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E-learning intention material using TAM: A case study

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ABSTRACT

COVID-19 pandemic has impacted various walks of life. A critical aspect of human development is education, which has been transformed from traditional face-to-face to online education. Various researchers have studied the impact of online modes of education on the learning curve of students. This research envisions identifying the intention among students on whether to continue e-learning or revert to face-to-face mode. Factors like Perceived Usefulness, Perceived Ease of Use, and Behavioral Intention is studied through Technology Acceptance Model (TAM). To evaluate the model, structure analysis was conducted. Two hundred ninety-one students participated and responded to the questionnaire specially designed for this study. Based on the results obtained, academic motivation is positively related to Behavioral Intention, which is completely related to Perceived Usefulness and Perceived Ease of Use. Knowledge Quality and Technology Fit are other salient factors that impact the students' perceived usefulness and ease of use. On the other hand, the relationships between Information Quality and Perceived Usefulness, Perceived Ease of Use and Behavioral Intention, and Social Influence and Behavioral were not supported because of insignificant relationships.

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1. Introduction

Electronic learning or eLearning is a learning system on the online medium where electronic resources deliver learning materials and impart knowledge, lessons, and learning instructions distantly. The most commonly used tools for eLearning include Learning Management System (LMS) (e.g., Moodle), video conferencing solutions (e.g., Zoom), virtual tutoring, and digital libraries [1]. eLearning is very effective. Study has shown that students can retain as much as 25 to 60 percent of the learning materials when participate in eLearning in comparison to only 8 to 10 percent retention in traditional classroom [2]. 63 percent schools in the United States use eLearning platforms and more than 50 percent American graduates deem eLearning as a better alternative of traditional classroom [3]. In corporate settings, it was found in study that eLearning saves 40 to 60 percent time when completing in comparison to traditional face-to-face learning [4]. It is predicted that the global eLearning market will reach USD 325 billion by 2025 [5].

Along with threatening human lives and causing economic crisis, COVID-19 has also threatened to put the education system on hold. To limit the spread of COVID-19 infection, governments in about 120 countries around the world have ordered for the closure of schools or universities and in-person classes [6]. On the other hand, World Bank has reported that COVID-19 has resulted closure of schools in 180 countries [7]. World Economic Forum has published that about 1.2 billion school students in 186 countries are suffered due to COVID-19 [2]. Overall, nearly 13 percent of the total number of students worldwide are interrupted because of COVID-19 [8]. The closure of schools and universities has not only interrupted the regular education but also caused to increase the dropout of students, especially the disadvantaged students. In long-run, it is anticipated that COVID-19 would worsen the skill development, productivity and employment opportunity of students due to interruption and discontinuation in education [7].

eLearning, nowadays, is an essential alternative for schools and universities all over the world to offer their academic courses interrupted by COVID-19 [9]. As eLearning facilitates distant learning, its role during COVID-19 pandemic has become bigger and crucial [10]. The lockdown and closure of the educational institutes due to COVID-19 have created a very high demand for eLearning [11]. Following the COVID-19 restrictions, billions of students glob-

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ally are unable to attend classes physically. Subsequently, schools and uninvesting are migrating to eLearning to continue their students' education without interruption. As a 'new normal', eLearning is now the most feasible and useful alternatives of face-to-face teaching and learning to continue the academic schedules during pandemic [12]. It is reported that the eLearning market will grow at a compound rate of 10.3 percent until 2027 as an impact of COVID-19 [13].

While COVID-19 has caused high demand for eLearning, the recent studies have shown some critical factors determining the eLearning adoption. For instance, eLearning system quality factors (e.g., accessibility, availability, reliability and usability), culture factors, self-efficacy factor, and trust factor [10]. Need for good preparation and student–teacher interaction are also important to implement eLearning [14]. Studies have reported both positive and negative inclination among students towards e-learning; therefore, contextual study is important for finding the factors that might affect eLearning adoption [15].

Originally proposed by Davis in 1986, Technology Acceptance Model (TAM) has been a significant model that assisted researchers to identify and explain the factors influencing the users' behavior toward the acceptance of technology [16]. Until now, TAM has been widely used in information technology research [17]. The two main factors that TAM consists are perceived ease of use (PEOU) and the perceived usefulness (PU). In TAM, PEOU and PU are the most common factors that are used to explain the variance in users' behavior intention (BI) and then the actual use (AU). Because of high capability of TAM in explaining technology adoption, researchers frequently add external factors (e.g., self-efficacy) to extend TAM to explain the technology adoption better [18]. Researchers use TAM in various contexts with different samples to explain variance in users' behavior intention to use technology. Like TAM, researchers also widely use Unified Theory of Acceptance and Use of Technology (UTAUT) to explain variance in technology adoption, however, studies have shown that TAM has been more commonly and dominantly used by researchers [19].

In the area of eLearning adoption study, researchers have used external factors such as self-efficacy, innovativeness, technology anxiety, perceived enjoyment, facilitating conditions, information quality, system quality, and social norm most commonly to extend TAM [20]. Overall, TAM is considered as a comprehensive model for investigating eLearning adoption by students [21]. In Saudi Arabia context, TAM based study was conducted to improve the use of eLearning [22]. On the other hand, TAM was used to predict the acceptance of eLearning in Saudi Arabia in past [23]. Earlier, TAM was used to find the factors influencing eLearning in higher education in Saudi Arabia [24,25]. TAM based study was also conducted in UAE, the neighboring country of Saudi Arabia, to find the factors significant in eLearning adoption [26].

However, there is no TAM based study in Saudi Arabia which has investigated the intention to continue using eLearning by the students in Saudi universities after COVID-19. Therefore, to fill this study gap, this study aims to extend TAM to investigate the external factors which might determine the Saudi university students' intention to continue using eLearning in the post-COVID-19 period in future. Since COVID-19 outbreak, it is reported that 1.2 million Saudi users are studying through eLearning mediums [27]. Therefore, it is important to know what factors would influence them to continue eLearning after COVID-19.

2. Related works and theoretical background

The number of universities which are offering eLearning is growing in Saudi Arabia [28]. The Ministry of Education (MoE) in Saudi Arabia has established the National Centre of eLearning and Distance Learning to facilitate eLearning across the country [29]. After COVID-19, the universities in Saudi Arabia are increasingly offering eLearning facilities [30]. In Saudi context, there are a few important studies that have studied eLearning. Alasmari has used UTUAT model and found that learning expectancy, effort expectancy, and social influence, mobiles are the important determinants of mobile eLearning adoption in Saudi Arabia [31]. Previously, the study by Walabe and Luppicini (2020) emphasized on understanding the complex interplay among important factors that might influence eLearning in Saudi Arabia [32]. On the other hand, another study shows that self-efficacy, user satisfaction, and user resistance are strong influencing factors in eLearning adoption in Saudi Arabia [33]. Also, another previous study showed that students' characteristics, instructor's characteristics, learning environment, instruction design, and supports are critical success factors for eLearning in Saudi Arabia [34]. Besides, found that eReadiness in critical for the success of eLearning in Saudi Arabia [35].

On the other hand, a good number of studies on eLearning adoption have used TAM to examine the factors affecting eLearning adoption. For instance, Baby and Kannammal [36] used TAM to design a user-centric framework for e-learning solutions. [37] used TAM to access students' acceptance of artificial intelligence-based assessment on eLearning platform. In Malaysian context, [38] used TAM to explain students' acceptance of eLearning in universities. They added three external factors, namely instructor characteristics, self-efficacy, course design, to TAM for their study. On the other hand, [26] applied TAM to explain the factors importance for the acceptance of eLearning in UAE. [39] studied the acceptance of eLearning by extending TAM in Jordan. [40] found that attitudes and perceived usefulness strongly determine students' use and acceptance of eLearning. Similarly, [41] reported that attitude and patronized (facilitating condition) can strongly predict the variance in using eLearning based on their TAM based study. Likewise, in Iraq context, [42] showed that computer self-efficacy strongly explains the variance in PU and PEOU. They extended TAM by adding self-efficacy, perceived satisfaction, and learning styles as external constructs.

3. Research model and hypotheses

In order to study the impact of various factors on eLearning, nine factors were considered. There factors can be formulated as shown in Fig. 1. Certain factors like Knowledge Quality (KQ) and Information Quality (IQ) do contribute towards Perceived Usefulness (PU), while Technology Fit (TF) and Self-Efficacy (SE) contributes toward Perceived Ease of Use (PEU). Two other factors such as Social Influence (SI) and Academic Motivation (AM) combined with PI and PEI contributes towards Behavioral Intention (BI).

4. Results and discussion

Measurement model shows the internal reliability as well as the convergent and discriminant validity of the constructs [43]. Measurement model helps to know how well each construct is measured by its indicators. As Table 1 shows, Cronbach's alpha and composite reliability values (Table 1) help to measure the internal reliability to know how well a survey is measuring what a researcher wants the survey to measure. A value between 0.6 and 0.7 for Cronbach's alpha and the composite reliability confirms that internal reliability, which is achieved for this study. Then, the researchers have looked convergent validity which is present if AVE is more than 0.5 [44]. Table 1 shows that the convergent valid-

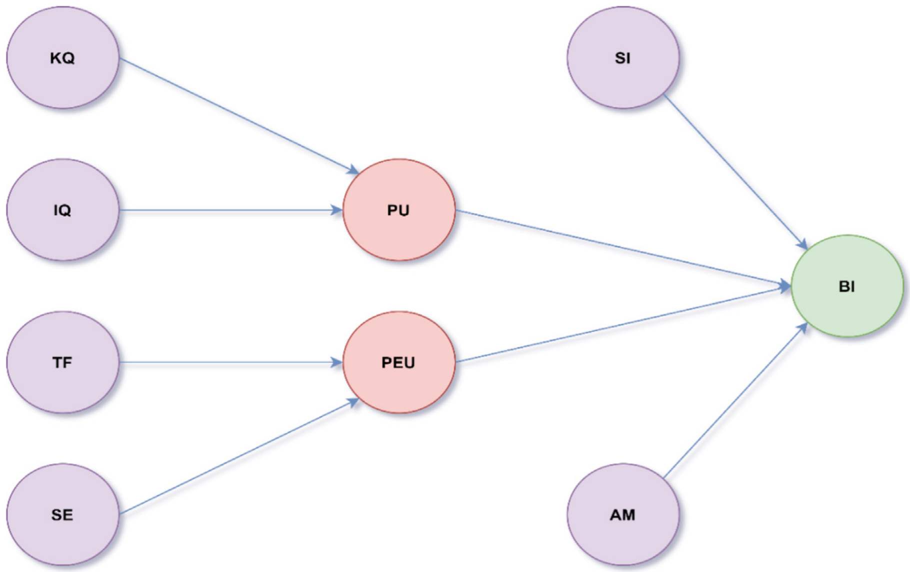

Fig. 1. The Model: Conceptual research model. (KQ = Knowledge Quality, IQ = Information Quality, TF = Technology Fit, SE = Self-Efficacy, PU = Perceived Usefulness, PEU = Perceived Ease of Use, SI = Social Influence, AM = Academic Motivation, BI = Behavioral Intention).

Table 1
Construct Reliability and Validity.

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AM	0.856	0.933	0.874
BI	0.857	0.903	0.702
IQ	0.785	0.841	0.519
KQ	0.656	0.773	0.566
PEU	0.777	0.870	0.691
PU	0.663	0.816	0.596
SE	0.667	0.776	0.536
SI	0.677	0.741	0.606
TF	0.689	0.840	0.724

ity for every construct is achieved as the AVE for every construct is above 0.5.

On the other hand, Table 2 shows the factor loadings of each item to examine the amount of relevance of any item in explaining their respective construct [45]. The recommended value of factor loadings should be more than 0.5 or 0.6, depending on whether a construct is nearly developed or established. Henceforth, according to Table 2, the items used for each construct are relevant. Further, discriminant validity indicates that a construct is free from redundant items. Table 3 informs that the square root of the AVE of all the constructs is greater than each construct's correlation with other constructs, as a result, discriminant validity is proved [46].

4.1. Structural model

In the analysis of the structural model, the researchers have tested the acceptance and rejection of the hypotheses proposed. For that, the bootstrap analysis in SmartPLS calculated the path coefficient (β), t statistics, and P Value for each hypothesis (Table 4). A hypothesis is rejected when the p value more than 0.05 and the t statistic is less than 1.96. The result shows that the p values were less than 0.05 for the relationships between Academic Motivation (AM) and Behavioral Intention (BI) (b = 0.620, t = 16.11), Knowledge Quality (KQ) and Perceived Usefulness (PU) (b = 0.677, t = 15.659), Perceived Usefulness (PU) and Behavioral Intention (BI) (b = 0.280, t = 5.210), Self-Efficacy (SE) and Perceived Ease of Use (PEU) (b = 0.318, t = 6.134, p = 0.000), and Technology Fit (TF) and Perceived Ease of Use (PEU) (b = 0.350, t = 6.195). Thus, the hypotheses H1, H3, H5, H6, and H8 were supported because of significant relationship.

On the other hand, the p values were more than 0.05 for the relationships between Information Quality (IQ) and Perceived Usefulness (PU) (b = -0.023, t = 0.914), Perceived Ease of Use (PEU) and Behavioral Intention (BI) (b = -0.020, t = 0.279), and Social Influence (SI) and Behavioral Intention (BI) (b = -0.035, t = 0.730). Thus, the hypotheses H2, H4 and H7 were not supported because of insignificant relationship.

5. Conclusion

The perception of the students about education has been impacted due to the recent COVID-19 pandemic outbreak. Education system has transformed the learning of the students from the traditional face-to-face to online mode. Technology Adapted Model (TAM) applied in this research reveals the impact of knowledge quality and technology fit on the behavioral intention. Such a behavioral intention impacts the academic motivation among students. Thus, the motivation towards online or the intention of reverting to face-to-face mode of learning is affected by various factors like knowledge quality and technology fit. Academic institutions need to adhere to standards when providing online education appropriate technology and knowledge quality.

CRediT authorship contribution statement

Madini O. Alassafi: Writing – original draft, Supervision, Software, Conceptualization, Methodology, Visualization, Validation, Writing – review & editing, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 2
Factor Loadings.

	AM	BI	IQ	KQ	PEU	PU	SE	SI	TF
AM1	0.939								
AM2	0.931								
BI1		0.900							
BI2		0.903							
BI3		0.817							
BI4		0.718							
IQ1			0.742						
IQ2			0.671						
IQ3			0.559						
IQ4			0.733						
IQ5			0.862						
KQ1				0.626					
KQ2				0.528					
KQ3				0.712					
KQ4				0.829					
PEU1					0.789				
PEU2					0.874				
PEU3					0.829				
PU1						0.742			
PU2						0.783			
PU3						0.791			
SE1							0.783		
SE2							0.685		
SE3							0.726		
SI1								0.958	
SI2								0.542	
TF1									0.840
TF2									0.861

Table 3
Correlation Matrix and Square Root of the Average Variance Extracted.

	AM	BI	IQ	KQ	PEU	PU	SE	SI	TF
AM	**0.935**								
BI	0.656	**0.838**							
IQ	0.722	0.737	**0.720**						
KQ	0.272	0.410	0.440	**0.683**					
PEU	0.219	0.263	0.395	0.566	**0.831**				
PU	0.182	0.361	0.254	0.661	0.602	**0.772**			
SE	−0.010	0.110	0.126	0.472	0.484	0.587	**0.732**		
SI	0.220	0.247	0.216	0.451	0.621	0.580	0.488	**0.779**	
TF	0.033	0.095	0.144	0.365	0.502	0.454	0.489	0.449	**0.851**

Table 4
Structural Model.

SL	Path	*B*	T Statistics	*P* Values	Comments
1	KQ -> PU	0.677	15.659	0.000	Accept
2	IQ -> PU	−0.023	0.914	0.361	Reject
3	TF -> PEU	0.350	6.195	0.000	Accept
4	SE -> PEU	0.318	6.134	0.000	Accept
5	PU -> BI	0.280	5.210	0.000	Accept
6	PEU -> BI	−0.020	0.279	0.781	Reject
7	SI -> BI	−0.035	0.730	0.465	Reject
8	AM -> BI	0.620	16.117	0.000	Accept

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