E-Learning Acceptance in the Post COVID-19 Period: A Case Study

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The experience lived by students during the COVID-19 pandemic will remain etched in their memory because they suddenly found themselves confined and they were forced to continue their studies entirely online from home. This article focuses on the study of factors that may influence students of the National School of Business and Management of Oujda in Morocco to continue using e-learning in the post COVID-19 period. The research model is based on the Technology Acceptance Model and is validated using structural equation methods. Data analysis showed the importance of the online course design factor on perceived ease of use and perceived usefulness. It revealed the direct influence of these two factors on the use of the e-learning system, which is also influenced indirectly by social influence through the mediatization of perceived usefulness.

Keywords: e-learning, higher education, post COVID-19 period, TAM

INTRODUCTION

The coronavirus pandemic has forced all countries in the world, including Morocco, to take urgent measures to curb its spread. Establishments of all levels of education and their corollaries (administrations, companies, etc.) had to align themselves with the decisions taken concerning confinement. Thus, universities, in order not to block the educational service provided to a large part of the population, had to adopt distance education. However, distance learning in an ordinary situation requires careful preparation and detailed planning that was not made possible by the time and technical constraints that teachers were facing, following the sudden decision to lock down. In this particular context, the two stakeholders in the learning mechanism (teachers and learners) have forced themselves to face this new fact.

The current investigation focused on the learner and aims to study the determinants of e-learning use during the post COVID-19 period. The first section of this work interests in the theoretical count in which the foundations of the adoption of technologies will be highlighted, in particular those linked to e-learning adoption. The second section presents the conceptual framework and hypothetical model. The third part deals with the empirical study, the data analysis, and the hypotheses test. The last section presents a discussion of the results and the proposed recommendations.

LITERATURE REVIEW

Several authors have taken an interest in the use of new technologies by developing theoretical models to examine the factors that can influence user behavior. These models are generally based on the Theory of Reasoned Action (TRA) of Fishbein & Ajzen (1975), the Theory of Diffusion of Innovation (TDI) of Rogers (2010), the Technology Acceptance Model (TAM) of Davis (1986) and other theories. Despite the variety of models, the TAM remains the most commonly used model in studies relating to the acceptance and adoption of technology (Scherer et al., 2019). Its objective is to explain the adoption behavior of technology by introducing external factors, perceived ease of use (PEU), perceived usefulness (PU), attitude towards use, and behavioral intention. The main factors of TAM are PEU and PU. PEU is defined as a measure that an individual can easily understand and use a computer, while PU can be defined as the tendency of an individual to use an application to improve their job (Davis, 1989). The importance of these two factors lies in the fact that they determine the intention of use. Indeed, if a user finds a technology easy and useful, he will intend to use it. Given the success of this model, several researchers have developed other models based on the original TAM. These models have included other variables to increase the amount of variance explained and to ensure a better understanding of the behavioral intentions of users according to the contexts studied. The main works that have been carried out in this direction are TAM2 and UTAUT (Unified Theory of Acceptance and Use of Technology) models of Venkatesh & Davis (2000a) and Venkatesh et al. (2003) respectively. Concerning TAM2, the authors included other determinants to the two main factors of the original model, while for the UTAUT, the authors synthesized and integrated eight models and theories. The explanatory ability of these last two models has been approved by industry and academic sectors and is widely applied in relevant research concerning the technology of information (Lee et al., 2010).

In TAM, many external variables explain PU and PEU. Also, PEU may influence PU. Yousafzai et al. (2007) classified these external variables into four categories: the characteristics of organizations, those of information and communication technologies, those of people, and other variables. Atarodi et al. (2019) made a summary of these external variables and then classified them according to those that only influence PU, those that only influence PEU and those that influence both PU and PEU. These authors mention that whatever their category, most of these external variables simultaneously influence PEU and PU.

In the context of the acceptance of e-learning, the analysis carried out by Jimenez et al. (2021) showed that the most common external variables used to extend TAM are computer self-efficacy, experience, innovation, perceived enjoyment, computer-related anxiety, facilitating conditions, social norm, the quality of the content, the quality of the system. For example, Lee et al. (2009) added the external variables namely the teaching material, the characteristics of the instructor, the content design, and the playfulness of e-learning. Farahat, (2012) used the social influence (SI) variable. Ibrahim et al. (2017) extended the TAM by adding instructor characteristics, course design, and self-efficacy as external variables. Al-Azawei et al. (2017) added the external variables which are learning styles, self-efficacy, and perceived satisfaction to the TAM. Sri et al. (2022) added facilitating conditions as an external variable in their study.

CONCEPTUAL FRAMEWORK AND HYPOTHETICAL RESEARCH MODEL

The objective of our research is to study the e-learning acceptance by students of the National School of Business and Management of Oujda (NSBMO) in Morocco, during the post-period of COVID-19. The model adopted for this research was developed based on the technology acceptance model in its second version TAM2 which reintegrated the SI component: an important construct in the TRA subsequently discarded by the original TAM. In our context, we have introduced two external variables which are SI and online course design (OCD) in addition to the three basic variables of TAM which are PU, PEU, and use of an e-learning system (UELS).

SI is the extent to which a student is influenced by their social environment. It is defined as the individual's perception that people important to him think he should or should not perform the behavior in question (Fishbein & Ajzen, 1975). This factor has been added in previous works to directly determine the adoption of the technology (e.g., Venkatesh & Morris, 2000b; Van Raaij & Schepers, 2008; Al-Okaily, 2020). Moreover, previous studies have also used SI as a determinant of PU (e.g., Fishbein & Ajzen, 1975; Farahat, 2012; Shankar & Datta, 2018; Al-Okaily et al., 2020; Aljazzaf et al., 2020) and PEU (e.g., Farahat, 2012; Al-Gahtani, 2016; Binyamin et al., 2019; Al-Okaily, 2020). These studies show that students will perceive online learning as easy and useful if the social environment that influences them deems it so. Then we can postulate the following hypotheses:

H1: *SI positively affects PU.*

H2: *SI positively affects PEU.*

H3: *SI positively affects the UELS.*

Previous works (e.g., Lee et al., 2009; Ibrahim et al., 2017) introduced course design or content design as an external variable to study e-learning acceptance by the learners. This construct is defined as the extent to which the online learning content made available to students is designed in such a way that it meets their needs and expectations. The online course design has been shown to predict PEU. Thus, in our context, we postulate the following hypotheses:

H4: *OCD positively affects PEU.*

H5: *OCD positively affects PU.*

As for the relationship between the two fundamental constructs of TAM, several studies have shown that PEU has a positive effect on PU (e.g., Fishbein & Ajzen, 1975; Pituch & Lee, 2006; Lee et al., 2009; Farahat, 2012; Al-Okaily et al., 2020). Thus, we postulate the following hypothesis:

H6*: PEU positively affects PU.*

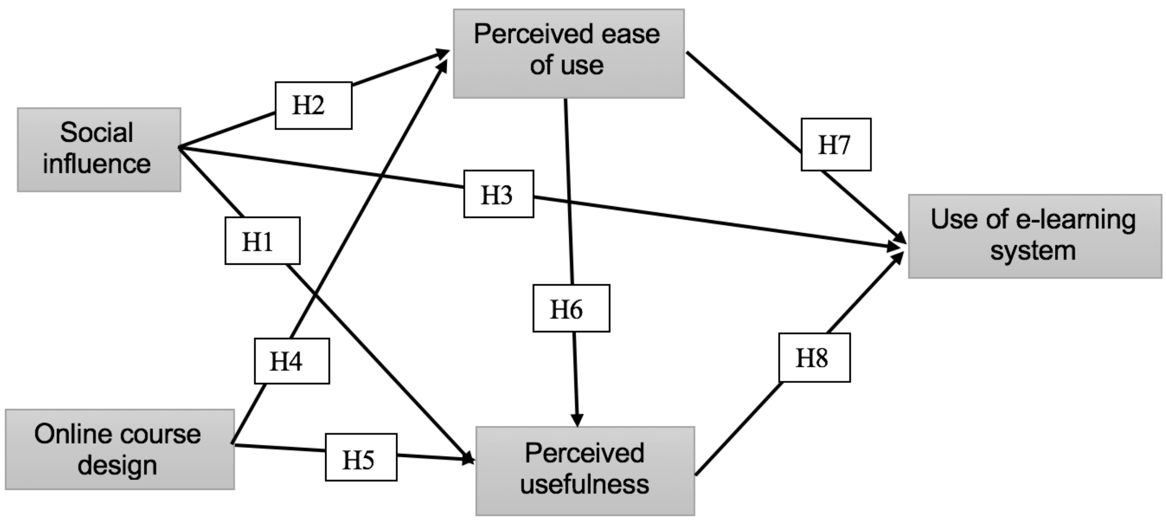
In the context of the COVID-19 pandemic and following the works of Schillewaert et al. (2005) and Van Raaij & Schepers, (2008), we will limit ourselves to the current use of online learning as the only dependent variable, without examining the intentions of use. Current usage intensity is going to be measured in terms of how often a specific tool (such as Moodle or Classroom) is used to participate in e-learning according to Van Raaij & Schepers, (2008) and Arteaga Sánchez & Duarte Hueros (2010). We, therefore, postulate the following hypotheses:

H7: *PEU positively affects the UELS.*

H8: *PU positively affects the UELS.*

Thus, we propose in Figure 1, the hypothetical model of our research:

FIGURE 1
HYPOTHETICAL MODEL



RESEARCH METHOD AND DATA ANALYSIS

To test the concepts that can influence the use of the e-learning system in these circumstances of the pandemic of COVID-19, we conducted an empirical study with students from the NSBMO via an electronic questionnaire. The number of responses retained after the purification of the data was 535 responses representing approximately half of the students enrolled in all levels of the school. All items of constructs are measured using the five-point Likert scale. Table 1 shows the definition of each construct.

TABLE 1
DEFINITION OF CONSTRUCTS OF THE RESEARCH MODEL

Construct	Definition
SI	The extent to which students are influenced by their social environment.
OCD	The extent to which online courses are designed to simplify their understanding and meet the needs of students.
PEU	The extent to which students think that using online learning will be easy and without technical issues.
PU	The extent to which students think online learning will increase their productivity.
UELS	The extent to which students participate in online learning.

The data collected were analyzed with SPSS 23 and AMOS 23. First, the study of the measurement model was carried out to assess the internal reliability, and the convergent and discriminant validity of the constructs. Then, the study of the structural model was carried out using the structural equation methods to test the validity or rejection of the proposed research hypotheses.

Measurement Model

Measuring the reliability and the internal consistency of scales allows us to know to what extent a survey measures what we want the survey to measure (Alassafi, 2022). Cronbach's alpha indicator (α) and composite reliability (CR) were used. The threshold considered for α and (CR) is 0.7 each (Bollen, 1987; Hair et al., 1995). Table 2 shows that for each construct, the values α and (CR) are greater than 0.7. This implies that all the constructs of the model have good internal consistency. Regarding validity, it allows us to designate the degree to which a scale perfectly measures the concept under study. For this, convergent validity and discriminant validity were used. Convergent validity means that all the variables (items) of the same construct are correlated with each other, which implies that these variables explain their construct well. This can be measured by the factor loadings of the variables which should ideally have a value greater than 0.7 (Hair et al., 2019) or at the limit a value greater than 0.5 (Peterson, 2000; Van Raaij & Schepers, 2008; Sri et al., 2022). A second criterion related to convergent validity is the average variance extracted (AVE) which must be greater than 0.5 (Hair et al., 2019) which means that each variable linked to a construct shares more variance (more than 50%) with it than with another construct. Table 2 shows that the factor loadings of the variables are greater than the threshold value of 0.5, which explains that each variable is correlated with its construct. Moreover, the AVE of each construct exceeds 0.5. This implies that the convergent validity of the model is verified. Discriminant validity checks whether all the constructs of the model are distinct. For this, the square root of the AVE of each construct must be greater than the correlation between this construct and the rest of the constructs in the model (Henseler et al., 2015). The matrix of inter-construct correlations in Table 3 shows that the square root of the AVE (value on the diagonal) of each construct is greater than the cross-correlations with the other constructs. In summary, all of the constructs in our research model demonstrate adequate reliability and validity to initiate the structural model. To check the goodness of fit of the measurement model to the data collected, we used the goodness of fit indices most commonly used in empirical research. Table 4 shows that the values of the indices relating to our model respect the recommended thresholds (Bollen, 1987, 1989; Ramos de Luna et al., 2019) and reveal a good adjustment of the model.

TABLE 2
CONVERGENT VALIDITY (FACTOR LOADING AND AVE) AND RELIABILITY (CRONBACH'S ALPHA AND COMPOSITE RELIABILITY)

Constructs of the model	Items	Factors loading	AVE	α	CR
OCD	OCD_a	**0.831**	**0.666**	**0.898**	**0.888**
	OCD_b	**0.814**			
	OCD_c	**0.765**			
	OCD_d	**0.851**			
SI	SI_a	**0.873**	**0.631**	**0.818**	**0.833**
	SI_b	**0.884**			
	SI_c	**0.591**			
PU	PU_a	**0.915**	**0.751**	**0.853**	**0.857**

Constructs of the model	Items	Factors loading	AVE	α	CR
	PU_b	**0.815**			
PEU	PEU_a	**0.842**	**0.699**	**0.908**	**0.902**
	PEU_b	**0.942**			
	PEU_c	**0.825**			
	PEU_d	**0.721**			
UELS	UELS _a	**0.718**	**0.567**	**0.720**	**0.724**
	UELS _b	**0.787**			

TABLE 3
MATRIX OF INTER-CONSTRUCT CORRELATIONS AND SQUARE ROOTS OF THE AVE ON THE DIAGONAL

	UELS	OCD	SI	PEU	PU
UELS	**0.753**				
OCD	0.635	**0.816**			
SI	0.336	0.444	**0.794**		
PEU	0.614	0.757	0.381	**0.836**	
PU	0.559	0.754	0.461	0.565	**0.866**

Structural Model and Hypothesis Testing

Before testing the hypotheses stipulated above, the overall goodness of fit of the structural model (Figure 2) to the data collected was carried out using the goodness of fit indices. Table 4 shows that the values of the indices relating to our structural model respect the recommended thresholds and indicate that it presents a good adjustment (Bollen, 1987, 1989; Ramos de Luna et al., 2019).

FIGURE 2
THE STRUCTURAL MODEL

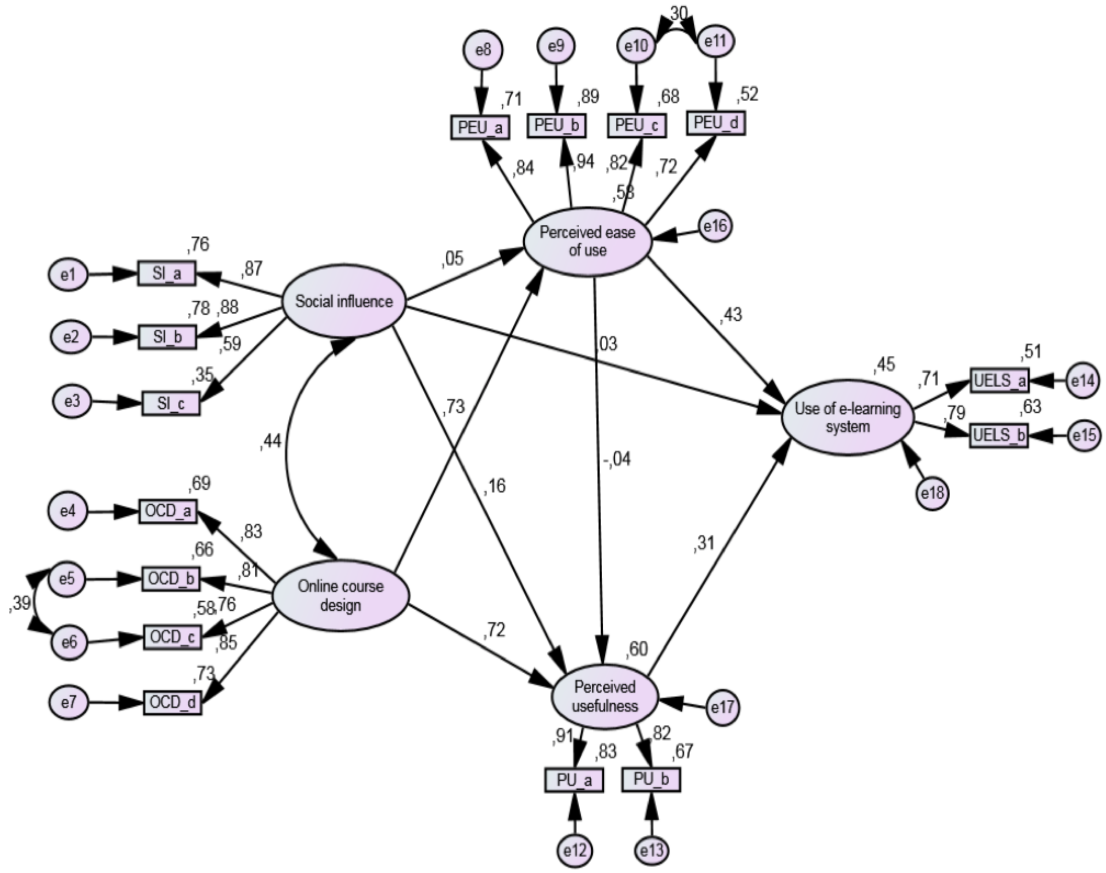


TABLE 4
GOODNESS OF FIT INDICES OF THE MEASUREMENT MODEL AND THE STRUCTURAL MODEL

Index	Recommended value	Measurement model	Structural model
Chi-square by degree of freedom: **χ^2/ddl**	< 3	2.057	2.101
Goodness of Fit Index: **GFI**	> 0.9	0.962	0.961
Adjusted Goodness of Fit: **AGFI**	> 0.9	0.941	0.940
Root Mean square Residual: **RMR**	< 0.1	0.044	0.047
Standardized Root Mean square Residual: **SRMR**	< 0.09	0.0304	0.0325
Root Mean Square Error of Approximation: **RMSEA**	< 0.08	0.044	0.045
Normed Fit Index: **NFI**	> 0.9	0.969	0.968
Tuckler-Lewis Index: **TLI**	> 0.9	0.978	0.978
Comparative Fit Index: **CFI**	> 0.9	0.984	0.983

The analysis of the structural links between the different constructs of the model made it possible to calculate the path coefficients (β), the p-value (p), and the critical ratio (CR) for each of the model's hypotheses. The β describes the positive or negative effect of the relationship between two constructs. The CR is given by the quotient of the β and the estimated value of the standard error (SE). A hypothesis is accepted if the CR is greater than 1.96 and the p-value is less than 0.05. Table 5 shows that SI has a significant positive effect on PU (β = 0.185; CR = 3,708; $p < 0.001$). OCD has a significant effect on PEU (β = 0.828; CR = 14.009; $p < 0.001$) and PU (β = 0.849; CR = 9.498; $p < 0.001$). PEU has a positive effect on UELS (β = 0.438; CR = 7.006; $p < 0.001$) and PU has a positive effect on UELS (β = 0.306; CR = 4.936; $p < 0.001$). Thus, hypotheses H1, H4, H5, H7 and H8 are validated. On the other hand, hypotheses H2, H3, and H6 are rejected because of the non-significance of the relationships between SI and PEU (β = 0.062; CR = 1.355; p = 0.175), between SI and use UELS (β = 0.029; CR = 0.482; p = 0.630) and between PEU and PU (β = -0.043; CR = -0.660; p = 0.510).

TABLE 5
THE RESULTS OF HYPOTHESIS TESTS

	Relationship			B	SE	CR	P	Decision
H1	SI	→	PU	0.185	0.050	3.708	***	Accepted
H2	SI	→	PEU	0.062	0.045	1.355	0.175	Rejected
H3	SI	→	UELS	0.029	0.060	0.482	0.630	Rejected
H4	OCD	→	PEU	0.828	0.059	14.009	***	Accepted
H5	OCD	→	PU	0.849	0.089	9.498	***	Accepted
H6	PEU	→	PU	-0.043	0.065	-0.660	0.510	Rejected
H7	PEU	→	UELS	0.438	0.062	7.006	***	Accepted
H8	PU	→	UELS	0.306	0.062	4.936	***	Accepted

*** $p < 0.001$

DISCUSSION AND RECOMMENDATIONS

In this research, we studied the factors that could influence the students of the NSBMO to continue using e-learning in the post COVID-19 period. The model we adopted is composed of five constructs, namely: SI, OCD, PEU, PU, and UELS. The analysis of the links between these constructs showed that OCD strongly influences PEU and PU under the work of Lee et al. (2009). This shows the importance of this factor in the e-learning system. In our context, the more the online courses are adapted to the expectations of the students and are designed in an easy-to-understand way and the teaching materials arranged online are easy to use, the more the students consider online learning to be useful and its use is easy. The results also reveal that SI affects PU consistent with previous findings (Fishbein & Ajzen, 1975; Van Raaij & Schepers, 2008; Farahat, 2012; Shankar & Datta, 2018; Al-Okaily et al., 2020; Aljazzaf et al., 2020). This indicates that the influence of the social environment of students (family, friends, classmates…) plays an important role in the usefulness of e-learning. The more useful others find using this learning, the more students find it useful and important to them. On the other hand, in our context, it was shown that SI does not have a significant effect on the PEU contrary to previous works (e.g., Farahat, 2012; Al-Gahtani, 2016; Binyamin et al., 2019; Al-Okaily et al., 2020). Moreover, it was found that SI does not have a direct effect on the use of e-learning contrary to previous works (e.g., Venkatesh & Morris, 2000b; Al-Okaily et al., 2020) but, the effect is only indirect through the PU which will play the role of a mediator following the work of Van Raaij & Schepers, (2008). The results of the analysis also show that using an e-learning system is directly influenced by PU and PEU in line with several works (e.g., Schillewaert et al., 2005; Mousa et al., 2020). This indicates that students who, on the one hand, are convinced that distance learning will help them ameliorate their performance and increase their productivity, and on the other hand, can easily use this learning without technical problems, are likely to continue to use e-learning. Based on these findings, it was found that the use of e-learning is indirectly influenced by online course design through the mediatization of PU and PEU. Therefore, it would be important to design very attractive and quality courses to motivate students to follow their online courses correctly, whether in synchronous or asynchronous mode, especially since in recent years, means of distraction have become more and more abundant. For this, training for teachers is necessary to improve the scripting of their online courses. Training can also be scheduled for the benefit of students to master and make user-friendly use of the most used platforms such as in our case: Moodle; Classroom, Zoom, etc. This is by minimizing the technical problems related to access to these platforms, especially those related to the quality of the connection to the Internet network. Regarding the costs of this connection, we recommend making special packages for students to encourage their participation in online learning, especially since we have seen, according to student comments, that during confinement, some of the students could not attend the courses arranged online because they could not afford to pay the connection costs from home. We also find that online learning is indirectly influenced by SI through the mediatization of perceived usefulness. This implies that the social environment of the student is involved in the process of online learning. Therefore, we recommend the education system, in particular the university, launch advertising posts on the media to make the student's entourage aware of the importance of online learning.

CONCLUSION

This article aims to examine the determinants that may influence students to continue the use of e-learning during the post COVID-19 period. The results of our study indicate that SI is a predictor of PU, OCD is a predictor of PU, and PEU which are in turn predictors of the use of e-learning. These results are consistent with what exists in the literature. Recommendations have been proposed to encourage students to continue using e-learning. This case study was limited to NSBMO students, we intend to extend our study to all students from other Moroccan university schools by considering other external variables.

REFERENCES

Alassafi, M.O. (2022). E-learning intention material using TAM: A case study. *Materials Today: Proceeding*, *61*, 873–877.

Al-Azawei, A., Parslow, P., & Lundqvist, K. (2017). Investigating the effect of learning styles in a blended e-learning system: An extension of the technology acceptance model (TAM). *Australasian Journal of Educational Technology*, *33*(2). https://doi.org/10.14742/ajet.2741

Al-Gahtani, S.S. (2016). Empirical investigation of e-learning acceptance and assimilation: A structural equation model. *Applied Computing and Informatics*, *12*(1), 27–50.

Aljazzaf, Z.M., Al-Ali, S.A., & Sarfraz, M. (2020). e-Participation Model for Kuwait e-Government. *International Journal of Advanced Computer Science and Applications*, *11*(2), 192–199.

Al-Okaily, M., Alqudah, H., Matar, A., Lutfi, A., & Taamneh, A. (2020). Impact of COVID-19 Pandemic on Acceptance of e-learning System in Jordan: A Case of Transforming the Traditional Education Systems. *Humanities & Social Sciences Reviews*, *8*(4), 840–851.

Arteaga Sánchez, R., & Duarte Hueros, A. (2010). Motivational factors that influence the acceptance of Moodle using TAM. *Computers in Human Behavior*, *26*, 1632–1640.

Atarodi, S., Berardi, A.M., & Toniolo, A.M. (2019). Le modèle d'acceptation des technologies depuis 1986: 30 ans de développement. *Psychologie du Travail et des Organisations*, *25*(3), 191–207.

Binyamin, S.S., Rutter, M., & Smith, S. (2019). Extending the technology acceptance model to understand students' use of learning management systems in Saudi higher education. *International Journal of Emerging Technologies in Learning*, *14*(3), 4–21.

Bollen, K.A. (1987). Total, direct, and indirect effects in structural equation models. *Sociological Methodology*, *17*, 37–69.

Bollen, K.A. (1989). *Structural equations with latent variables* (Vol. 210). John Wiley & Sons, Toronto.

Davis, F.D. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Thesis. Retrieved from http://dspace.mit.edu/handle/1721.1/15192

Davis, F.D. (1989). Perceived usefulness, Perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–339.

Farahat, T. (2012). Applying the Technology Acceptance Model to Online Learning in the Egyptian Universities. *Procedia, Social and Behavioral Sciences*, *64*, 95–104.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley.

Hair, J.F., Anderson, R.E., Tatham, R.L., & William, C.B. (1995). *Multivariate Data Analysis with Readings*. Englewood Cliffs, New Jersey: Prentice Hall, 4. Auflage.

Hair, J.F., Risher, J.J., Sarstedt, M., & Ringle, C.M. (2019). When to Use and How to Report the Results of PLS-SEM. *European Business Review*, *31*(1), 2–24.

Henseler, J., Ringle C.M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Ibrahim, R., Leng, N.S., Yusoff, R.C.M., Samy, G.N., Masrom, S., & Rizman, Z.I. (2017). E-learning acceptance based on technology acceptance model (TAM). *Journal of Fundamental and Applied Sciences*, *9*(4S), 871–889.

Lee, B.C., Yoon, J.-O., & Lee, I. (2009). Learners' acceptance of e-learning in South Korea: Theories and results. *Computers and Education*, *53*(4), 1320–1329.

Lee, Y.C., Li, M.L., Yen, T.M., & Huang, T.H. (2010). Analysis of adopting an integrated decision-making trial and evaluation laboratory on a technology acceptance model. *Expert Systems with Applications*, *37*(2), 1745–1754.

Mousa, A.H., Mousa, S.H., & Obaid, H.A. (2020). Advance Acceptance Status Model for E-learning Based on University Academics and Students. *IOP Conference Series: Materials Science and Engineering*, *671*, 012031. https://doi:10.1088/1757-899X/671/1/012031

Peterson, R. (2000). A meta-analysis of variance accounted for and factor loadings in exploratory factor analysis. *Marketing Letters*, *11*, 261–275.

Pituch, K.A., & Lee, Y.K. (2006). The influence of system characteristics on e-learning use. *Computers and Education*, *47*(2), 222–244.

Ramos de Luna, I., Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2019). Mobile payment is not all the same: The adoption of mobile payment systems depending on the technology applied. *Technological Forecasting & Social Change*, *146*, 931–944.

Rogers, E.M. (2010). *Diffusion of innovations*. Simon and Schuster.

Scherer, R., Siddiq F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, *128*, 13–35.

Schillewaert, N., Ahearne, M.J., Frambach, R.T., & Moenaert, R.K. (2005). The adoption of information technology in the sales force. *Industrial Marketing Management*, *34*, 323–336.

Shankar, A., & Datta, B. (2018). Factors affecting mobile payment adoption intention: An Indian perspective. *Global Business Review*, *19*(3S), S72–S89.

Sri, R.N., Yuyun, T.W., & Anggi, P. (2022). Acceptance analysis of NUADU as e-learning platform using the Technology Acceptance Model (TAM) approach. *Procedia Computer Science*, *197*, 512–520.

Van Raaij, E.M., & Schepers, J.J.L. (2008). The acceptance and use of a virtual learning environment in China. *Computers & Education*, *50*(3), 838–852.

Venkatesh, V., & Davis, F.D. (2000a). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204.

Venkatesh, V., & Morris, G.M. (2000b). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behaviour. *MIS Quarterly*, *24*(1), 115–139.

Venkatesh, V., Morris, G.M., Davis, G.B., & Davis, F.D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478.

Yousafzai, S.Y., Foxall, G.R., & Pallister J.G. (2007). Technology acceptance: A meta-analysis of the TAM: Part 1. *Journal of Modelling in Management*, *2*(3), 251–280.