavioural intention and technology usage. This model is

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regarded as having greater explanatory power than the TAM and UTAUT models, which have been used to describe users' behavioural intentions towards various technologies (Venkatesh *et al.*, 2012). In addition, the predictive validity of the UTAUT 2 model in the consumer context is superior to that of earlier models because the variance in behavioural intentions, as well as use behaviour, is substantial in comparison to the UTAUT baseline model (Venkatesh *et al.*, 2012).

1.1. Study Problem:

The previous literature (i.e. Duarte and Pinho, 2019; El-Masri and Tarhini, 2017) has suggested that UTAUT 2 constructs such as including effort expectancy, social influence, hedonic motivations, facilitating conditions, price value, habit, and performance expectancy have been employed in understanding the behavioural intention of various technology-related products, services, and platforms. Most of the investigation carried out in previous research includes commercial mobile phone applications from clothing to retail, games, and other platforms. However, literature has been found to be lacking in the context of education technology (Ed-Tech) products such as online learning platforms and mobile apps. Thus, a gap in the literature exists that calls for an understanding of the problem of the adoption of online mobile learning applications in educational settings. The most important aim of this study is to analyse the adoption of Saudi university students towards online learning apps. Saudi university students are always keen to learn using the most convenient tools, but when it comes to learning through the adoption of technology, their behaviour may deviate from that norm (Ejiaku, 2014). Many factors could affect the behavioural intentions of students towards the adoption of online learning apps. Therefore, based on the UTAUT 2 model, this study claims that these factors involve effort expectancy, facilitating conditions, social influence, hedonic motivations, performance expectancy, price value, and habit. This study aims to highlight the role of these influential factors on behavioural intention to use online learning apps. Moreover, this study investigates the influence of behavioural intention to use online learning apps on actual user behaviour.

2. Literature Review

2.1. Performance Expectancy:

Performance expectancy is defined as 'the degree to which an individual believes that using a technology will provide benefits in performing certain activities' (Venkatesh *et al.*, 2003: 447). Social cognitive theory, TAM, and innovation diffusion theory all use the utilitarian features of a particular technology as a powerful predictor of its adoption by society (Chuah *et al.*, 2016). According to Alalwan *et al.* (2017), customers are more likely to acquire a technology that they see as having a greater benefit in daily utility. In their study, Lee *et al.* (2012) verified that the perceived usability of a mobile app increases customers' intent to utilise it. In their study on information systems, Taiwo and Downe (2013) determined that performance expectancy is the biggest predictor of behavioural intention. Therefore, the efficiency of online learning apps and their performance can be motivating factors to adopt these apps. Thus, it can be hypothesised that:

H_1*: *Performance expectancy positively affects behavioural intentions to use online learning apps.

2.2. Effort Expectancy:

Venkatesh *et al.* (2003) defined the concept of effort expectancy as 'the degree of ease of use associated with the use of technology'. In the adoption phase, the ease of use of the technology has a favourable effect on the consumer's attitude about adopting it (Satama, 2014). Therefore, previous studies indicated that latent variables associated with effort expectancy are relevant in predicting the intention of an individual to adopt the latest technology (Venkatesh *et al.*, 2012). Moreover, previous studies have revealed a positive and strong relationship between effort expectancy and behavioural intentions in different contexts, including internet banking, mobile banking, m-payments, and tourism apps (Alalwan *et al.*, 2017; Gupta *et al.*, 2018). Therefore, the effort expectancy of online learning apps could impart a significant role in influencing the behavioural intentions of adopting them. Thus, it can be hypothesised that:

H_2*: *Effort expectancy positively affects behavioural intentions to use online learning apps.

2.3. Social Influence:

Social influence is defined as 'the degree to which an individual perceives that important others believe he or she should use the new system' (Venkatesh *et al.*, 2003: 451). Two researchers, Fishbein and Ajzen, first discussed the concept of social influence (Chandrasekara *et al.*, 2021). They then created and conceptualised the theory of planned behaviour (TPB), a new adoption model of intentional behaviour. In this model, social influence (or subjective norms) was the most significant indicator of intention to accept innovation. Mobile apps facilitate users' interactions with significant individuals, thereby strengthening their social influence in this setting (Yuan *et al.*, 2015). In addition, many researchers have found social influence to be an important predictor of behavioural intentions in different settings, including mobile-based shopping, tourism apps (Gupta *et al.*, 2018), restaurant apps, internet banking, and e-learning systems (El-Masri and Tarhini, 2017). Thus, social influence can also substantially impact behavioural intention to use online learning apps. So, it can be hypothesised that:

H_3*: *Social influence positively affects behavioural intentions to use online learning apps.

2.4. Facilitating Conditions:

Considering the UTAUT 2 model (Venkatesh *et al.*, 2012), facilitating conditions are related to the idea of perceived behavioural control in the TPB. It is defined as users' perception that they have the information, resources, and support required to participate in a certain behaviour (Venkatesh *et al.*, 2003). These variables and assets either encourage or impede the acceptance and utilisation of technology (Yuan *et al.*, 2015). Therefore, consumers are motivated to acquire technologies for which they have access to resources and perceive compatibility with technologies they have already adopted (Alalwan *et al.*, 2017). Many studies have demonstrated the beneficial and positive effect of facilitating conditions on various behavioural intents (Alalwan *et al.*, 2017; Keong *et al.*, 2012). Consequently, it could also impact the intention to use online learning apps. Thus, it can be hypothesised that:

H_4*: *Facilitating conditions positively affect behavioural intentions to use online learning apps.

2.5. Hedonic Motivation:

Hedonic motivation is the 'fun or pleasure derived from using a technology' (Venkatesh *et al.*, 2012). Researchers have asserted, based on the current data on information management, that hedonic motivations (intrinsic motives/perceived enjoyment) have a major impact on users' willingness to adopt the latest technology (Van Der Heijden, 2004). Users of apps tend to utilise technologies that are interesting and have original, inventive features and functions (Alalwan *et al.*, 2017). While developing a hedonic-motivation system adoption model, Heidelberg-Lowry *et al.* (2013) asserted that intrinsic motivations such as curiosity, control, and joy substantially impact the adoption of technology. Moreover, the influence of hedonic motivations has been investigated in different contexts, including online games, mobile health adoption, and fitness apps (Duarte and Pinho, 2019). Therefore, hedonic motivations can play a significant role in behavioural intention to use online learning apps. Thus, we hypothesise that:

***H*$_5$*: Hedonic motivations positively affect behavioural intentions to use online learning apps.*

2.6. Price Value:

Price value is a significant predictor of e-learning adoption. It is defined as the consumer's cognitive trade-off between the perceived benefits of the mobile application and the monetary cost of using it (Faqih, 2020). Zeithaml (1988) defined the notion of a price value in the context of education as the evaluation of individuals of the advantage received versus the costs paid in adopting augmented reality in educational contexts. Consequently, price value measures the net benefit derived from the application of technology. In reality, however, individuals constantly seek to maximise their net gain. This indicates that, if the uptake and usage of technology provide beneficial benefits, individuals will tolerate the technology's price (Faqih, 2020). Therefore, price value can play a significant role by influencing behavioural intentions to use online learning apps significantly. Thus, we hypothesise that:

***H*$_6$*: Price value positively affects the behavioural intentions to use online learning apps.*

2.7. Habit:

Habit can be defined in two unique ways. First, a habit is a repeated behaviour pattern (Kim and Malhotra, 2005). Second, a habit could be an automatic previous behaviour (Lamayem *et al.*, 2007). Additionally, researchers have modelled the direct and indirect effects of a habit via behavioural intention (Venkatesh *et al.*, 2012). Habits can foster behavioural intent among individuals. Consequently, it can affect intentions to use online learning apps. Therefore, it can be hypothesised that:

***H*$_7$*: Habit positively affects behavioural intentions to use online learning apps.*

***H*$_8$*: Habit positively affects the actual use of online learning apps.*

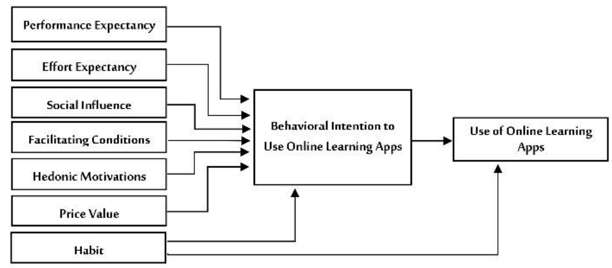
2.8. Behavioural Intention:

Behavioural intention describes an individual's intention to employ a certain technology for a variety of functions. Additionally, behavioural intention could be used to assess an individual's level of commitment to participate in a certain behaviour (Ngai *et al.*, 2007). Several researchers have highlighted that behavioural intention to use could have a substantial influence on actual system use (Ayeh *et al.*, 2012). Behavioural intention can significantly lead to the actual use of technology (Venkatesh *et al.*, 2003; 2012). Therefore, it can be hypothesised that:

***H*$_9$*: Behavioural intention positively affects the actual use of online learning apps.*

Based on the discussion above, the UTAUT 2 model for online learning app adoption among Saudi university students is shown below:

Figure 1: UTAUT 2 model for online learning app adoption



3. Methodology

3.1. Study Methodology:

The aim of this study is to highlight the behavioural intention to use online learning apps and the adoption behaviour of these apps by using the UTAUT 2 model. This study has utilised an exploratory research design; thus, data were collected using a questionnaire survey. The technique of the survey enables the researcher to gather the data in a shorter time from a larger sample. The items used for establishing the questionnaire to measure the study constructs are adopted from different valid studies conducted previously. Because Arabic is the most often used language for online apps at Saudi universities, the questionnaire was initially developed in English and then translated into Arabic.

3.2. Measures and Measurements:

In designing the questionnaire, the instrument used is important. To maintain the validity and reliability of the instruments, items were adopted from existing models of studies with some contextual modifications. As a result, items from previous studies were used to construct scales for each variable. These items were then evaluated on a five-point Likert scale, i.e. 1 (strongly disagree) to 5 (strongly agree). This study used a total of four items for measuring performance expectancy, which were adopted from Marchewka and Kostiwa (2007) and Venkatesh *et al.* (2012). Table 1 shows the items used for the questionnaire and their adoption source.

Table 1: UTAUT 2 Model Scale for Online Learning Apps

Construct	Variables and Items	Source
Performance expectancy	I find online learning apps useful in my studies. Using online learning apps increases my chances of achieving things that are important to me. Using online learning apps helps me accomplish various activities related to my studies more quickly. Using online learning apps increases my productivity in my studies.	Marchewka and Kostiwa (2007), Venkatesh *et al.* (2012)
Effort expectancy	Learning how to use online learning apps is easy for me. My interaction with online learning apps is clear and understandable. I find online learning apps easy to use. It is easy for me to become skilful at using online learning apps.	Venkatesh *et al.* (2012)
Social influence	People who are important to me think that I should use online learning apps in my studies. People who influence my behaviour think that I should use online learning apps in my studies. People whose opinions I value prefer that I use online learning apps in my studies.	Venkatesh *et al.* (2012)
Facilitating conditions	I have the resources necessary to use online learning apps in my studies. I have the knowledge necessary to use online learning apps. Mobile apps on my mobile phone are compatible with other technologies I use. I can get help from others when I have difficulties using online learning apps.	Venkatesh *et al.* (2012)
Hedonic motivations	Using online learning apps in my studies is fun. Using online learning apps in my studies is enjoyable. Using online learning apps in my studies is very entertaining.	Venkatesh *et al.* (2012)
Price value	Online learning apps are reasonably priced. The services that I have access to through my online learning apps are worth their cost. At the current price, online learning apps provide excellent value.	Venkatesh *et al.* (2012)
Habit	The use of online learning apps has become a habit for me. I am addicted to using online learning apps. I must use online learning apps. Using online learning apps has become natural to me.	Venkatesh *et al.* (2012)
Behavioural intentions to use online learning apps	I intend to continue using online learning apps in my studies. I will always try to use online learning apps in my studies. I plan to continue to use online learning apps frequently in	Venkatesh *et al.* (2012)

Construct	Variables and Items	Source
	my studies.	
Use behaviour of online learning apps	I regularly use my online learning apps in my studies. Online learning app usage is a pleasant experience. I currently use my mobile phone as a supporting tool in my studies. I spend a lot of time on online learning apps in my studies.	Venkatesh *et al.* (2012)

3.3. Sampling and Data Collection:

The study's target population were students at Jazan University, Saudi Arabia. Male accounted for 68% while female students were 32%; undergraduate students were 64% while 34% of respondents were graduate students. Their data were collected via an online questionnaire developed on Qualtrics, as the goal was to reach the maximum target population using non-probability and convenience sampling techniques. The questionnaire was translated into Arabic for the sake of convenience as most of the targeted population studying at Jazan University speak Arabic. The link was shared with 1,000 students from Jazan University, from which 245 responses were gathered. Hence, a response rate of about 24% was achieved, which is appropriate for investigation. Therefore, the utilisable sample for this study was 245 respondents.

3.4. Analytical Analysis:

To conduct statistical analysis, covariance-based structural equational modelling (CB-SEM) was utilised. SPSS V26 was used to analyse the demographics, but AMOS was utilised for detailed data analysis. In the first stage, reliability and validity were tested, and in the second stage, hypothesis testing was conducted to learn which hypotheses were accepted or rejected.

4. Results

4.1. Data Normality:

Data normality was tested using kurtosis and skewness statistics, and the results are presented in Table 2. The results reveal that the values of kurtosis are -0.83 to 1.91, and skewness values are -1.38 to -0.52. For data normality, skewness values are less than 3, and kurtosis values are less than 10, which confirms data normality. Descriptive statistics are also shown in Table 2. The mean values are 3.92 to 4.61 on a five-point Likert scale, which shows strong agreement among the respondents.

Table 2: Descriptive Statistics and Test of Data Normality

Variables	Mean	Std. Deviation	Skewness	Kurtosis
Performance Expectancy	3.92	1.00	-0.52	-0.68
Effort Expectancy	4.61	0.50	-0.84	-0.57
Social Influence	4.33	0.86	-1.38	1.91
Facilitating Conditions	4.03	1.07	-0.75	-0.67
Hedonic Motivations	4.08	1.04	-0.89	-0.19
Price Value	4.28	0.89	-1.35	1.70
Habit	3.94	1.05	-0.58	-0.83
Behavioural Intention to Use Online Learning Apps	4.16	0.93	-0.97	0.23
Use Behaviour of Online Learning Apps	4.12	1.02	-0.98	-0.02

N=245.

4.2. Sampling Adequacy and Factor Analyses' Suitability:

The Kaiser–Meyer–Olkin (KMO) test and Bartlett's test are commonly utilised for testing sampling adequacy. Hair *et al.* (2010) recommended that, for sampling adequacy, the KMO index value must be greater than 0.80. Results are shown in Table 4 and reveal a value of 0.92 for the KMO index, which indicates excellent sampling adequacy. In addition, the suitability of the factor analysis was tested with the help of Bartlett's test of sphericity. Results show significant results (X^2=676.08; df=496; P<.001), which validates the suitability of factor analysis.

4.3. Factor Analysis:

Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were used to test the scale's validity. All measurement items have a loading range between 0.696 and 0.949, which indicates excellent loading values; hence, no item was deleted from the final measurement model.

Table 3: Exploratory Factor Analysis

Construct	Items	Loadings
Performance Expectancy (PE)	I find online learning apps useful in my studies.	0.856
	Using online learning apps increases my chances of achieving things that are important to me.	0.863
	Using online learning apps helps me accomplish various activities related to my studies more quickly.	0.858
	Using online learning apps increases my productivity in my studies.	0.709
Effort Expectancy (EE)	Learning how to use online learning apps is easy for me.	0.696
	My interaction with online learning apps is clear and understandable.	0.795
	I find online learning apps easy to use.	0.799
	It is easy for me to become skilful at using online learning apps.	0.791
Social Influence (SI)	People who are important to me think that I should use online learning apps in my studies.	0.842
	People who influence my behaviour think that I should use online learning apps in my studies.	0.770
	People whose opinions I value prefer that I use online learning apps in my studies.	0.772
Facilitating Conditions (FC)	I have the resources necessary to use online learning apps in my studies.	0.906
	I have the knowledge necessary to use online learning apps.	0.897
	Mobile apps on my mobile phone are compatible with other technologies I use.	0.874
	I can get help from others when I have difficulties using online learning apps.	0.891
Hedonic Motivations (HM)	Using online learning apps in my studies is fun.	0.844
	Using online learning apps in my studies is enjoyable.	0.879
	Using online learning apps in my studies is very entertaining.	0.949
Price Value (PV)	Online learning apps are reasonably priced.	0.743
	The services that I have access to through my online learning apps are worth their cost.	0.851
	At the current price, online learning apps provide excellent value.	0.829
Habit (HB)	The use of online learning apps has become a habit for me.	0.914
	I am addicted to using online learning apps.	0.849
	I must use online learning apps.	0.915
	Using online learning apps has become natural to me.	0.929
Behavioural Intention to Use Online Learning Apps (BI)	I intend to continue using online learning apps in my studies.	0.808
	I will always try to use online learning apps in my studies.	0.817
	I plan to continue to use online learning apps frequently in my studies.	0.784
Use Behaviour of Online Learning Apps (UB)	I regularly use my online learning apps in my studies.	0.824
	Online learning app usage is a pleasant experience.	0.861
	I currently use my mobile phone as a supporting tool in my studies.	0.831
	I spend a lot of time on online learning apps in my studies.	0.808

N=245.

In addition, CFA was used to verify the validity and reliability of the data prior to testing the measurement model's fitness; the results of CFA are presented in Table 4. Reliability of the data was tested using values of composite reliability (CR). Nunnally and Bernstein (1994) recommended that CR values must be higher than 0.70 for construct reliability. The results shown in Table 4 reveal that CR values of all constructs are greater than the recommended value of 0.70, which confirms construct reliability. As per the suggestion of the study (Hair *et al.*, 2010), discriminant and convergent validity were utilised to test the construct validity. Convergent validity is determined by using the value of CR and AVE (average variance extracted). Values higher than 0.50 for AVE and 0.70 for CR confirm convergent validity (Hair *et al.*, 2010). The results indicated that values of AVE are well above 0.50, and CR values are also greater than the recommended criteria of 0.70.

Table 4: Validity Analysis

Variables	CR	AVE	PE	EE	SI	FC	HM	PV	HB	BI	UB
PE	0.89	0.68	0.824								
EE	0.85	0.6	0.371**	0.771							
SI	0.84	0.63	0.406**	0.676**	0.795						
FC	0.94	0.8	0.783**	0.390**	0.493**	0.892					
HM	0.92	0.8	0.567**	0.415**	0.531**	0.221**	0.892				
PV	0.85	0.66	0.376**	0.437**	0.551**	0.320**	0.593**	0.809			
HB	0.95	0.81	0.562**	0.525**	0.638**	0.358**	0.790**	0.541**	0.902		
BI	0.85	0.65	0.596**	0.332**	0.496**	0.281**	0.529**	0.306**	0.468**	0.803	
UB	0.9	0.69	0.475**	0.500**	0.722**	0.418**	0.632**	0.282**	0.774**	0.675**	0.831

N=245; diagonal bold are square root of AVE. **Correlation is significant at the 0.01 level (2-tailed).

The discriminant validity is determined using the values of the square root of AVE, the values of correlation, and the heterotrait-monotrait ratio (HTMT) values (Fornell and Larcker, 1981). Moreover, Fornell and Larcker (1981) recommended that, for discriminant validity, the square root of AVE values must be greater than the constructs' correlation. According to Henseler *et al.* (2015), for discriminant validity, HTMT values should be less than 0.90. HTMT results are presented in Table 5; the results confirm discriminant validity, as all

HTMT values are less than 0.90.

Table 5: HTMT Analysis

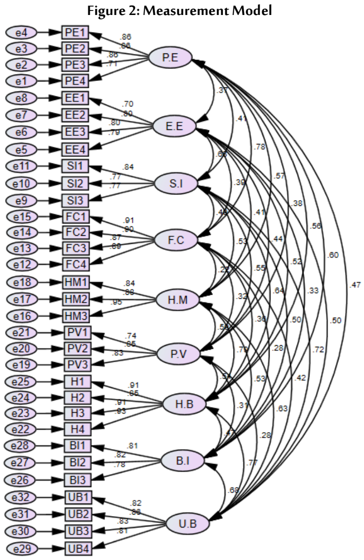
	PE	EE	SI	FC	HM	PV	HB	BI	UB
PE	-								
EE	0.38	-							
SI	0.42	0.67	-						
FC	0.84	0.39	0.501	-					
HM	0.53	0.42	0.54	0.23	-				
PV	0.37	0.45	0.561	0.321	0.555	-			
HB	0.52	0.54	0.666	0.361	0.791	0.541	-		
BI	0.59	0.34	0.504	0.284	0.539	0.296	0.474	-	
UB	0.46	0.51	0.725	0.419	0.64	0.273	0.78	0.677	-

N=245.

4.4. Measurement Model:

Before testing the hypothesised relationships, measurement model fitness was tested. CFA was used to test the model fitness; the results are shown in Table 6. Following Hu and Bentler (1999), measurement model fitness was tested using the most commonly used fit indices: 'Chi-square (χ^2/df), Tucker–Lewis Index (TLI), Comparative Fit Index (CFI), Incremental Fit Index (IFI), and Root Mean Square Error of Approximation (RMSEA)'. The results revealed excellent model fit (χ^2/df=2.19, RMSEA=0.07, IFI=0.92, TLI=0.91, and CFI=0.92), as values for all fit indices satisfy Hu and Bentler's model-fit criteria.

Figure 2: Measurement Model



4.5. Test of Hypotheses:

To test the hypothesised relationship, structural equation modelling (SEM) was utilised. The current study hypothesised nine relationships among latent variables, and the results are shown in Table 6. The results illustrate positive and significant relationships between performance expectancy and behavioural intention to use online learning apps (β=0.390; P<.001); between effort expectancy and behavioural intention to use online learning apps (β=0.140; *P*<.001); between social influence and behavioural intention to use online learning apps (β=0.330; *P*<.001); between facilitating conditions and behavioural intention to use online learning apps (β=0.250; *P*<.001); between hedonic motivation and behavioural intention to use online learning apps (β=0.470; *P*<.001); between price value and behavioural intention to use online learning apps (β=0.220; *P*<.001); and between habit and behavioural intention to use online learning apps (β=0.420; *P*<.001). Thus, hypotheses H_1 through H_7 were accepted. Moreover, the results reveal that there is a significant and positive relationship between behavioural intention to use online learning apps and the use of online learning apps, which leads to acceptance of hypothesis H_8 (β=0.440; *P*<.001).

Table 6: Test of Hypotheses

Relationships	Estimate	S.E	*P*
Performance Expectancy → Behavioural intention to use online learning apps	0.39	0.06	***
Effort Expectancy → Behavioural intention to use online learning apps	0.14	0.04	***
Social Influence → Behavioural intention to use online learning apps	0.33	0.06	***
Facilitating Conditions → Behavioural intention to use online learning apps	0.25	0.07	***
Hedonic Motivations → Behavioural intention to use online learning apps	0.47	0.07	***
Price Value → Behavioural intention to use online learning apps	0.22	0.06	***
Habit → Behavioural intentions to use online learning apps	0.42	0.07	***
Habit → Use of online learning apps	0.44	0.06	***
Behavioural Intention to Use Online Learning Apps → Use of online learning apps	0.77	0.09	***

*****P<.001; N=245.**

This study's foremost objective is to analyse Saudi university students' adoption of online learning apps.

5. Discussion

The UTAUT theory is among the latest to be developed, but UTAUT 2 is more advanced and has the potential to affect behavioural intentions. Nevertheless, its significance within the context of education, and particularly in the context of online learning apps, has not been given enough consideration. In addition, marketing managers, educators, and educational policymakers can consider the applications of this theory for analysing Saudi university students' behavioural intentions towards technology-based learning.

Numerous studies have demonstrated the usefulness of the UTAUT 2 theory for predicting diverse behavioural outcomes, but this paper is the first to examine the behavioural intention of Saudi university students towards the adoption and use of online learning apps. First, it highlighted the influence of UTAUT 2 elements (i.e. effort expectancy, social influence, hedonic motivation, facilitating conditions, price value, and habit) on behavioural intention to use online learning apps and the use of online learning apps. Second, it examined the role of behavioural intentions to use online learning apps on the actual use of online learning apps.

The first hypothesis was designed to analyse the influence of performance expectancy on the behavioural intention to use online learning apps because it is a crucial factor for the ability to predict technology adoption behaviours (Ayeh *et al.*, 2012). The results also highlighted that the performance expectancy of online learning apps could enhance the behavioural intention to use them. The second hypothesis of this study, H_2, was developed to determine the effect of effort expectancy on behavioural intention to use online learning apps. The results supported the hypothesis by explaining the relevance of studying the intention of using online learning apps. The existence of effort expectancy can persuade Saudi university students to develop the intention to utilise online learning apps. Similarly, Miladinovic and Hong (2016) highlighted that effort expectancy is the most crucial factor, after habit, that can enhance behavioural intention. The results of this study have indicated that Saudi university students are confident that the effort expectancy can enhance their intention to use online learning apps. Therefore, in line with the intention to use online learning apps, educators and educational organisations should emphasise effort expectancy.

Learning motivation and, more importantly, social influence can influence behavioural intentions and can more significantly and positively influence the behavioural intention of using e-learning portals as compared with facilitating conditions (Keong *et al.*, 2012). Therefore, there is a dire need to examine the influence of social influence in determining the behavioural intention to use online learning apps. To identify the relationship between social influence and behavioural intention to use online learning apps, the third hypothesis of this study, H_3, was developed. The beneficial impact of social influence in the measurement model evaluation is expected, as this construct of UTAUT 2 is heavily correlated with the behavioural intention to use online learning apps. In addition, multiple studies support the conclusion that social influence can increase behavioural intention (Leow *et al.*, 2021). The fourth hypothesis of this study (H_4) was developed to analyse the relationship between facilitating conditions and behavioural intention to use online learning apps. The results highlighted that facilitating conditions could significantly influence the behavioural intentions of Saudi university students towards using online learning apps. Numerous past studies have indicated a significant or positive influence of facilitating conditions on behavioural intention from various perspectives, which supports these findings (Hossain *et al.*, 2017). To examine the effect of hedonic motivations, price value, and habit on the behavioural intention to use online learning apps, H_5, H_6, and H_7 were developed. The results highlighted that these elements of UTAUT 2 can positively influence Saudi university students' intentions towards online learning apps. H_8 was developed to analyse the relationship between habit and the actual use of online learning apps; the results demonstrated that habit is a strong factor that can influence the actual use of online learning apps. Habit is an important external factor that can significantly influence behavioural intentions (Liao *et al.*, 2006) and actual usage behaviours. The last hypothesis was designed to analyse the relationship between behavioural intention to use online learning apps and actual usage of online learning apps; the results found that the use of these apps depends upon strong behavioural intentions.

6. Conclusion

The education sector of Saudi Arabia must meet the global environment for its long-term survival; in this environment, the most crucial factor is technology. Therefore, this study focused on examining the behavioural intentions and actual usage of Saudi university students regarding online learning apps through the lens of the UTAUT 2 theory. The results highlighted that all the elements of UTAUT 2, including performance expectancy, effort expectancy, social influence, hedonic motivations, price value, and habit, can influence the behavioural intentions of Saudi university students towards using online learning apps. Moreover, these behavioural intentions can lead to actual usage.

7. Implications

This study has focused on the broad theory of UTAUT 2 to analyse the influence of its elements on the behavioural intention to use online learning apps. Therefore, it has several theoretical and practical implications. In terms of theoretical implications, this study has extended the literature on UTAUT 2 and behavioural intention to use online learning apps. This study is significantly different from prior studies on UTAUT 2, as they focused on the customer's behavioural intentions and ignored the implications of this theory in the educational context. Researchers and academicians can use the results of this study as a guide for developing online learning apps to engage students. In terms of practical implications, this study can encourage practitioners, policymakers, and educators to focus on performance expectancy, effort expectancy, social influence, habit, price value, and hedonic motivation when designing online learning apps for Saudi university students.

8. Limitations and Recommendations

This study is broad in context, but it still has several limitations that future studies focusing on technology adoption or technology adoption behaviours in the educational context should consider. First, this study has focused only on examining the behavioural intentions of Saudi university students towards using online learning apps; future studies can focus on students of any other country. Second, this study has examined the behavioural intention to use online learning apps; studies in the future can focus on behavioural intention towards artificial intelligence in learning by gathering data from teachers. Third, the UTAUT 2 model can be extended by one essential element of subjective knowledge to broadly examine technology adoption behaviours.

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