Factors Regarding Behavioral Intention Toward Post-Pandemic MOOCs Massive Online Courses (MOOCs) Post-pandemic

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Abstract. The Covid-19 pandemic boosted the rise of massive open online courses (MOOCs); seeking to position themselves as a viable and effective alternative. However, after this, the course dropout rate reached 90%; generating a loss of potential users in a market estimated at US $ 20.8 billion worldwide by 2023. The article proposes to analyze what could affect the continuity of these courses. To do this, it was proposed that the quality of the content, the relative advantage, compatibility, perceived usefulness, attitude and social influence are variables that influence the behavioral intention towards MOOCs.

A quantitative, explanatory and cross-sectional study was carried out over time. For this, a non-probabilistic convenience sample of 304 valid responses was reached through an online survey with Likert scale questions (1-5), which was applied the PLS-SEM technique to validate the hypotheses through the Smart PLS software. Their most important results were that compatibility and relative advantage have a positive effect on perceived usefulness. However, no relationship was found between content quality and perceived usefulness. Furthermore, perceived usefulness has a positive effect on social influence and students' attitude, but not on their behavioral intention.

Keywords: Content Quality; Compatibility; Relative Advantage; Perceived Usefulness; Attitude; Social Influence; Behavioral Intention; MOOCs.

1 Introduction

Massive open online courses, better known as MOOCs (Massive Open Online Courses), are characterized by encouraging massive participation, thanks to their available and open access, and by allowing access through various platforms and devices, in both synchronous and asynchronous modes [1].

Despite the large consumption of massive online courses during the Covid- 19 pandemic, certain disadvantages have been identified, such as the lack of guidance and standards of the content they offer; causing only a small percentage of users to be willing to complete a course or obtain a certificate, evidencing a low retention rate [2] and [1].

In this sense, some variables stand out to understand the behavioral intention towards these courses. For example, the compatibility against user needs [3]; the relative advantage when evaluating a technological innovation against others [4]; perceived

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usefulness and attitude [5] and social influence, as environmental opinions can influence consumer decisions [6]. Thus, the purpose of the study is to find out the relationships of such variables on the behavior of online course learners.

2 Literature Review

2.1 Content Quality (CQ)

The content quality (CQ) variable refers to the ability of a system to provide high quality content; which is related to the richness of the educational content and the frequency of its updates in an online course platform [7] and [8]. Both aspects are critical for users to perceive such a platform as attractive and useful [7] and [8].

The CQ variable has been investigated in a unidimensional way [7], [9] and [10]. On the other hand, [9] and [10] claim that there is a significant effect by CQ on perceived usefulness in the online course platform domain when they consider it to be useful, easy, complete and diverse.

H1: Content quality (CQ) has a positive effect on perceived usefulness (PU) in the category of MOOCs.

2.2 Compatibility (COMP)

Defined as the perception of the consistency or coherence of a system with respect to the standards, requirements, values and experiences of students and users; which will enrich their learning [11], [2] and [3].

It is worth considering that COMP has been studied as a unidimensional variable [2] and [4]. According to [12], [2] and [4], COMP has a positive effect on perceived usefulness (PU).

H2: Compatibility (COMP) has a positive effect on Perceived Usefulness (PU) in the MOOCs category.

2.3 Relative Advantage (RA)

Degree of perception that a product or service is better than the ideas it replaces or the existing system [4]. Also, according to [13] and [4], this variable is studied in a unidimensional way. On the other hand, according to [2], [3] and [4], it is a variable of great importance in motivating students' intention to accept MOOCs; because RA has a positive influence on perceived usefulness (PU) since, if students perceive that this new system (MOOCs) provides them with greater advantage than the previous traditional learning system, it will be considered of greater usefulness.

H3: Relative Advantage (RA) has a positive effect on Perceived Usefulness (PU) in the MOOCs category.

2.4 Perceived Usefulness (PU)

Perceived usefulness refers to the degree to which a user believes that employing a certain platform will improve his or her performance in some activity [14]; considering the efficiency, productivity and overall benefits of the system to improve user performance [15].

On the other hand, both [16] and [17] posit that this variable significantly influences attitude; while [18] and [19] refer that it has a positive and significant impact on behavioral intention.

H4: Perceived Usefulness (PU) positively influences Attitude (ATT) in the category of MOOCs.

H5: Perceived Usefulness (PU) has a positive impact on Behavioral Intention (BI) in the MOOCs category.

2.5 Attitude (ATT)

It expresses the degree to which the user acquires a positive or negative feeling towards online courses [20]. In the view of [14], even if users do not show a positive attitude towards technology, they will use it if they notice that the benefits are evident. On the other hand, attitude is considered a unidimensional variable [21]. On the other hand, [16], [17] and [22] reveal that there is a significant and positive relationship between ATT and behavioral intention (BI).

H6: Attitude (ATT) has a direct and positive effect with Behavioral Intention (BI) in the MOOCs category.

2.6 Social Influence (SI)

[21] point out that it is the influence due to the opinion of third parties regarding the use of an information system. On the other hand, this variable, is investigated as unidimensional [23] and [24].

According to [25] and [24], SI influences PU, considering that, faced with the decision to use MOOCs, users appreciate ratings from people they consider relevant. On the other hand, [6] and [22] argued that SI positively influences BI; as their environment beliefs and opinion about MOOCs can strongly impact them.

H7: Social Influence (SI) has a positive impact on Perceived Usefulness (PU) in the category of MOOCs.

H8: Social Influence (SI) positively influences Behavioral Intention (BI) in the MOOCs category.

2.7 Behavioural Intention (BI)

Behavioral intention, known by its acronym BI, is defined as the indicator that a person is prepared to behave in a certain way [26] or the strength of a person's commitment to perform a particular behavior [27]. Under the context of e-learning, BI was studied as a unidimensional construct [28], which determines users' willingness to accept online learning platforms [29].

3 Method

A quantitative, cross-sectional, correlational approach was applied. In addition, non-probabilistic convenience sampling was considered following the model of [23]. The survey was conducted from June 3 to July 25, 2022; focusing on students from high schools located in Metropolitan Lima who were users of MOOCs platforms in the period of the last twelve months prior to the dissemination of the survey.

In relation to the sample, 304 valid responses were obtained; of which 51.6% were female, 48.4% male and 68.1% were between 18 and 25 years old. Also, the platforms with the highest number of users according to our survey were Crehana (24%), Coursera (20.8%), Domestika (19.3%) and Netzun (14.6%). The data was collected via Google Forms and distributed on Facebook, Instagram and WhatsApp. It should be noted that confidentiality protocols were respected.

The questionnaire consisted of filter questions, demographic questions and variable indicators. CQ was composed of five items [30], RA of four items [31], COMP had three items [3], PU with three items [32], ATT with four items [30], SI with 3 items of [33]. Finally, BI was measured with 3 items from [34]. The items were measured using a 1-5 point Likert scale [35]. Finally, the statistical test was PLS-SEM [4]; while Smart

PLS software was used to analyze the data which allows for more accurate estimates [28], [34], [6] and [33].

4 Results

First, an indicator was removed from the PU variable for having values above 0.90 in the HTMT test [36]. Following this modification, the relationships between the variables were reassessed based on the results obtained using the PLS-SEM technique for the analysis of the reflexive research model [36]. In line with this, the selected variables and indicators show a satisfactory level of reliability, as they have a value above 0.7 [37].

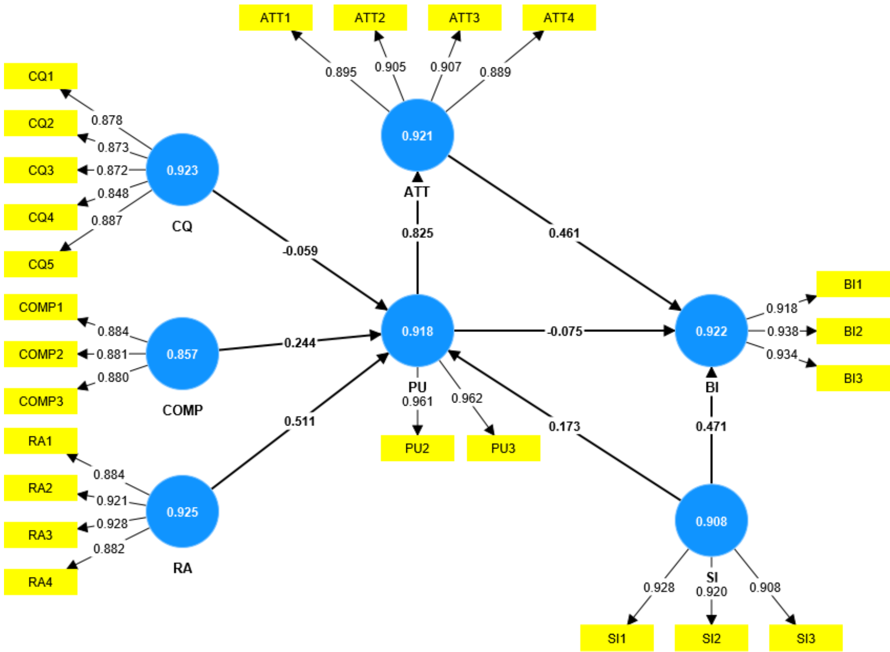

Fig. 1. Resarch model with loadings

Table 1. *Reflective measurements model*

Study construct	Construct-items	Loadings	AVE	Cronbach´s alpha	Rho_A	Composite Reliability
		>0.70	>0.50	>0.80	>0.70	>0.70
ATT	ATT1	0.895	0.808	0.921	0.921	0.944
	ATT2	0.905				
	ATT3	0.907				
	ATT4	0.889				
BI	BI1	0.918	0.865	0.922	0.924	0.951
	BI2	0.938				
	BI3	0.934				
COMP	COMP1	0.884	0.777	0.857	0.860	0.913
	COMP2	0.881				
	COMP3	0.880				
CQ	CQ1	0.878	0.760	0.923	0.951	0.941
	CQ2	0.873				
	CQ3	0.872				
	CQ4	0.848				
	CQ5	0.887				

PU	PU2	0.961	0.925	0.918	0.918	0.961
	PU3	0.962				
RA	RA1	0.884	0.817	0.925	0.926	0.947
	RA2	0.921				
	RA3	0.928				
	RA4	0.882				
SI	SI1	0.928	0.844	0.908	0.908	0.942
	SI2	0.920				
	SI3	0.908				

With regard to convergent validity, which was assessed through the average variance extracted (AVE), it can be observed that the values of the variables analyzed are greater than 0.50, which indicates that they are acceptable values [38]. Likewise, in relation to the reliability of internal consistency, according to [39], the values of Cronbach's Alpha are acceptable as they are greater than 0.80. Likewise, the rho_A values exceed 0.70; being acceptable [38]. In addition, on the composite reliability, it can be seen that they have satisfactory degrees of reliability, as they are values that are greater than 0.70 [38]. See Table 1.

Then, we proceeded to evaluate the discriminant validity through the analysis of correlations of Heterotrait-Monotrait Ratio (HTMT); considering that, there are no problems related to the discriminant value of the constructs being below 0.90. This being a standard threshold according to [36]. See Table 2.

Table 2. Discriminant validity **(**HTMT criterion)

	ATT	BI	COMP	CQ	PU	RA	SI
ATT							
BI	0.836						
COMP	0.847	0.809					
CQ	0.782	0.816	0.885				
PU	0.896	0.675	0.794	0.685			
RA	0.895	0.725	0.860	0.844	0.844		
SI	0.864	0.857	0.760	0.721	0.735	0.800	

Subsequently, it was found that there is no collinearity between the constructs through the variance inflation factor (VIF), as the values were between 1.000 and 4,580 [38]. Likewise, the calculation of R^2 was performed, in which it is observed that the values of PU, ATT and BI are moderate, as their values are 0.635, 0.680 and 0.678 respectively. In this sense, ATT is the variable that explains the model to a greater extent.

Table 3. Result for hypothesis testing

	Path coefficient	Confidence interval		P values	f^2	Decision
		2.5%	97.5%			
H1:CQ → PU	-0.059	-0.187	0.071	0.371	0.003	Unsupported
H2: COMP → PU	0.244	0.098	0.403	0.002	0.052	Supported
H3: RA → PU	0.511	0.324	0.701	0.000	0.195	Supported
H4: PU → ATT	0.825	0.770	0.868	0.000	2.126	Supported
H5: PU → BI	-0.075	-0.216	0.051	0.263	0.006	Unsupported
H6: ATT → BI	0.461	0.312	0.603	0.000	0.144	Supported
H7: SI → PU	0.173	0.058	0.292	0.004	0.036	Supported
H8: SI → BI	0.471	0.352	0.591	0.000	0.257	Supported

After the structural equation modeling, in which a bootstrapping of 5000 subsamples was carried out, it was obtained as results that H2, H3, H4, H6, H7 and H8 are valid by having a p-value below 0.05 [38] See Table 3.

Finally, the ability of the constructs to be predictors with respect to the evaluated relationships was evaluated, so it is evident that PU, ATT and BI are predictive, considering their predictive relevance values of 0.636, 0.712 and 0.633 respectively. This is because the accuracy and predictive relevance of the constructs will be higher as long as the Q^2 values are greater than 0.15 [38].

5 Discussion and conclusions

From the results obtained, it has been found that CQ is not significantly related to PU or BI. In the first case, users prioritized other aspects, such as compatibility [2] or that the platform fits their learning style and provides an enjoyable and satisfying experience [2]. In the second, consumers would no longer consider usefulness as a benefit as the supply of MOOCs and educational services available during the pandemic was limited.

On the other hand, the findings show that there is a relationship between COMP and PU. Therefore, considering that the use of virtual platforms enhances learning performance and is compatible with their values and behavioral patterns [13] and [2], COMP can be seen as the key to enhance consumers' acquisition of MOOCs. Furthermore, the relationship between AR and PU was validated; suggesting that relative advantage is important to some extent for perceived usefulness as consumers perceive these online courses to be superior to other traditional learning methods [3].

Regarding the relationship between PU and ATT, it is concluded that their relationship is positive and strong; and thus, there would be a greater willingness to purchase them [40], [41] and [42]. Furthermore, it could be concluded that ATT is a determinant factor in BI, which would imply that, in order to increase the acquisition of the service, it is crucial to provide an efficient platform, which will generate a positive user attitude towards MOOCs [43].

Similarly, the results show a positive relationship between SI and PU. Therefore, it is concluded that it is important for users to value online courses by their environment, as it depends on this for them to consider it beneficial and make the decision to purchase it [44] and [24]. Finally, SI influences BI and it should be taken into consideration that users expect their immediate environment to prefer the use of online platforms for learning or that they are inclined towards this type of educational service over other learning methods, as it will directly affect their decision making [33].

5.1 Limitations and future research

The main limitations observed are focused on the information collected on the basis of the sample selected, since, being a convenience sample, the results are biased. Likewise, it was considered that the geographical location of the respondents contributes to the fact that it cannot be extrapolated. On the other hand, it is suggested to include variables such as perceived ease of use, brand equity, brand image, satisfaction, perceived enjoyment and loyalty. Furthermore, given that the findings and recommendations have been generated based on a specific sample, considering that they are high school students in the city of Lima, it is recommended that research be conducted in other geographical contexts, so that the results generated can be compared.

References

[1] Voudoukis, N., & Pagiatakis, G. (2022). Massive Open Online Courses (MOOCs): Practices, Trends, and Challenges for the Higher Education. *European Journal of Education and Pedagogy*, *3*(3), 288–295. https://doi.org/10.24018/ejedu.2022.3.3.365

[2] Al-Rahmi, W. M., Yahaya, N., Alamri, M. M., Alyoussef, I. Y., Al-Rahmi, A. M., & Kamin, Y. (2019). Integrating innovation diffusion theory with technology acceptance model: supporting students' attitude towards using a massive open online courses (MOOCs) systems. *Interactive Learning Environments*, *29*(8), 1380–1392. https://doi.org/10.1080/10494820.2019.1629599

[3] Mehra, A., Paul, J., & Kaurav, R. P. S. (2020). Determinants of mobile apps adoption among young adults: theoretical extension and analysis. *Journal of Marketing Communications*, *27*(5), 481–509. https://doi.org/10.1080/13527266.2020.1725780

[4] Ullah, N., Al-Rahmi, W. M., Alzahrani, A. I., Alfarraj, O., & Alblehai, F. M. (2021). Blockchain technology adoption in smart learning environments. *Sustainability*, *13*(4), 1801. https://doi.org/10.3390/su13041801

[5] Ameen, N., Willis, R., Abdullah, M. N., & Shah, M. (2018). Towards the successful integration of e-learning systems in higher education in Iraq: A student perspective. *British* Journal of Educational Technology, 50(3), 1434–1446. https://doi.org/10.1111/bjet.12651

[6] Zhang, Z., Cao, T., Shu, J., & Liu, H. (2020). Identifying key factors affecting college students' adoption of the e-learning system in mandatory blended learning environments. *Interactive Learning Environments*, *30*(8), 1388–1401. https://doi.org/10.1080/10494820.2020.1723113

[7] Lee, Y. (2006). An empirical investigation into factors influencing the adoption of an e-learning system. *Online Information Review*, *30*(5), 517–541. https://doi.org/10.1108/14684520610706406

[8] Al-Mekhlafi, A. B. A., Othman, I., Kineber, A. F., Mousa, A. A., Zamil, A. M. A. (2022). Modeling the Impact of Massive Open Online Courses (MOOC) Implementation Factors on Continuance Intention of Students: PLS-SEM Approach. *Sustainability, 14*(9). https://doi.org/10.3390/su14095342

[9] Calisir, F., Altin Gumussoy, C., Bayraktaroglu, A. E., & Karaali, D. (2014). Predicting the intention to use a web-based learning system: Perceived content quality, anxiety, perceivedsystem quality, image, and the technology acceptance model. *Human Factors and Ergonomics In Manufacturing*, *24*(5), 515–531. https://doi.org/10.1002/hfm.20548

[10] Almaiah, M. A., Jalil, M. A., & Man, M. (2016). Extending the TAM to examine the effects of quality features on mobile learning acceptance. *Journal of Computers in Education*, *3*(4), 453–485. https://doi.org/10.1007/s40692-016-0074-1

[11] Moore, G. C., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research, 2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

[12] Ismail, H. (2016). Intention to Use Smartphone through Perceived Compatibility, Perceived Usefulness, and Perceived Ease of Use. *JDM (Jurnal Dinamika Manajemen), 7*(1), 1-10. https://doi.org/10.15294/jdm.v7i1.5748

[13] Lee, Y.-H., Hsieh, Y.-C., & Hsu, C.-N. (2011). Adding Innovation Diffusion Theory to theTechnology Acceptance Model: Supporting Employees' Intentions to use E-Learning Systems. *Journal of Educational Technology & Society*, *14*(4), 124–137. http://www.jstor.org/stable/jeductechsoci.14.4.124

[14] Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance ofInformation Technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

[15] Tahar, A., Riyadh, H. A., Sofyani, H., & Purnomo, W. E. (2020). Perceived Ease of Use, Perceived Usefulness, Perceived Security and Intention to Use E-Filing: The Role of Technology Readiness. *The Journal of Asian Finance, Economics and Business, 7*(9), 537–547. https://doi.org/10.13106/jafeb.2020.vol7.no9.537
[16] Park, S. Y. (2009). An Analysis of the Technology Acceptance Model in Understanding University Students' Behavioral Intention to Use e-Learning. *Journal of Educational Technology & Society*, *12*(3), 150–162. http://www.jstor.org/stable/jeductechsoci.12.3.150
[17] Boateng, R., Mbrokoh, A. S., Boateng, L., Senyo, P. K., & Ansong, E. (2016). Determinants of e-learning adoption among students of developing countries. *The InternationalJournal of Information and Learning Technology*, *33*(4), 248–262. https://doi.org/10.1108/IJILT-02-2016-0008
[18] Lee, Y. (2006). An empirical investigation into factors influencing the adoption of an e- learning system. *Online Information Review*, *30*(5), 517–541. https://doi.org/10.1108/14684520610706406
[19] Humida, T., al Mamun, M. H., & Keikhosrokiani, P. (2021). Predicting behavioral intention to use e-learning system: A case-study in Begum Rokeya University, Rangpur, Bangladesh. *Education and Information Technologies*, *27*(2), 2241–2265. https://doi.org/10.1007/s10639-021-10707-9
[20] Hussein, Z. (2017). Leading to Intention: The Role of Attitude in Relation to Technology Acceptance Model in E-Learning. *Procedia Computer Science*, *105*, 159–164. https://doi.org/10.1016/j.procs.2017.01.196
[21] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of In- formation Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540
[22] Abdou, D. & Jasimuddin, S. M. (2020). The Use of the UTAUT Model in the Adoption of E-Learning Technologies: An Empirical Study in France Based Banks. *Journal of Global Information Management (JGIM), 28*(4), 38-51. http://doi.org/10.4018/JGIM.2020100103
[23] Tarhini, A., Masa'deh, R., Al-Busaidi, K. A., Mohammed, A. B., & Maqableh, M. (2017). Factors influencing students' adoption of e-learning: a structural equation modeling approach. *Journal of International Education in Business*, *10*(2), 164–182. https://doi.org/10.1108/JIEB-09-2016-0032
[24] Alami, Y., & El Idrissi, I. (2022). Students' adoption of e-learning: evidence from a Moroccan business school in the COVID-19 era. *Arab Gulf Journal of Scientific Research*, *40*(1), 54–78. https://doi.org/10.1108/AGJSR-05-2022-0052
[25] Park, Y., Son, H., & Kim, C. (2012). Investigating the determinants of construction profes- sionals' acceptance of web-based training: An extension of the technology acceptance model. *Automation in Construction*, *22*, 377–386. https://doi.org/10.1016/J.AUTCON.2011.09.016
[26] Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-t
[27] Ngai, E. W. T., Poon, J. K. L., & Chan, Y. H. C. (2007). Empirical examination of the adoption of WebCT using TAM. *Computers & Education*, *48*(2), 250–267. https://doi.org/10.1016/j.compedu.2004.11.007
[28] Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior*, *45*, 359–374. https://doi.org/10.1016/j.chb.2014.07.044
[29] Salloum, S. A., Mhamdi, C., Al Kurdi, B., & Shaalan, K. (2018). Factors affecting the Adoption and Meaningful Use of Social Media: A Structural Equation Modeling Ap- proach. *International Journal of Information Technology and Language Studies (IJITLS), 2*(3), 96–109. http://journals.sfu.ca/ijitls

[30] Salloum, S. A., Qasim Mohammad Alhamad, A., Al-Emran, M., Abdel Monem, A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE Access*, *7*, 128445–128462. https://doi.org/10.1109/ACCESS.2019.2939467

[31] Khlaisang, J., Teo, T., & Huang, F. (2019). Acceptance of a flipped smart application for learning: a study among Thai university students. *Interactive Learning Environments*, *29*(5), 772–789. https://doi.org/10.1080/10494820.2019.1612447

[32] Ameen, N., Willis, R., Abdullah, M. N., & Shah, M. (2018). Towards the successful integration of e-learning systems in higher education in Iraq: A student perspective. *British* Journal of Educational Technology, 50(3), 1434–1446. https://doi.org/10.1111/bjet.12651

[33] Meet, R. K., Kala, D., & Al-Adwan, A. S. (2022). Exploring factors affecting the adoption of MOOC in Generation Z using extended UTAUT2 model. *Education and information technologies, 27*(7), 10261–10283. https://doi.org/10.1007/s10639-022-11052-1

[34] Abbas, T. (2016). Social factors affecting students' acceptance of e-learning environments in developing and developed countries. *Journal of Hospitality and Tourism Technology*, *7*(2), 200–212. https://doi.org/10.1108/JHTT-11-2015-0042

[35] Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. *Com- puters in Human Behavior*, *56*, 238–256. https://doi.org/10.1016/j.chb.2015.11.036

[36] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discrimi- nant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

[37] Ringle, C. M., Wende, S. & Becker, J. M. (2015). *SmartPLS 3*. Boenningstedt: SmartPLS GmbH. www.smartpls.com.

[38] Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial Least Squares Structural Equation Modeling. *Handbook of Market Research*, 1–40. Springer International Publishing. https://doi.org/10.1007/978-3-319-05542-8_15-1

[39] Dijkstra, T. K., & Henseler, J. (2015). Consistent and asymptotically normal PLS estima- tors for linear structural equations. *Computational Statistics & Data Analysis*, *81*, 10–23. https://doi.org/10.1016/j.csda.2014.07.008

[40] Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, *67*, 221–232. https://doi.org/https://doi.org/10.1016/j.chb.2016.10.028

[41] Wang, Y., Hong, A., Li, X., & Gao, J. (2020). Marketing innovations during a global cri- sis: A study of China firms' response to COVID-19. *Journal of Business Research*, *116*, 214–220. https://doi.org/10.1016/j.jbusres.2020.05.029

[42] Wang, K. (2023). The Perception and Behavioral Intention Toward MOOCs: Undergradu- ates in China. *The International Review of Research in Open and Distributed Learning*, *24*(1), 22–46. https://doi.org/10.19173/irrodl.v24i1.6677

[43] Gao, L., Vongurai, R., Phothikitti, K., & Kitcharoen, S. (2022). Factors Influencing Uni- versity Students' Attitude and Behavioral Intention Towards Online Learning Platform in Chengdu, China. *ABAC ODI Journal Vision. Action. Outcome, 9*(2), 21-37. https://doi.org/10.14456/abacodijournal.2022.2

[44] Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, *67*, 221–232. https://doi.org/https://doi.org/10.1016/j.chb.2016.10.028