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The Impacts of Perceived Content Quality, Computer Self Efficacy, and Course Attributes on Behavioral Intention: The mediating roles of and Subjective Norms, Perceived Ease of Use, and Perceived Usefulness

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Abstract

The theory of e-learning acceptance is now moving forward to explore the very attributes of the e-learning happening, to ensure quality and relevance of an overall e-learning system. This study uses a survey of 301 students registered with the Public Authority for Applied Education and Training (PAAET) in Kuwait to explain the impacts of perceived content quality, computer self-efficacy, course attributes on behavioral intention. The PLS-SEM analysis suggest, that content quality, computer self-efficacy, and course attributes are important for generating the overall behaviour intention to use e-learning. In this regard, the research has importantly found that these impacts mediates through the subjective norms of the learners and their perceptions, including those related with the ease of use and the usefulness of the e-learning. These findings are important in the new theoretical and policy contexts of moving the technology adoption towards more intrinsic features of the e-learning, particularly in e-learning systems, introduced by the governments in relatively new countries to the e-learning.

Keywords: E-learning, content quality, self-efficacy, course attributes, behavioural intention, subjective norms, ease of use, usefulness.

Introduction

The recent surge in the technology as response to Covid-19 was more a necessity than an opportunity in education as part of maintaining physical distancing (Saxena et al., 2021). In this pretext, in addition to health services, education is considered the most affected sector in both Kuwait and throughout the world. In this regard, both

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technological development and its adoption in the education sectors are concerns to both theorists and policy makers. On the adoption side, the learners are seem to be now more incharge in terms of self-regulation of their learning and adoption of any technology for it (Liaw & Huang, 2013). It is consequently, important that most of the e-learning systems be evaluated from the users or learners point of views, as their experiences would count more towards the adoption of technology based education (MacDonald & Thompson, 2005).

Additionally, both teachers cum researchers and students have now got more opportunities to pose themselves as collaborative and collective learners. With this mindset, universities are emerging as groups of leaners. Here the focus is on expending technology adoption to finding the efficacy, quality, and other operational factors of the learning system (Yunusa & Umar, 2021). This is important, particularly in the context when universities and organisations both are competing on learning and moving towards knowledge based work that is technologically enabled too (Hsia et al., 2014). This research focuses on finding the impact of perceived content quality, computer self-efficacy, course attributes on with behavioral intention with mediating roles of and subjective norms, perceived ease of use, and perceive usefulness. It is important that these elements of e-learning be centered to the learners because learners still have computer-related phobia and more clarifications are required (Saade & Kira, 2009). Next section present a literature review to reflect upon the recent debates on the e-learning adoption an effectiveness. Afterwards a methodology is developed.

Literature Review

In e-learning the one the significant concerns of both academics and students in terms of ensuring the quality of the learning delivered online (Jung, 2011; Liaw & Huang, 2013). The perception of e-learning quality primarily arise out of the very demand of e-learning itself, where the e-learning is perceived as a quality service by the learners and their experiences therefore matters (MacDonald & Thompson, 2005). In this regard, the e-learning quality be considered as service quality to regard as the content are fine, reliability, and responsiveness are there. It is because these factors “play a significant role in perceived e-learning quality, which in turn affects learners' satisfaction and future intentions to enroll in online courses” (Udo et al., 2011). As in e-learning the

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learning is more collaborative in nature through shared platforms (Yunusa & Umar, 2021), therefore e-learners in the shared platforms are also the key content creators as and when they work together to create the content, format it, and also develop the very process of delivering the same. Therefore, the learners be given a greater role in the very understanding and designing of these e-learning systems (Jamatia, 2012). The re-focus of the e-learning towards the learners can be interpreted as a new paradigm shift in building and implementing e-learning systems (B.-C. Lee et al., 2009).

In this emergent context of both teachers and learners a content co-creators, the e-learning have both element of the course ant its contents and the serving the same. Therefore, these two elements must be combined with the quality content be serviced using various service delivery principles (Uppal et al., 2018). The congruence in course and serving it well, can bring in unprecedented expansion of the e-learning where quality of various elements such as content, admin, teaching supports, and the connectivity, will remain be great concerns for the learners (Elango et al., 2008). In this respect, when social distancing is a requirement, ensuring the learners satisfaction is emerging as new phenomenon, where reliability, and web content have greater role in it (Saxena et al., 2021).

The e-learning adoption, whether as a matter of choice or compulsion, has now entered into a new stage of debates about the very structural and satisfaction aspects as the e-learning adoption (Yunusa & Umar, 2021). As the e-learning adoption has now been considered becoming more and more a regular phenomenon. I addition to satisfaction other identified benefits of e-learning, an equality relevant question is why some learners are dissatisfied, in their learning experience with e-learning (Liaw, 2008).

In Arab world in particular, the phenomenon of e-learning and its quality aspects such as satisfaction with it, are still new phenomena, where one can expect interesting contextual learnings as governments are trying to implement e-learning as viable alternate learning (Adel, 2017). In this regard it is important to study the e-learning acceptance and its quality enhancement, in the context where the e-learning is happening in more a public sector environment to see the emergent the e-learning acceptance and quality factors.

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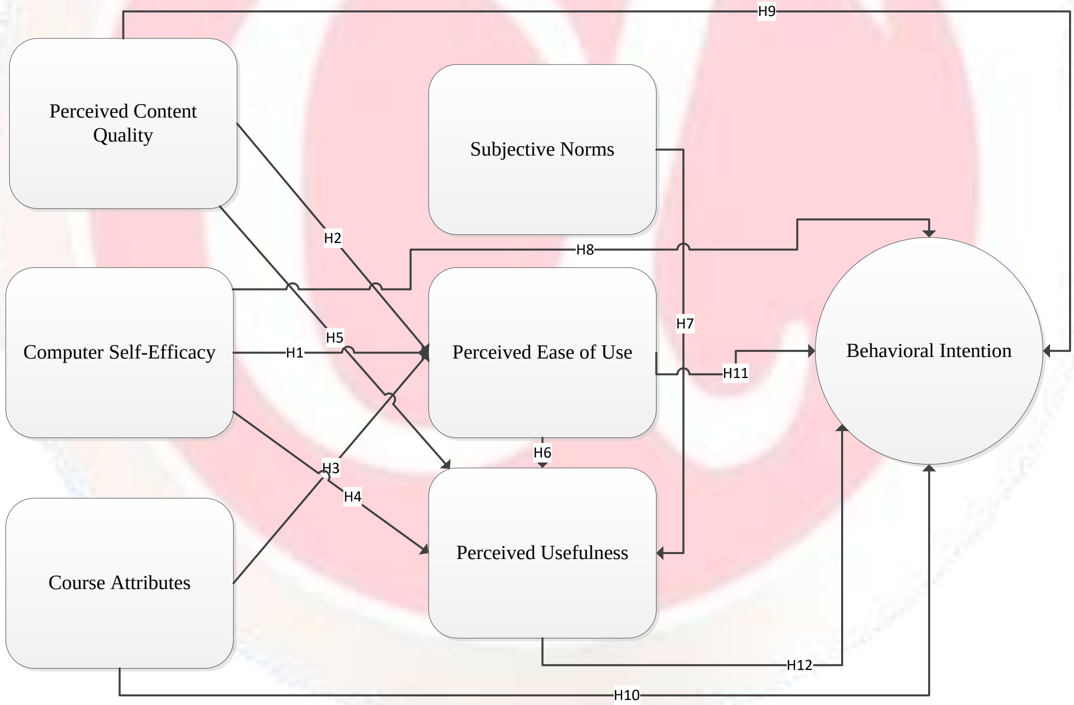
Methodology

This study followed a survey methodology to generate generalizable finings. In the questionnaire survey, 301 students have participated. The sample size is selected based on the convention in the literature on e-learning adoption using questionnaire survey and PLS-SEM method for analysis. As for example a sample studies have used 259 students (Balaban et al., 2011) and in another similar 239 students are used (Dominici & Palumbo, 2013). The respondents were purposefully chosen, as they have extensive use of the e-learning at the Public Authority for Applied Education and Training (PAAET). The data was collected between 12-March to 2-May 2021.

Figure 1 shows the framework followed by the hypothesis of the research.

Figure 1: Theoretical framework



H1: Computer self-efficacy impacts perceived ease of use.

H2: Perceived content quality impacts perceived ease of use.

H3: Course attributes impact perceived ease of use.

H4: Computer self-efficacy impacts perceived usefulness.

H5: Perceived content quality impacts perceived usefulness.

H6: Perceived ease of use impacts perceived usefulness.

H7: Subjective norms impacts perceived usefulness.

H8: Computer self-efficacy impacts perceived behavioral intention.

H9: Perceived content quality impacts perceived behavioral intention.

H10: Course attributes impact perceived behavioral intention.

H11: Perceived ease of use impacts perceived behavioral intention.

H12: perceived usefulness impacts perceived behavioral intention.

For the data analysis purpose the study has adopted the partial least squares-structural equation modeling (PLS-SEM) through SmartPLS V.3.2.7 software (Ringle et al., 2013). Two steps are followed in the analysis process. Firstly a measurement model is development an afterwards a structural model is established (Hair et al., 2017). PLS-SEM has been chosen as it has been proved working well with complex models such as in this study (Hair Jr. et al., 2016) and also helps in both developing and testing theoretical model with more rigor than simple regression (Urbach Frederik, 2010). PLS-SEM is particularly useful because it provide a holistic analysis of both measurement and structural models (Barclay et al., 1995), thus ensure both reliability of the methods and validity of the topic.

Analysis and Interpretations

Descriptive Statistics

The percentages and frequencies of use of e-learning systems were determined after collecting data on age, education, online experience, hours of use, and frequency of use. In terms of Gender, females (n = 193, 64%) were the most common. The group aged 18 to 22 made up over half of the participants (n = 142, 47%). Among those who indicated their level of education, "High school" (n = 263, 87%) was the most common response. In terms of years spent online, the most common range was 3-5 (n = 114, 38%). 5+ hours per week is the most common usage of e-learning systems (n = 164, 54%). For

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the variable Frequency of utilizing e-learning systems, the range 8-14 was by far the most common (n = 141, 47%). Table 1 provides frequency and percentage distributions.

Table 1

Frequency Table for Nominal Variables

Variable	*N*	*%*	Cumulative *%*
Gender			
Male	108	35.88	35.88
Female	193	64.12	100.00
Age			
18-22	142	47.18	47.18
23-26	96	31.89	79.07
27-30	46	15.28	94.35
more than 30	17	5.65	100.00
Education			
High school	263	87.38	87.38
Others	38	12.62	100.00
Online experience			
Less than one year	7	2.33	2.33
1-2	89	29.57	31.89
3-4	114	37.87	69.77
5 and more	91	30.23	100.00
Hours of using e-learning systems			
Less than one hours	5	1.66	1.66
1-2	20	6.64	8.31
3-4	112	37.21	45.51
5 and more	164	54.49	100.00
Frequency of using e-learning systems			
Less than 7 times	64	21.26	21.26
8-14	141	46.84	68.11
15-21	47	15.61	83.72
22 and more	49	16.28	100.00

Partial Least Squares Path Modeling

The latent variables PCQ, CSE, CAT, SN, PEOU, PU, and BI were tested in a partial least squares path modeling (PLS-PM) study to see if they could sufficiently explain the data. The purpose of PLS-PM is to provide a detailed description of the network of variables and their connections.

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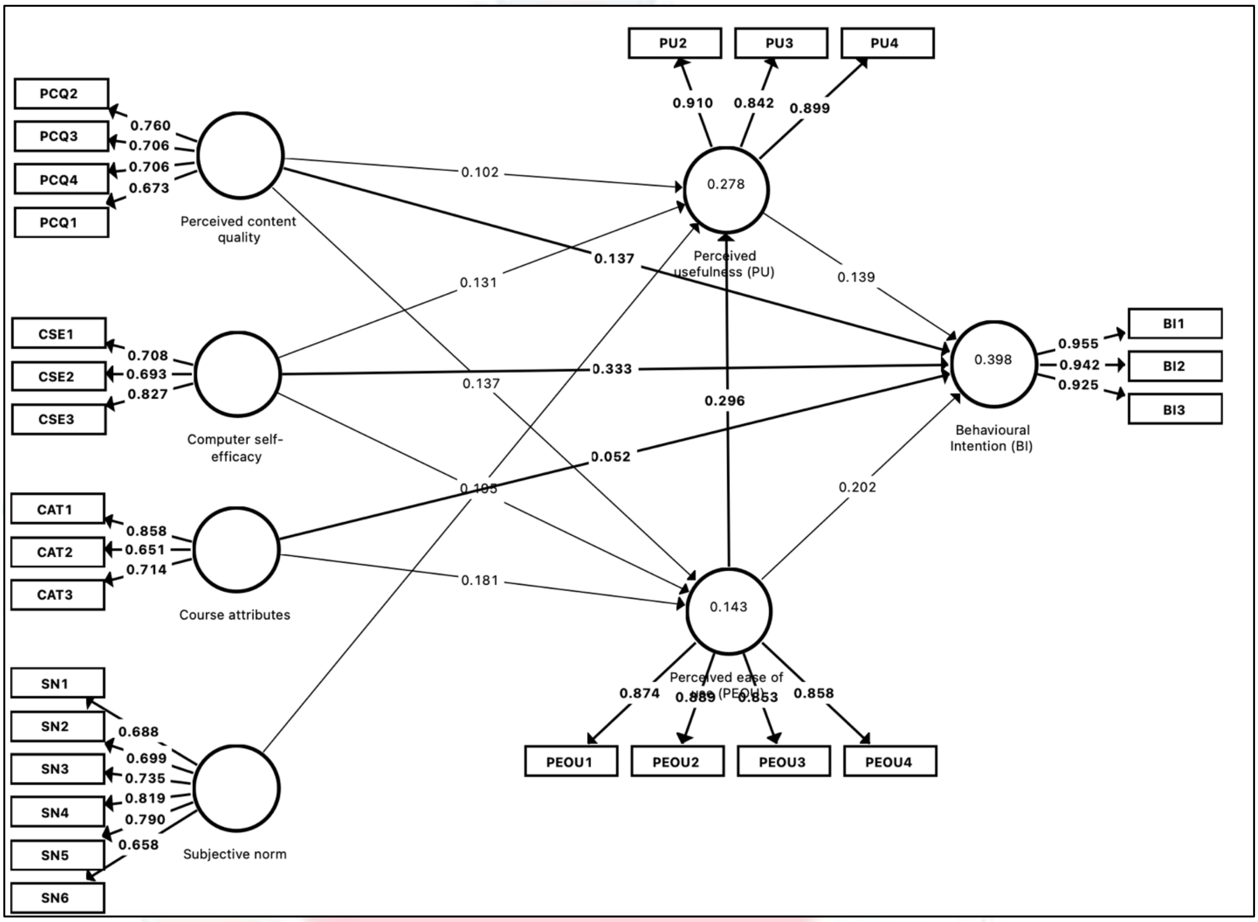
Both the measurement and structural models' reliability were evaluated to determine the PLS-PM model's reliability. The PLS-PM regressions were investigated following model validation. Figure 2 depicts the PLS-PM model diagram.

Figure 2

Node diagram for the PLS-PM model with loadings shown.



Unidimensionality, loadings, communalities, and crossloadings of the indicator variables were analyzed to evaluate the measurement model, also known as the outer model. The relevance of each loading was evaluated using bootstrapping.

Each reflective indicator must have a positive correlation with the latent construct. Each indication should improve if the value of the latent variable does. Unidimensionality of indicators is what Sanchez (2013) calls this phenomenon. Cronbach's alpha () and Dillon-rho Goldstein's () were computed to examine the unidimensionality of indicators. Cronbach's alpha >.70 and Dillon-rho Goldstein's >.70 are critical levels for assuming that indicators are unidimensional. Unidimensionality was not observed for the PCQ,

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CSE, or CAT, all of which are latent variables. These latent variables' negatively associated indicators could bias the study; they should be discounted or eliminated (Sanchez, 2013). Table 2 shows the reliability coefficients calculated using Cronbach's alpha and Dillon-rho. Goldstein's

Table 2

Unidimensionality of Indicators. for Each Latent Construct.

Construct	Indicator Type	Number of items	α	ρ
PCQ	Reflective	4	0.69	0.81
CSE	Reflective	3	0.65	0.81
CAT	Reflective	3	0.63	0.80
SN	Reflective	6	0.85	0.89
PEOU	Reflective	4	0.90	0.93
PU	Reflective	3	0.86	0.92
BI	Reflective	3	0.94	0.96

Note. Unidimensionality does not apply to formative indicators or latent variables with only one indicator variable.

In order to find any reflective indicators that had insufficient loadings for the latent variables, we looked at the factor loadings and communalities for the reflective indicators. The variability in each indicator should explain at least 50% of its latent variable construct (|loading| >.707; communality >.50), and each indicator should be assigned a value between 0 and 1. (Henseler, 2017; Henseler et al., 2009, 2015; Sanchez, 2013). If such is not the case, we classify it as a light loading. PCQ4, PCQ1, CSE2, CAT2, SN6, and SN1 are examples of reflecting indicators that have modest loadings. It is necessary to do an analysis on these indicators in order to identify whether or not they actually belong in the model. The loadings and communalities for the measurement model are presented in Table 3.

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Table 3

Outer Model Summary Table for the PLS-PM Model.

Construct	Item	Loading	Mean	Standard Deviation
Perceived content quality	PCQ1	0.71	3.33	0.919
	PCQ2	0.77	3.34	1.148
	PCQ3	0.63	3.36	1.184
	PCQ4	0.76	3.17	1.065
Computer self-efficacy	CSE1	0.83	3.6	1.08
	CSE2	0.7	3.52	1.146
	CSE3	0.75	3.32	1.178
Course attributes	CAT1	0.73	3.85	1.008
	CAT2	0.7	2.76	1.268
	CAT3	0.84	3.74	1.086
Subjective norm	SN1	0.7	3.82	0.937
	SN2	0.81	3.77	0.913
	SN3	0.82	3.59	0.887
	SN4	0.79	3.4	0.96
	SN5	0.73	3.64	0.859
	SN6	0.69	3.19	0.966
Perceived ease of use (PEOU)	PEOU1	0.85	3.33	1.046
	PEOU2	0.88	3.63	1.033
	PEOU3	0.9	3.59	0.991
	PEOU4	0.9	3.48	1.082
Perceived usefulness (PU)	PU2	0.91	3.69	0.818
	PU3	0.85	3.47	0.936
	PU4	0.9	3.54	0.838
Behavioural Intention (BI)	BI1	0.92	3.48	1.063
	BI2	0.95	3.59	1.031
	BI3	0.96	3.51	1.005

The influence of Perceived Ease of Use, Subjective Norms, and Perceived Usefulness on the Impact of Perceived Content Quality, Computer Self-Efficacy, and Course Characteristics on With Behavioral Intention: The Mediating Roles of and Subjective Norms.

In order to determine whether or not the model is valid, the crossloadings were investigated for the reflective indicators as well. When an indicator is found to have a larger absolute loading on a latent variable that is not the one to which it is assigned, this is an example of crossloading (Henseler, 2017; Henseler et al., 2009, 2015; Sanchez, 2013). The fact that the model did not contain any crossloadings for reflective indicators suggests that the structure of the latent variables that were defined is adequate for the data. Table 4 contains the crossloadings that have been determined.

Table 4

Loadings and Crossloadings the Outer Model.

Indicator	PCQ	CSE	CAT	SN	PEOU	PU	BI
PCQ4	0.71	0.35	0.30	0.36	0.31	0.26	0.24
PCQ3	0.77	0.52	0.38	0.30	0.22	0.31	0.38
PCQ1	0.63	0.41	0.19	0.31	0.21	0.23	0.16
PCQ2	0.76	0.47	0.45	0.30	0.23	0.28	0.46
CSE3	0.56	0.83	0.34	0.41	0.21	0.39	0.57
CSE2	0.37	0.70	0.32	0.38	0.19	0.17	0.30
CSE1	0.42	0.75	0.36	0.37	0.27	0.25	0.44
CAT3	0.29	0.28	0.73	0.34	0.24	0.24	0.26
CAT2	0.40	0.35	0.70	0.46	0.26	0.26	0.27
CAT1	0.39	0.37	0.84	0.25	0.34	0.29	0.42
SN6	0.39	0.42	0.40	0.70	0.24	0.24	0.33
SN5	0.30	0.35	0.31	0.81	0.27	0.36	0.22
SN4	0.36	0.40	0.36	0.82	0.24	0.26	0.29
SN3	0.37	0.40	0.29	0.79	0.18	0.27	0.23
SN2	0.30	0.39	0.33	0.73	0.16	0.26	0.27
SN1	0.26	0.35	0.30	0.69	0.18	0.28	0.26
PEOU4	0.29	0.28	0.32	0.26	0.85	0.47	0.36
PEOU3	0.31	0.24	0.37	0.28	0.88	0.42	0.35
PEOU2	0.28	0.25	0.31	0.22	0.90	0.38	0.33
PEOU1	0.30	0.25	0.31	0.23	0.90	0.41	0.35
PU2	0.37	0.33	0.32	0.38	0.46	0.91	0.43
PU3	0.24	0.30	0.29	0.30	0.41	0.85	0.42
PU4	0.37	0.36	0.31	0.31	0.40	0.90	0.49
BI3	0.43	0.55	0.39	0.35	0.38	0.50	0.92
BI2	0.45	0.56	0.45	0.31	0.37	0.48	0.95
BI1	0.40	0.58	0.39	0.32	0.38	0.45	0.96

Note. The bolded items are the specified loadings for each indicator.

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The bootstrapping procedure was carried out using a total of 500 resamples. The loadings on the reflecting indicators were evaluated, whereas the weights on the formative indicators were analyzed. An alpha level of 0.05 was used in the calculation of the confidence intervals for the given parameter estimations, which were used to assess whether or not there was statistical significance (Henseler et al., 2009; Sanchez, 2013; Chinn, 2010). Because each reflecting manifest variable has a large loading, this suggests that each latent variable explains a considerable percentage of each reflective indicator. The bootstrapped weights were not investigated because there were no formative indicators to consider. The results for the bootstrapped loadings are presented in Table 5.

Table 5

Bootstrap Results for the Loadings of Each Indicator.

Path	Original	*M*	*SE*	95% CI
PCQ → PCQ4	0.71	0.70	0.06	[0.57, 0.79]
PCQ → PCQ3	0.77	0.77	0.04	[0.67, 0.84]
PCQ → PCQ1	0.63	0.62	0.08	[0.45, 0.76]
PCQ → PCQ2	0.76	0.76	0.05	[0.64, 0.85]
CSE → CSE3	0.83	0.83	0.04	[0.75, 0.89]
CSE → CSE2	0.70	0.70	0.08	[0.51, 0.82]
CSE → CSE1	0.75	0.75	0.05	[0.63, 0.84]
CAT → CAT3	0.73	0.73	0.06	[0.57, 0.84]
CAT → CAT2	0.70	0.70	0.07	[0.55, 0.81]
CAT → CAT1	0.84	0.84	0.04	[0.74, 0.91]
SN → SN6	0.70	0.69	0.05	[0.56, 0.78]
SN → SN5	0.81	0.81	0.03	[0.73, 0.86]
SN → SN4	0.82	0.82	0.03	[0.74, 0.87]
SN → SN3	0.79	0.79	0.04	[0.70, 0.85]
SN → SN2	0.73	0.72	0.05	[0.62, 0.81]
SN → SN1	0.69	0.69	0.06	[0.57, 0.79]
PEOU → PEOU4	0.85	0.85	0.03	[0.79, 0.90]
PEOU → PEOU3	0.88	0.88	0.02	[0.83, 0.92]
PEOU → PEOU2	0.90	0.89	0.02	[0.85, 0.93]
PEOU → PEOU1	0.90	0.90	0.02	[0.85, 0.93]
PU → PU2	0.91	0.91	0.02	[0.86, 0.93]
PU → PU3	0.85	0.84	0.04	[0.76, 0.90]
PU → PU4	0.90	0.90	0.02	[0.86, 0.93]

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BI → BI3	0.92	0.92	0.02	[0.86, 0.95]
BI → BI2	0.95	0.95	0.01	[0.93, 0.97]
BI → BI1	0.96	0.96	0.01	[0.94, 0.97]

Note. Estimates based on 500 samples.

The structural or inner model was evaluated by looking at the R2-values for each endogenous variable, the goodness of fit (GoF) index for the model, and the average variance extracted (AVE) for each latent variable with reflecting indicators. The reliability of the inner model was also evaluated with the help of the bootstrapping method. Table 6 contains a presentation of the inner model summary table, and Figure 2 depicts the inner model node diagram.

Table 6

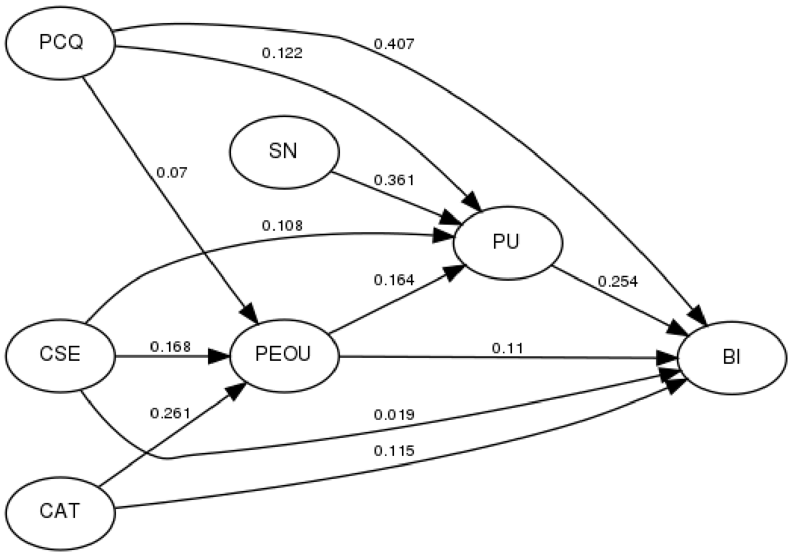
Structural Model Summary.

Construct	Type	R^2	AVE
PCQ	Exogenous	--	0.52
CSE	Exogenous	--	0.58
CAT	Exogenous	--	0.58
SN	Exogenous	--	0.57
PEOU	Endogenous	0.17	0.78
PU	Endogenous	0.32	0.78
BI	Endogenous	0.47	0.89

Note. For constructs with formative factors, AVE is not assessed; R^2 is not calculated for exogenous variables.

Figure 2

Inner node diagram for the PLS-PM model



The R^2-values were calculated for each endogenous variable to determine if the relationships among the latent variables are appropriate. Each endogenous variable should have an R^2-value ≥ .20 (Sanchez, 2013). The following endogenous latent variables had an R^2-value < .20: PEOU. Any relationship with a low R^2-value should be considered for removal from the model, since only a small percentage of variability is explained by the other independent latent variable(s). Table 6 shows the R^2-values.

The calculated results of the average variance retrieved for each construct were used to check the hypothesis that each latent variable possesses a robust association with its reflected indicators. It is recommended that each latent variable have an AVE that is less than.50, which indicates that the latent variable is responsible for explaining at least 50% of the variance in the indicators (Henseler et al., 2009; Sanchez, 2013; Chinn, 2010). Only reflective variables are taken into account when assessing AVE. There was not a single latent variable that had a low AVE, which suggests that each and every latent variable was responsible for a sizeable percentage of the indicator's variance. Table 6 has the AVE values that can be looked up.

The bootstrapping procedure was carried out using a total of 5000 resamples. An alpha value of 0.05 was used to determine whether or not the regression routes were significant after the regression coefficients were analyzed using confidence intervals that ranged from 95% to 100%. (Henseler et al., 2009; Sanchez, 2013; Chinn, 2010).

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CSE did not significantly predict PEOU, *B* = 0.17, 95% CI [-0.03, 0.34], suggesting there is no relationship between CSE and PEOU. PCQ did not significantly predict PEOU, *B* = 0.07, 95% CI [-0.09, 0.25], suggesting there is no relationship between PCQ and PEOU. CAT significantly predicted PEOU, *B* = 0.26, 95% CI [0.09, 0.42], indicating a one-unit increase in CAT will increase the expected value of PEOU by 0.26 units. CSE did not significantly predict PU, *B* = 0.11, 95% CI [-0.04, 0.27], suggesting there is no relationship between CSE and PU. PCQ did not significantly predict PU, *B* = 0.12, 95% CI [-0.04, 0.28], suggesting there is no relationship between PCQ and PU. PEOU significantly predicted PU, *B* = 0.16, 95% CI [0.03, 0.33], indicating a one-unit increase in PEOU will increase the expected value of PU by 0.16 units. SN significantly predicted PU, *B* = 0.36, 95% CI [0.20, 0.51], indicating a one-unit increase in SN will increase the expected value of PU by 0.36 units. CSE did not significantly predict BI, *B* = 0.02, 95% CI [-0.15, 0.19], suggesting there is no relationship between CSE and BI. PCQ significantly predicted BI, *B* = 0.41, 95% CI [0.27, 0.54], indicating a one-unit increase in PCQ will increase the expected value of BI by 0.41 units. CAT did not significantly predict BI, *B* = 0.12, 95% CI [-0.02, 0.24], suggesting there is no relationship between CAT and BI. PEOU did not significantly predict BI, *B* = 0.11, 95% CI [-0.03, 0.24], suggesting there is no relationship between PEOU and BI. PU significantly predicted BI, *B* = 0.25, 95% CI [0.10, 0.42], indicating a one-unit increase in PU will increase the expected value of BI by 0.25 units. Table 7 shows the regression results for the inner model with bootstrapping.

Table 7

Bootstrap Results for the Inner Model Regression Paths.

Path	Original B	*SE*	95% CI	T Statistics (|O/STDEV|)	P-value	Remark
CSE → PEOU	0.17	0.1	[-0.03, 0.34]	2.231	0.026	Supported
PCQ → PEOU	0.07	0.09	[-0.09, 0.25]	1.92	0.055	Not supported
CAT → PEOU	0.26	0.08	[0.09, 0.42]	2.647	0.008	Supported
CSE → PU	0.11	0.07	[-0.04, 0.27]	1.95	0.052	Not supported
PCQ → PU	0.12	0.08	[-0.04,	1.482	0.139	Not

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			0.28]			supported
PEOU → PU	0.16	0.08	[0.03, 0.33]	4.705	0.000	Supported
SN → PU	0.36	0.07	[0.20, 0.51]	2.978	0.003	Supported
CSE → BI	0.33	0.08	[0.21, 0.44]	5.472	0.000	Supported
PCQ → BI	0.41	0.07	[0.27, 0.54]	2.022	0.044	Supported
CAT → BI	0.12	0.07	[-0.02, 0.24]	0.926	0.355	Not supported
PEOU → BI	0.21	0.07	[0.08, 0.31]	3.514	0.000	Supported
PU → BI	0.25	0.08	[0.10, 0.42]	2.298	0.022	Supported

Note. Estimates based on 500 samples.

Discussion

This study has evaluated the web of relationships to evaluate the impact of perceive content quality, computer self-efficacy, course attributes on behavioral intention with the he mediating roles of and subjective norms, perceived ease of use, and perceive usefulness. The hypotheses are tested using PLS-SEM. The data analysis has supported 8 hypotheses and the remaining 4 hypotheses have not been supported.

Among the supported hypotheses, both computer self-efficacy and course attributes have been found to affecting the perceived ease of use. These results are logical, as when the learners know about the usage of computer and also now about the nature of the subject thought then both collectively create a positive perception of the e-learning be easy. It has also been suggested that the course attributes are primarily perceived through the very personality of the in structure and the e-learners assume that as part of the course as found “by comparing online and on-ground courses containing similar course structures created by five different instructors from marketing, management, engineering and mathematics.” (Anitsal et al., 2008, p. 1). In this regard, however, perceived content quality was not found affecting the perceived ease of use. This is, perhaps, show the over whelming shadow of the instructors compared to the content use in a course. Also, since in e-learners also take part in the content creation in terms of sharing documents, assignments, editing, and other activities (Malita & Grosseck, 2018) and they therefore do not considering it contributing to the perceived ease of use, as feel the very responsibility and rigor that they put in.

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The computer self-efficacy and perceived content quality are also not found affecting the perceive usefulness of the e-learning, whereas when the perceived ease of use is found affecting the perceived usefulness. These findings have important clues related to how the e-learning acceptance work in Kuwait context. It is because since most of the e-learning is introduced through PAAET and because of Covid-19, so the e-learning adoption was taken as compulsion. The e-learners have therefore, paid more attention to the perception of it being an easier transition compared other considerations of content quality and computer self-efficacy. These findings are particularly relevant in the context when the e-content is socially constructed by multiple participants and not just by the instructors (MacDonald & Thompson, 2005) and even these are created by the learners themselves (Jamatia, 2012). Similarly, the efficacy also now more internal to the e-learners (Liaw, 2008), it has therefore been taken for granted. The subjective norms of e-learners are, however, found impacting the perceived usefulness. This is, perhaps, because these subjective norms create expectations create a locale for the expectations from the the e-learning and such expectations are then interpreted to be associated with the usefulness, as found in other relevant studies too (Y. Lee, 2006).

The relationships evaluated in this paper ultimately converged into the behavioural intention to adopt and use e-learning. In this regard, the computer self-efficacy, perceive content quality perceived ease of use, and perceived usefulness are all found leading to generate the behavioural intention. Course attributes are, however, found not directly leading to the behaviour intention. These findings are important in terms of understanding the what factors are important at the very important stage of mental process when e-learning is adopted by the learners as supported by many recent studies (Daultani et al., 2021; Dominici & Palumbo, 2013; Hayashi et al., 2020; Manouselis & Sampson, 2003; Thongsri et al., 2020).

Conclusion

E-learning adoption and post adoption improvements both continues research concerns. This research has evaluated 12 hypotheses, to explain the impact of perceived content quality, computer self-efficacy, course attributes on behavioral intention: the mediating roles of and subjective norms, perceived ease of use, and perceive. 8 of the hypotheses are supported whereas no significant empirical support is found for the remaining 4

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hypotheses. From the e-learning improvement perspective, both theory and empirics have supported that computer self-efficacy is important for generating perceived ease of use, behaviour intention, whereas little evidence is found related whether it does have an impact on perceived usefulness. Perceived content quality is also found to be impacting the perceived ease of use and behavioral intention. Whereases little evidence is little evidence is found whether it affect the perceived usefulness. The course attributes are also found to be impacting the perceived ease but little evidence, of it being impacting behaviour intention, is found. Subjective norms are also found impacting perceived usefulness. The research further has elaborated the important mediating roles of subjective norms, perceived ease of use, and perceived usefulness. The research has important theoretical and practical implications in terms of both e-learning adoption as well as post-adoption improvements as it clarify the relative importance of perceived content quality, computer self-efficacy and course attributes for enhancing the overall behavioural intention. In future the thoughts may be carried forward to explore the e-learning adoption as a continues improvement model. In this regard, more exploratory studies will help in to go deeper into the details of content quality, course attributes, and computer self-efficacy as areas of improvements. These recommendations are important in the context when e-learning is widely spreading due to the covid-19 restrictions of keeping social distances.

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