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Investigating Students' Intentions to adopt MOOCs: An Application of Technology Acceptance Model (TAM)

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Abstract

The purpose of the study is to examine the predictors of students' intentions to adopt Massive Open Online Courses (MOOCs). A model comprising of the constructs of "Technology Acceptance Model" (TAM), along with "computer self-efficacy" and gender of students is proposed to study the students' behaviour towards adopting MOOCs. The study employs a descriptive research design wherein data pertaining to students' perceptions were gathered from a convenience sample of 196 respondents. The respondents (students) were selected from a reputed higher educational institution (HEI) in the National Capital Region (NCR) of Delhi, using non-random sampling. The data were analysed using "Exploratory Factor Analysis" (EFA) and "Multiple Regression Analysis" (MRA). The findings indicate that both the constructs of TAM namely, "perceived usefulness" and "perceived ease of use", as well as "computer self-efficacy", are significant predictors of students' behavioural intention to adopt MOOCs. However, the findings don't indicate any role of gender in determining the students' adoption intention of MOOCs.

Keywords: *Technology Acceptance Model (TAM), Massive Open Online Courses (MOOCs), Computer Self-Efficacy, Adoption Intention*

INTRODUCTION

The advancements in Information and Communication Technology (ICT) have transformed the educational landscape. The use of ICT has given rise to various educational innovations such as Massive Open Online Course (MOOCs). According to Kaplan & Haenlein (2016), MOOCs are open-access learning courses that are available online to a fairly large number of learners from random locations. MOOCs are offered by reputed educational institutions through various platforms viz., edX, Coursera Udemy, Udacity, Pluralsight, MIT, and Miriadax. These platforms are capable of handling large number of learners across the globe (Alario-Hoyos et al., 2014).

Recently, MOOCs have gained significant attention for providing online education to learners (Deimann, 2015; Reich, 2015). Because of the features such as openness and massiveness, MOOCs can be distinguished from the traditional forms of online education. MOOCs are increasingly becoming popular amongst the learners because of several advantages, such as accessibility, cost-effectiveness, and so on. Being online, MOOCs can be easily accessed by the learners from anywhere in the world (Barclay & Logan, 2013). These courses allow learners to access affordable educational courses (programmes) offered by reputed institutions/organizations (Kennedy, 2014). Moreover, pursuing education through MOOCs doesn’t require any eligibility criteria. All these advantages have led to strong and steady growth of MOOCs (Mulder & Janssen, 2013). Originally started from big European and American universities, MOOCs have now become immensely popular throughout the world (Aboshady et al., 2015; Bayne, 2015). India which is seeing a rapid rise in Internet users is leading the global growth in MOOCs’ enrolment after the USA (Chauhan, 2017).

Despite their steady rise and growth, MOOCs face many problems that are yet to be addressed; the most prominent one being the high dropout percentage (partial completion percentage) of MOOCs’ learners (Freitas et al., 2015). Reich and Ruipérez-Valiente (2019), showed that the average dropout rate of MOOCs is around 96%, which is astronomical. Many studies have tried to explain the probable causes of high dropout rates of learners from MOOCs. The studies have correlated the learners’ engagement and dropout behaviour (Freitas et al., 2015; Xiong et al., 2015). Researchers have pointed out that learners with higher engagement levels are less likely to drop out (Goldberg et al., 2015). The high dropout percentage and non-completion rates are a matter of concern for the MOOC developers and providers (Diver and Martinez, 2015).

Considering the opportunities as well as challenges of MOOCs, it is imperative to study the students’ (learners’) perspectives on the adoption/acceptance of MOOCs. Therefore, the present research attempts to explore the (determinants) factors that can affect the students’ attitude regarding adoption of MOOCs. Specifically, a model of influencing factors is proposed in the study, to predict the students’ behavioural intentions to adopt MOOCs. The proposed model is a combination of the constructs of “Technology Acceptance Model” (TAM) and two personal attributes of students namely, gender and computer self-efficacy.

Specifically, the study attempts to achieve the following objectives:

- To examine the influence of technological factors (i.e. perceived usefulness and perceived ease of use) on the students’ behavioural intention to adopt MOOCs
- To examine the influence of personal attributes of students (i.e. gender and computer self-efficacy) on their behavioural intention to adopt MOOCs

LITERATURE REVIEW

Previous studies on MOOCs adoption

Most of the research studies on MOOCs primarily talk about their development, business models, pedagogy, course formats, and student enrolments (Al-Rahmi et al., 2019). Few studies have empirically investigated the potential of MOOCs in enhancing the employability skills of students (Calonge and Shah, 2016).

Several studies have been conducted in the recent past to explain the students' acceptance behaviour towards MOOCs. These studies have come up with various factors that may influence students' behavioural intention to adopt MOOCs. For example, Mohamad and Rahim (2018) and Ma and Lee (2019) have found that perceived usefulness, performance expectancy, ease of use and perceived value of MOOCs are significantly associated with MOOCs adoption. Some other researchers such as Al-Shami et al. (2018) and Gao and Yang (2015) have opined that normative, coercive and mimetic pressures significantly explain the students' intention to adopt MOOCs. Wu and Chen (2017) argue that the unique features of MOOCs such as openness and reputation significantly influence the students' behaviour towards MOOCs. Fianu et al. (2018) opine that the instructional quality of MOOCs also determines the students' engagement in MOOCs. Few researchers (Khan et al., 2018; Wu and Chen, 2017) have indicated that social recognition also motivates the learners to adopt MOOCs.

Theoretical Background and Conceptual Framework

TAM (see Appendix 1) was introduced by Davis (1989), for explaining the acceptance, and use of technology and Information Systems (IS). There are two major constructs in TAM namely, "perceived usefulness" and "perceived ease of use" that are supposed to predict the behavioural intention to adopt a particular technology (Davis, 1989). "Perceived usefulness" is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance", and "perceived ease of use" is referred to as "the degree to which a person believes that using a particular system would be free from effort" (Davis 1989).

As opined by Park (2009), TAM has a great potential in predicting the users' intentions to use a technological innovation. Therefore, TAM is the most widely accepted models amongst the researchers for investigating the users' behaviour towards a technology (Wani and Ali, 2015). TAM has been used extensively within the educational contexts to explain the students' behaviour towards adopting various educational technologies. For example, Al-hawari and Mouakket (2010) highlighted the impact of the two constructs of TAM i.e. "perceived usefulness" and "perceived ease of use" on students' e-retention within the context of e-learning in United Arab Emirates (UAE). They concluded that "perceived usefulness" has direct positive relationships with students' e-retention. Al- Adwan et al. (2013) used TAM to explore students' attitudes towards accepting e-learning in the universities of Jordan. They concluded that "perceived usefulness" is a stronger predictor of acceptance behaviour, as compared to "perceived ease of use".

Though TAM is considered to be a powerful model for investigating technology acceptance, however few researchers argue that TAM should be integrated/extended with other external factors that can consider human and social factors as well (Legris et al., 2003). Considering this viewpoint, Yi and Hwang, (2003) extended TAM with learning goal orientation and self-efficacy to explain the acceptance of web-based IS. Similarly, Al-hawari and Mouakket (2010) integrated TAM with two variables namely enjoyment and blackboard design features to predict students' e-satisfaction.

Though there are sufficient studies in the literature that address the students' acceptance behaviour towards various educational technologies, however there is a lack of studies that specifically focus on the students' adoption of MOOCs (Gupta, 2019). In this study, we attempt to bridge this gap by proposing a model of factors to predict the students' behavioural intentions to adopt MOOCs. We extend TAM with two personal attributes of students namely, gender and computer self-efficacy. Gender of the user has been indicated as an important characteristic that determines the user's technology acceptance behaviour (Venkatesh and Morris, 2000). Males are considered to be more inclined to use a technological innovation, as compared to females (Venkatesh et al., 2003). Differences on the basis of gender have been observed within educational contexts also (Palos-Sanchez et al., 2018; Zhou and Xu, 2007). Computer self-efficacy (Park, 2007) is another personal attribute that is assumed to be a significant determinant of technology acceptance behaviour (Ottenbreit-

Leftwich, 2018). Hartman et al. (2019) opined that computer self-efficacy includes the technical knowledge and digital skills that are required to use ICT applications.

On the basis of the literature presented above, we propose the following hypotheses:

H1: Perceived usefulness of MOOCs has a significant positive impact on students' intentions to adopt MOOCs

H2: Perceived ease of use of MOOCs has a significant positive impact on students' intentions to adopt MOOCs

H3: Computer self-efficacy has a significant positive impact on students' intentions to adopt MOOCs

H4: Gender has a significant impact on students' intentions to adopt MOOCs

The proposed model is illustrated in Fig. 1.

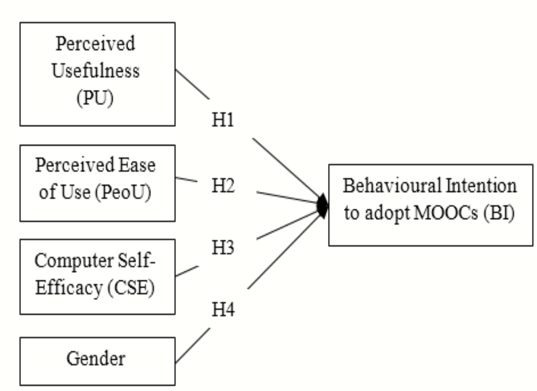

Fig. 1: Proposed Framework

METHODOLOGY

The study used the primary data collected from a sample of 196 students. The students were selected from a reputed higher educational institution in the National Capital Region of Delhi. Convenience sampling method (Saunders, 2011) was used to select the target respondents. A structured questionnaire was used as the survey instrument to gather data from the respondents. The questionnaire consisted of items related to the four model constructs namely, "perceived usefulness" (PU), "perceived ease of use" (PeoU), "computer self-efficacy" (CSE) and "behavioural intention" to adopt MOOCs (BI). The measures for these constructs were adapted from the existing scales in the literature. The items for PU, PeoU and BI were adapted from Davis (1989); and the items for CSE were adapted from Sun and Jeyaraj (2013). All these items were measured on a 1-5 Likert scale response format where 1=strongly disagree and 5=strongly agree. Apart from questions on these items, the questionnaire also consisted of questions related to the demographic characteristics of students.

Before administering the final survey, the questionnaire was pilot tested with 6 faculty members teaching in a B-School. The questionnaires were distributed to 220 students, out of which 196 usable questionnaires were collected. The sample consisted of 44% females and 56% males. The average age of the respondents was 18.5 years.

DATA ANALYSIS AND RESULTS

The collected data was analysed through statistical techniques using SPSS software. Firstly, Exploratory Factor Analysis (EFA) was applied to explore the underlying factor structure. Then Confirmatory Factor Analysis (CFA) was employed to validate the factor structure obtained through EFA. Next, the reliability testing was done for the extracted factors. Finally, Multiple Regression Analysis (MRA) was performed for hypothesis testing.

Exploratory Factor Analysis (EFA)

The results of EFA provided support for data adequacy as Bartlett's test of spehericity (chi square (df) = 1044.74 (55); $p<0.001$) was found to be significant. The large value of "Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy" (0.670) also provided support for data adequacy. Eigen value criteria with 'varimax' rotation was applied to extract the factors (Hair et al., 2006). As expected, 4 factors were extracted that explained 80.17% variation. All the indicators (items) were loaded on their respective factors (constructs), thereby indicating construct validity. The factor loadings are illustrated in Table 1.

Table 1: Factor Loadings

Factor		PU	PeoU	CSE	BI
Factor	**Item**				
PU	PU1	0.908			
	PU2	0.897			
	PU3	0.884			
PeoU	PeoU1		0.896		
	PeoU2		0.896		
	PeoU3		0.876		
CSE	CSE1			0.886	
	CSE2			0.848	
	CSE3			0.807	
BI	BI1				0.944
	BI2				0.943

Confirmatory Factor Analysis (CFA)

To confirm the factor structure obtained through EFA, we employed confirmatory factor analysis (CFA) using AMOS software. The measurement model comprising 11 items under 4 latent constructs (viz. PU, PEoU, CSE and BI) was evaluated for assessing the reliability and validity of the constructs. The results of the CFA are summarized in Table 2. The results indicate that the model fitness was adequately achieved as all the fitness indices met the recommended criteria (Hu and Bentler, 1999).

Table 2: Model Fitness

Fit Index	Recommended Criteria	Observed Value
X^2/df	<3	2.01
Comparative Fit Index (CFI)	>0.95	0.956
Tucker–Lewis Index (TLI)	>0.95	0.958
Standardized Root Mean Square Residuals (SRMR)	<0.05	0.048
Root Mean Square Error of Approximation (RMSEA)	<0.08	0.062

Since the measurement model was found to be fit, we assessed the validity and reliability of the latent constructs using the recommendations of Hair et al. (2010). The item loadings (see Table 3) of all the constructs were significant and above 0.5, providing support for convergent validity. Further, the average variance extracted (AVE) for all the constructs were greater than 0.5 further supporting the validity of the constructs.

Table 3: Convergent Validity

Factor		Item Loading	AVE
Factor	**Item**		
PU	PU1	0.770	
	PU2	0.803	0.629
	PU3	0.806	
PeoU	PeoU1	0.819	0.619
	PeoU2	0.740	
	PeoU3	0.799	
CSE	CSE1	0.770	0.629
	CSE2	0.803	
	CSE3	0.806	
BI	BI1	0.848	0.715
	BI2	0.843	

The discriminant validity was examined on the basis of the criterion recommended by Fornell and Larcker (1981). As can be observed from Table 4, the correlations between the constructs (off-diagonal values) were lesser than the squared roots of AVE (diagonal values). Thus, the discriminant validity was ensured.

Table 4: Discriminant Validity

	PU	PeoU	CSE	BI
PU	**0.793**			
PeoU	0.143	**0.787**		
CSE	0.180	0.209	**0.793**	
BI	0.522	0.339	0.457	**0.846**

The reliability of the model constructs was tested using Cronbach's alpha coefficient and Composite Reliability (CR). As indicated in Table 5, all the constructs were reliable as the values of Cronbach's alpha and CR were greater than 0.7 (Nunnally and Bernstein, 1994; Hair et al., 2018).

Table 5: Reliability Testing

Construct / Factor	No. of Items / Indicators	Cronbach's Alpha Coefficient	CR
Perceived Usefulness (PU)	3	0.882	0.836
Perceived Ease of Use (PeoU)	3	0.892	0.829

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Computer Self-Efficacy (CSE)	3	0.876	0.836
Behavioural Intention (BI)	2	0.884	0.834

Multiple Regression Analysis (MRA)

The proposed hypotheses were tested using MRA. The analysis was performed by taking PU, PeoU, CSE and gender as independent variables; and BI as the dependent variable. The variable gender was dummy coded (0=Male and 1=Female). The correlations between the variables are shown in Table 4. The table indicates that there was no concern of multicollinearity as the correlation coefficients between all the constructs were below the recommended threshold value of 0.90 (Hair et al., 2010). The residuals were normally distributed as observed from the P-P plot, indicated in Fig. 2. Hence the assumptions of MRA were adequately met.

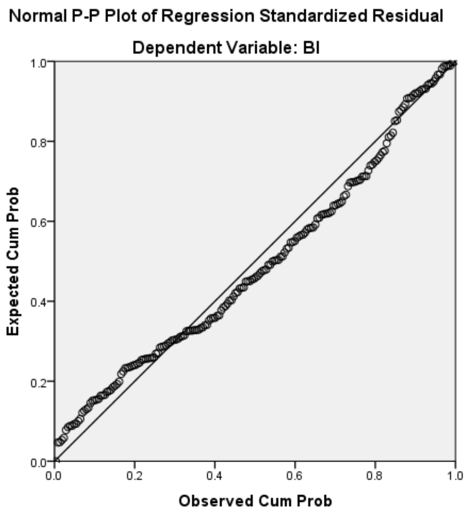

Fig. 2: Normal P-P Plot

The standardized coefficients for the three dependent variables are shown in Table 6. Overall, the regression model was found to be significant, as indicated by the F test: F=45.36 ($p<0.001$). The students' intention to adopt MOOCs was significantly predicted by the variables PU, PeoU and CSE. Hence the hypotheses H1-H3 were supported. Specifically, PU was found to be the strongest determinant of BI ($\beta=0.45$, $p<0.001$) followed by CSE ($\beta=0.35$, $p<0.001$) and PeoU ($\beta=0.28$, $p<0.001$). Gender was not found to be a significant influencer of BI ($\beta=0.01$, $p=0.846$). Hence the hypothesis H4 was not supported. Overall, the three variables i.e. PU, PeoU and CSE explained 47.6% variation in students' intention to adopt MOOCs.

Table 6: Results of MRA

Variable	Standardized β	t statistic	p-value
PU	0.45	8.46	0.000
PeoU	0.28	5.40	0.000
CSE	0.35	6.53	0.000
Gender	0.01	0.195	0.846

DISCUSSION OF FINDINGS

The findings of the study reveal that perceived usefulness is the strongest influencer of students' intentions to adopt MOOCs. This highlights the role of relative advantages of MOOCs in motivating the students to learn through MOOCs. Our findings are in line with those of Mohamad et al., (2018) and Ma and Lee (2019), who also argued for the important role of perceived usefulness in adopting MOOCs. If the students feel that MOOCs enhance their academic knowledge and performance, then they are more inclined towards adopting MOOCs. The usefulness of the learning material provided through MOOCs motivate the students to adopt MOOCs. Computer self-efficacy is emerged as the second most important influencer of students' adoption intentions. This implies that the students who are more tech savvy, are more attracted towards MOOCs. Since learning through MOOCs platforms requires some technical expertise and knowledge, hence computer self-efficacy is a strong determinant of students' behaviour towards adopting MOOCs. The important role of computer self-efficacy in adopting ICT applications has also been highlighted in previous researches (Ottenbreit-Leftwich, 2018; Hartman et al., 2019). Finally, ease of use is also found to be a significant variable that influences students' behavioural intentions. This implies that if the learners feel that MOOC platforms are easy to use and user-friendly, then they are more likely to accept MOOCs. The difficulties in accessing the study material and submitting the evaluations, may refrain students from accepting MOOCs. Al-hawari and Mouakket (2010) also argued for the positive influence of ease of use in adopting online courses and e-learning. The findings of the study don't support any significant role of gender in determining the adoption intentions of MOOCs. This signifies that males and females are equally likely to adopt MOOCs. Though this finding contradicts with some of the previous studies (Palos-Sanchez et al., 2018), however the insignificant role of gender can be attributed to the fact that gender differences in students of today's generation don't really impact their behaviour towards exploring innovative educational technologies.

IMPLICATIONS

The study suggests some important implications for MOOCs developers as well as academic institutions. Considering the importance of perceived usefulness, the developers should focus on developing MOOCs that really provide value to students in terms of enhancing their knowledge, skills and academic performance. The developers should consider designing MOOCs on recent topics in cutting-edge areas that can be used to develop skills of students as well as enhance their conceptual knowledge. Considering the importance of 'perceived ease of use' and 'computer self-efficacy', the developers should also consider the user friendliness of MOOCs platforms. The platforms should be easy to use so that students don't face technical difficulties in navigating through the platform, accessing the study material, and submitting the assignments. The academic institutions should also provide technical training to their students so that they can find MOOCs easy to use.

LIMITATIONS AND FUTURE SCOPE

The limitations of the study should be taken into consideration, while interpreting the findings of the study. The first limitation is that the study is based on a small sample collected through non random sampling method. Future studies may consider large samples that are more diverse in nature. Secondly the study has considered behavioural intention as the dependent variable. Though behavioural intention is considered as a direct determinant of actual usage, however future studies may include the actual usage of MOOCs in the model. Thirdly, the present study has used TAM as the theoretical model for studying students' behaviour towards adopting MOOCs. The present study may be extended by considering other models as well such as "Unified Theory of Acceptance and Use of Technology" (UTAUT), "Technology-Organization-Environment" (TOE) framework, "Theory of Planned Behaviour" (TPB), and so on. Finally, future studies may also adopt a longitudinal research design to study the dynamic behaviour of students towards accepting MOOCs.

REFERENCES

1. Aboshady, O. A., Radwan, A. E., Eltaweel, A. R., Azzam, A., Aboelnaga, A. A., Hashem, H. A., . . . Hassouna, A. (2015). Perception and use of massive open online courses among medical students in a developing country: Multicentre cross-sectional study. BMJ Open, 5(1), e006804. https:/doi.org/10.1136/bmjopen-2014-006804
2. Al-Adwan, A., Al-Adwan, A., & Smedley, J. (2013). Exploring students' acceptance of e-learning using Technology Acceptance Model in Jordanian universities. International Journal of Education and Development Using Information and Communication Technology *(*IJEDICT*)*, 9(2), 4–18.
3. Alario-Hoyos, C., Perez-Sanagustin, M., Delgado-Kloos, C., Parada G, H. A., & Munoz-Organero, M. (2014). Delving into participants' profiles and use of social tools in MOOCs. IEEE Transactions on Learning Technologies, 7(3), 260–266. https:/doi.org/10.1109/TLT.2014.2311807
4. Al-Al-hawari, M. A., & Mouakket, S. (2010). The influence of technology acceptance model (TAM) factors on students' e-satisfaction and e-retention within the context of UAE e-learning. Education, Business and Society*:* Contemporary Middle Eastern Issues, 3(4), 299–314. https:/doi.org/10.1108/17537981011089596

5. Barclay, C., & Logan, D. (2013). Towards an understanding of the implementation and adoption of massive online open courses (MOOCS) in a developing economy context. Paper presented at the In Proceedings Annual Workshop of the AIS Special Interest Group for ICT in Global Development, Milano, Italy.

6. Bayne, S. (2015). What's the matter with "technology-enhanced learning"? Learning, Media and Technology, 40(1), 5–20. https:/doi.org/10.1080/17439884.2014.915851

7. Belanger, Y., & Thornton, J. (2013). Bioelectricity*:* A quantitative approach Duke University*'*s first MOOC.

8. Brothers, P. (2017). MOOC learners in developing countries are vastly different than their developed world counterparts. Retrieved from https://medium.com/navitas-ventures/mooc-learners-in-developingcountries-are-vastly-different-than-their-developed-world-counterparts-1d7eb156bd4c

9. Calonge, D. S., & Shah, M. A. (2016). MOOCs, graduate skills gaps, and employability: A qualitative systematic review of the literature. International Review of Research in Open and Distributed Learning, 17(5), 67–90. https:/doi.org/10.19173/irrodl.v17i5.2675

10. Chauhan, J. (2017). An overview of MOOC in India. International Journal of Computer Trends and Technology, 49(2), 111–120. https:/doi.org/10.14445/22312803/IJCTT-V49P117

11. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of Information Technology. MIS Quarterly, 13(3), 319–340. https:/doi.org/10.2307/249008

12. Deimann, M. (2015). Current Issues in Emerging elearning the dark side of the MOOC-A critical inquiry on their claims and realities. Current Issues in Emerging Elearning, 2(1). Retrieved from http://umb.edu/ciee/vol2/iss1/3.

13. Diver, P., & Martinez, I. (2015). MOOCs as a massive research laboratory: Opportunities and challenges. Distance Education, 36(1), 5–25. https:/doi.org/10.1080/01587919.2015.1019968

14. Fianu, E., Blewett, C., Ampong, G. O. A., & Ofori, K. S. (2018). Factors affecting MOOC usage by students in selected Ghanaian universities. Education Sciences, 8(2), 1–15. https:/doi.org/10.3390/educsci8020070

15. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https:/doi.org/10.1177/002224378101800104

16. de Freitas, S. I., Morgan, J., & Gibson, D. (2015). Will MOOCs transform learning and teaching in higher education? Engagement and course retention in online learning provision. British Journal of Educational Technology, 46(3), 455–471. https:/doi.org/10.1111/bjet.12268

17. Gao, S., & Yang, Y. (2015). Exploring users' adoption of MOOCs from the perspective of the institutional theory. In WHICEB. Proceedings, 2015, (282–290).

18. Gupta, K. P. (2019). Investigating the adoption of MOOCs in a developing country: Application of technology-user-environment framework and self-determination theory. Interactive Technology and Smart Education, 17(4), 355–375. https:/doi.org/10.1108/ITSE-06-2019-0033

19. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed). Upper Saddle River, NJ: Prentice Hall.

20. Hartman, J., Moskal, P., & Dziuban, C. (2005). Educating the next generation.

21. Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling*:* a Multidisciplinary Journal, 6(1), 1–55. https:/doi.org/ 10.1080/10705519909540118

22. Jordan, K. (2014). Initial trends in enrolment and completion of massive open online courses. Learning, 15(1). Retrieved from http://www.irrodl.org/index.php/irrodl/article/view/1651. https:/doi.org/10.19173/irrodl.v15i1.1651

23. Kaplan, A. M., & Haenlein, M. (2016). Higher education and the digital revolution: About MOOCs, SPOCs, social media, and the Cookie Monster. Business Horizons, 59(4), 441–450. https:/doi.org/10.1016/j.bushor.2016.03.008

24. Khan, I. U., Hameed, Z., Yu, Y., Islam, T., Sheikh, Z., & Khan, S. U. (2018). Predicting the acceptance of MOOCs in a developing country: Application of Task-Technology Fit Model, Social Motivation, and self-determination Theory. Telematics and Informatics, 35(4), 964–978. https:/doi.org/10.1016/j.tele.2017.09.009

25. Kline, R. (2011). Principles and practice of structural equation modeling (3rd ed). New York, NY: Guilford Press.

26. Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use Information Technology? A critical review of the technology acceptance model. Information and Management, 40(3), 191–204. https:/doi.org/10.1016/S0378-7206(01)00143-4

27. Ma, L., & Lee, C. S. (2019). Investigating the adoption of MOOCs: A technology–user–environment perspective. Journal of Computer Assisted Learning, 35(1), 89–98. https:/doi.org/10.1111/jcal.12314

28. Mohamad, M., & Rahim, M. K. I. A. (2018). Factors influencing MOOCs continuance intention in Malaysia: A proposed conceptual framework. Journal of Humanities, Language, Culture and Business, 2(7), 61–72.

29. Mulder, F., & Janssen, B. (2013). Opening up education. Trend report. Open Educational Resources, 36–42.

30. Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed). New York, NY: McGraw-Hill.

31. Ottenbreit-Leftwich, A., Liao, J. Y. C., Sadik, O., & Ertmer, P. (2018). Evolution of teachers' technology integration knowledge, beliefs, and practices: How can we support beginning teacher's use of technology? Journal of Research on Technology in Education, 50(4), 282–304, https:/doi.org/10.1080/15391523.2018.1487350

32. Palos-Sanchez, P., Saura, J. R., Reyes-Menendez, A., & Esquivel, I. V. (2018). Users' acceptance of location-based marketing apps in tourism sector: An exploratory analysis. Journal of Spatial and Organizational Dynamics, 6(3), 258–270.

33. Park, S. (2009). An Analysis of the Technology Acceptance Model in Understanding University Students' Behavioural Intention to Use e-learning. Education Technology & Society, 12(3), 150–162.

34. Park, S. H., & Ertmer, P. A. (2007). Impact of problem-based learning (PBL) on teachers' beliefs regarding technology use. Journal of Research on Technology in Education, 40(2), 247–267. https:/doi.org/10.1080/15391523.2007.10782507

35. Reich, J. (2015). Rebooting MOOC research. Science, 347(6217), 34–35. https:/doi.org/10.1126/science.1261627

36. Reich, J., & Ruipérez-Valiente, J. A. (2019). The MOOC pivot. Science, 363(6423), 130–131. https:/doi.org/10.1126/science.aav7958

37. Sandeen, C. (2013). Integrating MOOCs into traditional higher education: The emerging "MOOC 3.0" era. Change*:* the Magazine of Higher Learning, 45(6), 34–39. https:/doi.org/10.1080/00091383.2013.842103

38. Saunders, M. N. (2011). 'Research Methods for Business Students', 5/e. India: Pearson Education.

39. Sun, Y., & Jeyaraj, A. (2013). Information Technology adoption and continuance: A longitudinal study of individuals' behavioral intentions. Information and Management, 50(7), 457–465. https:/doi.org/10.1016/j.im.2013.07.005

40. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal filed

studies. Management Science, 46(2), 186–204. https:/doi.org/10.1287/mnsc.46.2.186.11926

41. Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User acceptance of Information Technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https:/doi.org/10.2307/30036540

42. Wani, T. A., & Ali, S. W. (2015). Innovation diffusion theory: Review and scope in the study of adoption of smartphones in India. Journal of General Management Research, 2(2), 98–115.

43. 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(February), 221–232. https:/doi.org/ 10.1016/j.chb.2016.10.028

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/10.1016/j.chb.2016.10.028

45. Yi, M. Y., & Hwang, Y. (2003). Predicting the use of web-based information systems: Self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. International Journal of Human-Computer Studies, 59(4), 431–449. https:/doi.org/10.1016/S1071-5819(03)00114-9

46. Zhou, G., & Xu, J. (2007). Adoption of educational technology: How does gender matter? International Journal of Teaching and Learning in Higher Education, 19(2), 140–153.

Appendix 1: Technology Acceptance Model (Davis, 1989)