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Factors affecting social networks acceptance: An extension to the technology acceptance model using PLS-SEM and Machine Learning Approach

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A B S T R A C T

Once the university started using social media more, the researchers started focusing more on how social media applications were being adopted and what motivated it without being limited to class-rooms only. There is a need to conduct further research about how the utilization of social media to teach in university affects education. Considering this, delving deeper into the educational outcomes and a research model related to the experiences and results of social media use is the aim of this research. Apart from that, the Technology Acceptance Model (TAM) research that deals with the behavior intention of using social networking media, perceived playfulness, perceived ease of use and perceived usefulness has been used for testing what affects the utilization of social media for online-teaching in higher education of United Arab Emirates. There was an assessment of 580 quan-titative responses given by university students whose classroom sessions involved using social me-dia. In order to predict the behavioral intention of a pupil for using social networking media for e-learning in the higher education institutions, it is possible to take some help from the factors such as perceived playful-ness, perceived ease of use and perceived usefulness, as per the partial least squares (PLS) and machine learning evaluation. The suggested model helps teachers to get to know more about how classroom sessions can become more productive through social media usage.

1. Introduction

Owing to the Internet reaching new heights, the information world also experienced quite a few changes in terms of the storage, speed, recovery, and sharing of information no matter where the individual is from. Accordingly, there was the development of many internet technologies, including the social media network that took the world of communication and information sharing by storm. Now, society dramatically depends on social media, both positively and negatively (Mingle & Adams, 2015). The fields of education, research, communication, and learning have undergone significant changes through social media. Although there are several online tools available for communication, social networking sites (SNS) easily overpower all of them when it comes to bringing together people from the entire world (Aghazamani, 2010; Al Kurdi, Alshurideh, Salloum, Obeidat, & Al-dweeri, 2020; Alhashmi, Alshurideh, Al Kurdi, & Salloum, 2020). The perspectives of both schools and students have been taken into consideration for extensively researching social media (Akar & Mardikyan, 2014). From the assessment of how students play their part in blogs and Facebook, it was seen that such social media platforms have a positive impact on the performance of students (Gachago & Ivala, 2012). Lin, Hoffman, and Borengasser (2013) analyzed the perception of students about Twitter being a tool for education; it was found that students like to share information about their classes by using social media platforms. Prestridge (2014) researched how students use Twitter and found that their learning has improved, all thanks to Twitter. While Palmer (2013) conducted research on how universities use social media. When it comes to universities, there is the utilization of social media for recruiting students, communicating with alumni, teaching and

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learning, marketing, libraries, and student services. There are a number of research available on information systems for predicting, developing, and comprehending the factors that could affect the adoption of an innovation or a technology (Alshurideh et al. 2019; Alshurideh, Al Kurdi, and Salloum 2020). Theory of Reasoned Action (TRA)(Fishbein & Ajzen, 1975), Theory of Planned Behavior (TPB) (Ajzen, 1991), and other such studies use different robust and successful models for models or intention suited for acceptance of Technology in addition to other models such as Acceptance Model (Davis, 1989), TAM 2 (Venkatesh & Davis, 2000), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003), and other such technologies. The TRA model that introduced by Fishbein and Ajzen (1975) also focuses on the beliefs of people for justifying adoption behavior in addition to Morris and Dillion (1997) has been inherited by the TAM that Davis (1989) came up with. When it comes to the assessment of intention to use the acceptance of information technology, there is a high significance of this research model (Dutot 2015; Tan et al., 2012). This research mainly aims to have a better look at the intentions of university students in terms of social media usage for analyses. For this research, there is an assessment of the student behavior intention for using social media and the scarcity of associated research about how the entire world looks at this matter. This study will be based around TAM and perceived playfulness variables.

2. Research model and hypothesis

This research aims for the development of a framework that deals with how social network usage affects e-learning and university students interact with each other through the TAM (Technology Acceptance Model) when it comes to the UAE's universities. The research model can be found in Fig. 1. The research model has been used for formulating 5 hypotheses, which are examined by the study.

2.1 Perceived playfulness

Perceived playfulness (PP) is defined as "subjective enjoyment perceived while performing a specific behavior or activity " (Lieberman, 2014). It has been shown by various studies that PP has a positive effect on perceived usefulness and behavioral intention to use social networks (Alshurideh, Salloum, Al Kurdi, and Al-Emran, 2019; Chang et al., 2015; Padilla-MeléNdez, Del Aguila-Obra, and Garrido-Moreno, 2013). Hence, the hypothesis given below is put forward:

H_1: *Perceived playfulness (PP) predicts the perceived usefulness (PU).*
H_3: *Perceived usefulness (PU) predicts the intention to use social networks (IU).*

2.2 Perceived ease of use and perceived usefulness

Perceived ease of use (PEOU) is defined as "the degree to which an individual believes that using a particular system would be free of physical and mental effort" (Fred D Davis, 1989). Perceived usefulness (PU) refers to "the degree to which a person believes that using a particular system would enhance his/her job performance" (Fred D Davis, 1989). "Prior research found that PEOU and PU has a significant influence on the behavioral intention to use social networks (Alshurideh, Salloum, Al Kurdi, & Al-Emran, 2019; Dumpit & Fernandez, 2017). Based on previous research, the hypotheses include the following:

H_2: *Perceived ease of use (PEOU) predicts the perceived usefulness (PU).*
H_4: *Perceived usefulness (PU) predicts the intention to use social networks (IU).*
H_5: *Perceived ease of use (PEOU) predicts the intention to use social networks (IU).*

The research model in Fig. 2 has been developed by taking into consideration the hypotheses above that focus on the extended TAM model dealing with students' acceptance of social media technology or its acceptance.

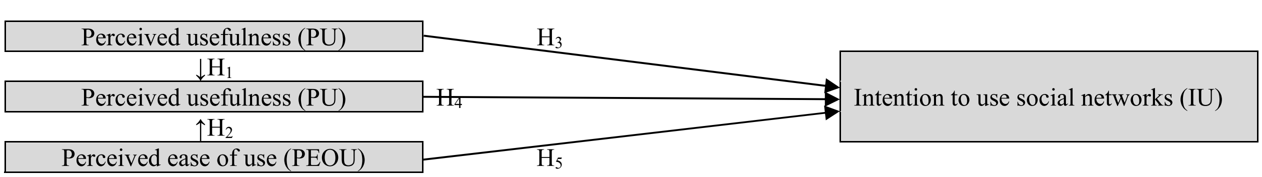

Fig. 1. The proposed model.

3. Research methodology

The individuals studying at two UAE universities, namely "the British University in Dubai and University of Fujairah" were taken as study participants. Self-administered surveys were used as a tool for data collection during the months of November and December 2020. Surveys were answered by the participants. The data was collected through a convenience sampling approach. The whole survey document was answered completely by 580 students out of 600 students who had been given the surveys to fill, accounting for a 96.6% rate of response. Out of these 580 surveys, 320 were filled by females and 260 by males. Almost half of the participants (52%) were 18 to 29 years of age. As far as their educational status is concerned, 59% of participants were enrolled in bachelor's program, 30% in master's program, and 11% in Ph.D.

4. Findings and discussion

4.1 Data Analysis

The developed theoretical model is evaluated in this study by using a couple of distinct techniques. One of the techniques involves the use of partial least squares-structural equation modeling (PLS-SEM) with the help of the SmartPLS tool (Ringle, Wende, & Becker, 2015). PLS-SEM was selected since it is known to yield precise results due to its unique feature of evaluation of measurement as well as a structural model at the same time (Barclay, Higgins, & Thompson, 1995). The other technique is machine learning algorithms, which are employed for the prediction of dependent variables included in the conceptual model with the help of Weka (Arpaci, 2019).

4.2 Measurement model assessment

The evaluation of the measurement model involves checking for its reliability and validity (Hair, J., Hult, G. T. M., Ringle, C., Sarstedt, M., Hair, J. F. F., Hult, G. T. M., … Sarstedt, 2016). Reliability is tested with the help of Cronbach's alpha and composite reliability (CR) measures. Both measures must have a value greater than or equal to 0.70(Hair et al., 2016). Table 1 reveals the results showing adequate reliability and validity since the tested measures showed satisfactory values. Hair (2016) recommended the measurement of the values of convergent and discriminant validities to test the validity. The convergent validity was tested by determining the values of the average variance extracted (AVE) and factor loadings. The acceptable values for AVE is ≥ 0.50 (Fornell & Larcker, 1981), while acceptable values of factor loadings are ≥ 0.70 (Hair, Black Jr, Babin, & Anderson, 2010). Table 1 clearly shows that the values of the two measures (AVE and factor loadings) corresponded with the acceptable values, thus confirming the convergent validity. (Henseler, Ringle, & Sarstedt, 2015) recommended testing the discriminant validity by determining the Heterotrait-Monotrait ratio (HTMT) values of correlations. Acceptable values for HTMT are < 0.85. Table 2 shows that all the values of HTMT were acceptable, thus verifying discriminant validity.

Table 1
Convergent validity

Constructs	Items	FL	CA	CR	AVE
Perceived Playfulness	PP1	0.751	0.736	0.740	0.599
	PP2	0.777			
	PP3	0.801			
Perceived Ease of Use	PEOU1	0.709	0.833	0.790	0.612
	PEOU2	0.871			
	PEOU3	0.860			
Perceived Usefulness	PU1	0.786	0.702	0.746	0.678
	PU2	0.803			
	PU3	0.745			
Intention to use social networks	IU1	0.863	0.804	0.868	0.778
	IU2	0.720			

Table 2
Discriminant validity for the measurement model using (HTMT).

	PP	PEOU	PU	IU
PP				
PEOU	0.205			
PU	0.351	0.563		
IU	0.635	0.456	0.263	

Note PP, perceived playfulness; PEOU, perceived ease of use; PU, perceived usefulness; IU, intention to use social networks.

4.3 Hypotheses testing and coefficient of determination

The structural equation modeling (SEM) approach (Davis, Bagozzi, & Warshaw, 1992) has been used to test the five hypotheses above together. The variance described (R^2 value) by each path and every hypothesized connection's path significance in the research model were assessed. The standardized path coefficients and path significance are demonstrated in Fig. 2 and Table 4. Also, table 3 shows that the R^2 values for perceived usefulness and intention to use social networks ranged between 0.766 and 0.820. Therefore, these constructs appear to have high predictive power (Liu, Liao, & Peng, 2005). Generally, the data supported all hypotheses. According to previous studies, all constructs were verified in the model (PP, PEOU, PU, and IU). Based on the data analysis hypotheses H1, H2, H3, H4, H5, and H5 were supported by the empirical data. The results showed that perceived usefulness (PU) significantly influenced perceived playfulness (PP) (β= 0.259, P<0.001), and perceived ease of use (PEOU) (β= 0308, P<0.001) supporting hypothesis H1 and H2 respectively. Intention to use social networks (IU) has significant effects on perceived playfulness (PP) (β= 0.889, P<0.001), perceived usefulness (PU) (β= 0.405, P<0.05), and perceived ease of use (PEOU) (β= 0.417, P<0.05) respectively; hence, H3, H4, and H5 are supported.

Table 3
"R^2 of the endogenous latent variables".

Constructs	R^2	Results
PU	0.766	High
IU	0.820	High

Note PU, perceived usefulness; IU, intention to use social networks.

Table 4
Results of structural modeling analysis.

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	PP → PU	0.259	16.007	0.000	Positive	Supported**
H2	PEOU → PU	0.308	18.113	0.000	Positive	Supported**
H3	PP → IU	0.889	15.408	0.001	Positive	Supported**
H4	PU → IU	0.405	2.535	0.026	Positive	Supported*
H5	PEOU → IU	0.417	3.687	0.012	Positive	Supported*

Note: PP, perceived playfulness; PEOU, perceived ease of use; PU, perceived usefulness; IU, intention to use social networks.

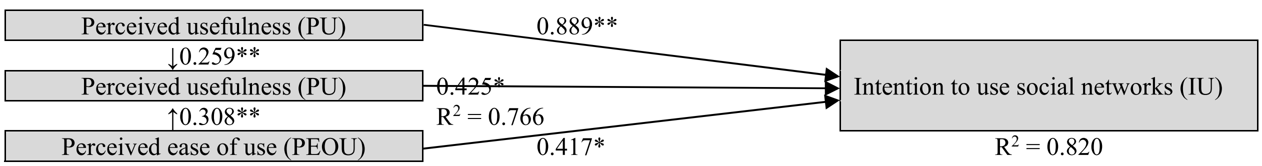

Fig. 2. Path test of the research model.

4.4 Hypotheses testing using machine learning algorithms

Different machine-learning classification algorithms of various methodologies, namely the Bayesian networks, decision trees, if-then-else rules, and neural networks were used in the current research for prediction of the association between constructs in the proposed theoretical model (Salloum, Alshurideh, Elnagar, & Shaalan, 2020a, 2020b). Weka (ver. 3.8.3) is a collection of various ML algorithms based on various classifiers such as BayesNet, AdaBoostM1, LWL, Logistic, J48, and OneR (Frank et al., 2009); it was employed in this research to test the predictive model. Results depicted in Table 5 revealed that other classifiers did not perform as efficiently as J48 in making predictions about perceived usefulness (PU) of perceived playfulness (PP) and perceived ease of use (PEOU). 10-fold cross-validation showed that the predictions made by J48 about the PU were 89.33% accurate, thus supporting H1 and H2. J48 was the classifier that outperformed other classifiers with respect to TP rate (.882), precision (.775), and recall (.781).

Table 5
Predicting the PU by PP and PEOU

"Classifier"	"CCI1 (%)"	"TP[2] Rate"	"FP[3] Rate"	"Precision"	"Recall"	"F-Measure"
"BayesNet"	80.45	.814	.220	.721	.659	.640
"Logistic"	81.45	.814	.275	.723	.609	.600
"LWL"	79.23	.792	.203	.756	.669	.660
"AdaBoostM1"	84.87	.848	.335	.739	.711	.702
"OneR"	84.03	.840	.348	.777	.726	.720
"J48"	89.33	.893	.678	.882	.853	.824

Table 6 clearly shows that the OneR and J48 classifiers outshined the other classifiers while making predictions of the intention to use social networks by perceived playfulness, perceived usefulness, and perceived ease of use. The OneR and J48 classifiers showed 88.25% accuracy while predicting the intention to use social networks, hence supporting H3, H4, and H5.

Table 6
Predicting the IU by PP, PU, and PEOU

"Classifier"	"CCI1 (%)"	"TP[2] Rate"	"FP[3] Rate"	"Precision"	"Recall"	"F-Measure"
"BayesNet"	80.05	.800	.260	.811	.810	.810
"Logistic"	81.77	.817	.310	.812	.801	.811
"LWL"	79.03	.790	.285	.800	.789	.790
"AdaBoostM1"	81.47	.814	.345	.811	.799	.795
"OneR"	88.25	.882	.316	.890	.889	.880
"J48"	88.25	.882	.076	.891	.882	.885

PLS-SEM and machine learning classification algorithms were employed in this study for testing the proposed model with the help of a complementary approach. This study is unique in the sense that it uses a multi-analytical approach and applies machine-learning algorithms for prediction intention to use social networks, which is very rarely found in the existing literature about information systems (IS). Remarkably, we can predict a dependent variable and validate a conceptual model by employing PLS-SEM, which is an appropriate choice if the study is an extension of an existing theory. Similarly, it is possible to predict a dependable variable on the basis of the independent variable by employing supervised machine learning algorithms provided there is already a defined dependent variable (Arpaci, 2019). Different machine-learning classification algorithms of various methodologies, namely the Bayesian networks, decision trees, if-then-else rules, and neural networks, are used in the study. The study outcomes revealed that J48 (a decision tree) mostly outperformed other classifiers. The main point is that the sample is divided into homogeneous subsamples with respect to the most important independent variable and continuous (numerical), and categorical variables are classified with the help of decision tree (nonparametric) (Arpaci, 2019). Conversely, significant coefficients were tested by employing PLS-SEM (a nonparametric procedure) by replacing the samples with a large number of sub-samples on a random basis.

5. Conclusion

The primary objective of the current research is to analyze how students perceive social media networking usage during their course at an open distance learning tertiary institution. The investigation also determined whether students are okay with social media networking usage, whether they are capable enough for discovering information from social media networking sites, and whether they think that the course material can be easily and efficiently studied online. For this purpose, there was the utilization of 'behavioral intention to use social networks', 'Perceived ease of use', 'Perceived usefulness', and 'perceived playfulness', which are the TAM constructs. With the help of this research, it was seen that the factors that include perceived usefulness, perceived ease of use, and perceived playfulness could be used for predicting the behavioral intention of a student for using social networking sites when it comes to e-learning in UAE's higher education.

5.1 Implications and discussion

The outcomes indicate that the confidence and capability of the students are essential in adopting social media technology. Some previous studies such as (Chang et al., 2015). Padilla-MeléNdez et al. (2013) also show that perceived playfulness, perceived usefulness, perceived ease of use maintains a positive influence upon students' behavioral intention to adopt social media technology. The present research has helped extract the mentioned conclusions. A positive influence of perceived playfulness, perceived ease of use and perceived usefulness upon students' behavioral intention to use social media technology. Similarly, for learning, social media application legislators and managers must attend to factors, which are essential for the development of learning and enhancing student efficiency for formulation and implementation of useful social media application. Within the current research, concentration has been placed upon general social media like Facebook, Instagram, Twitter and Google+. Similarly, participants made use of Facebook most as compared to other applications. Facebook leads the UAE social media market. For educational reasons, the adoption of "Social Networking Sites" needs to be understood since it influences the Educationist, Policy makers, Marketers and System developers. If the Technology Adoption process background is understood, creative strategies can be developed by the Practitioner to promote, diffuse and accept the powerful technologies. These have the ability to develop the teaching and learning process effectiveness.

5.2 Limitations and future work

Various limitations were associated with this study. The main limitation was that there was a poor generalization of outcomes to other institutes in the UAE or any other part of the world. This may be attributed to two causes; a) the collection of data from only two institutes, and b) choosing respondents based on a convenience sampling approach. Generalization of outcomes may be improved in future studies by addressing these issues. Another limitation of this study is that the actual use of m-learning systems was investigated only in the context of students. It is recommended to consider the actual use of social networking sites from the perspective of educators in the future. This will allow more comprehension of the implementation of such systems, and the factors influencing this implementation.

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