UNDERSTANDING THE DRIVERS AND BARRIERS TO TEACHER ADOPTION OF MOOCS IN HARYANA

Reetu Choudhary
Research Scholar, Department of Commerce
Chaudhary Bansi Lal University, Bhiwani, Haryana
E-mail: reetug65@gmail.com

Preeti Devi
Assistant Professor, Department of Commerce
Chaudhary Bansi Lal University, Bhiwani, Haryana
E-mail: preeti.commerce@cblu.ac.in

HSB Research Review
Vol. 20 (1&2)
Jan - June 2025
July - Dec. 2025
ISSN: 0976-1179
31-44
The current issue and full text archive of this journal is available at https://www.gjust.ac.in/Page/Index_2_cap/HSB-Research-Review/3348

ABSTRACT

This study employs a modified Technology Acceptance Model (TAM) that provides an insight on acceptance of MOOCs in Haryana from the point of view of teachers. By combining multidimensional constructs, the research aims to identify the factors and effects on adoption intention of MOOCs. The survey was conducted to 287 educators, and the analysis conducted with the help of Partial Least Squares Structural Equation Modelling (PLS 4.0). All hypotheses are supported by the empirical findings demonstrating that the external factors and perceived variables have a statistically significant impact on the intentions to adopt MOOCs. Being the first empirical study to be carried out in Haryana and focusing on the teacher point of view, the research provides essential information about the processes that make MOOCs acceptance a reality. The results outline the main driving factors, limitations and the practical implications of the research on the improvement of digital pedagogy among the faculty of Haryana.

Keywords: TAM, MOOCs, Teacher's Intention, PLS 4.0, Task Technology Fit

INTRODUCTION

In the sphere of education, online learning has emerged as an important technological change, characterized by its rapid diffusion, and by its skilful use of digital technologies in order to simplify the delivery of educational information. Instructional structures and pedagogical practices have therefore undergone a radical change in respect to the worldwide penetration of technology. By connecting students worldwide and removing geographical barriers, technology in education fosters a global learning environment where students can access course materials from anywhere at any time. Massive Open Online Courses (MOOCs) is in demand by the result of technology's expanding role in online education. MOOCs are currently the most popular way of delivering online courses in the world today. Such programs are inclusive of various platforms and are intended to be able to accommodate an equally unlimited number of participants. MOOCs have experienced a consistent rise in popularity since they were first introduced in 2008; by 2024, 220 million students had registered in at least one MOOC, covering around 6,850 courses. They are offered on well-known websites like Coursera, edX and Udacity.

It is not a common practice in modern education to get instructor who is unfamiliar with massive open online courses (MOOCs); even rarer is the finding of an educator who is not now planning to use these materials in blended learning designs or who does not plan to adopt them in the near future. It has been shown by empirical research that MOOCs deepen the instructional strategies of teachers (Sarnou & Schug, 2025; Garrison & Kanuka, 2004; Morris, 2014; Sharpe *et al.,* 2006). It is note that the analytical overview of 35 years of scholarly publications revealed that MOOCs became an issue in the period between 2010 and 2014 (Richter & Naidu, 2016). MOOCs have gained scholarly interest over the last several years with respect to integrating them into blended learning and how they could enhance classroom courses taught traditionally. MOOCs can certainly become a useful supplement resource in helping teachers as well as students realize their overall goals. The modern digital and web technologies offer many transformational opportunities to the Indian higher education system and thus they improve e-teaching learning environment (Chomal & Saini, 2013). Technological development has increased the growth of new disruptive online pedagogical models, and thus made it possible to instruct large groups of undergraduate students at significantly lower fiscal cost and MOOC is one of such disruptive models (Joseph & Nath, 2013). Massive open online course (MOOC) is a term commonly referred to in the singular form to describe this growing environment of online education. Its growing popularity can be linked to various developments concurrently, such as those in the technology sector, such as improved mobile networks, the spread of inexpensive laptops, tablets and smart phones, the increased availability of broadband and cloud storage solutions, increased computing power, and the rise of social media. The open courseware program was the first initiated by the Massachusetts Institute of Technology (MIT) and aimed to make education more affordable and accessible, which was later to be adopted by many universities and institutions across the globe, including those in India (Rao *et al.,* 2015). In last few years, In India participation in MOOCs has grown at a rapid pace. As a reaction to this development and the corresponding call to ensure inclusive education, both the government and non-government organizations have started offering MOOCs on services such as mooKIT, NPTEL, IITBX, and SWAYAM (Chauhan, 2017). In the case of higher education, Gross Enrolment Ratio (GER) has been steadily increasing to around 2228% by 2022; the National Education Policy 2020 has set a target of 50 percent GER by 2035. India has a number of obstacles to overcome in order to guarantee universal access to high-quality education. India has to research intensively on modern and alternative ways of pedagogy even as it simultaneously identifies the best ways through which it can introduce its student body to flourish. It is only through this type of strict questioning that the country can hope to be able to attain the truly sustainable education. Despite the tempting flexible + affordable nature of MOOCs, thus making it accessible to the process of lifelong and sustainable learning, one must question the numerous elements that are at play in inspiring the educators to integrate the courses in their teaching plan. Jose State University carried out three different courses where the Udacity material was included as an example of blended learning that includes MOOCs. This program has highlighted why continued student engagement is very important in achieving academic success as illustrated by Firmin *et al.,* 2014. A Coursera MOOC on "Machine Learning" was utilized at Vanderbilt University to test another example. Students gave mostly positive feedback, with many expressing gratitude for the freedom to study at their own speed (Bruff *et al.,* 2013).

MOOCs and Their Benefits in the Current Educational Landscape

The idea behind MOOCs is the combination of multiple components, including openness, knowledge sharing, mass communication, and e-learning, which developed from distance learning. MOOCs are described by Andersen and Ponti (2014) as "structured and organized open educational resources in the form of a course with participation from educators or organizers." Openness, a crucial component of MOOCs, is essential for encouraging creativity and innovation, according to Siemens (2013). In contrast to traditional courses, MOOCs necessitate the additional skills of platform specialists, IT specialists, instructional designers, and videographers (Wikipedia, 2020). Compared to traditional teaching and learning methods, MOOCs' openness also calls for a different approach to accreditation and assessment. MOOCs provide an appropriate solution for e-learning, flipped classroom and open education teaching in the context of globalized education and the difficulties presented by financial constraints (Yuan & Powell, 2013). The majority of MOOCs are free and available to anybody with internet access, claims Ryan (2013). Learning can take place whenever and wherever it is most convenient for the individual. According to a survey of accounting professors from different Spanish universities, MOOCs are generally seen favourably, with respondents emphasizing their adaptability and capacity to encourage self-directed learning (Delgado *et al.*, 2016). MOOCs are a good way to teach entrepreneurship because they facilitate group learning and support students' emotional growth, according to Atabi and DeBoer (2014). This study specifically focuses on the use of MOOCs educators rather than learners in this study. The study makes use of the term's "teacher" and "educator" interchangeably.

Relevance of the Study in India

Developing nations like India encounter struggled with providing everyone access to high-quality education because of its tight budget, lack of faculty, and poor physical infrastructure. Although these problems are not specific to India, the size and unique conditions of the nation make its difficulties especially formidable. Therefore, it is essential to investigate how MOOCs might be able to overcome these constraints and improve blended learning. Numerous initiatives have been started in an effort to increase access to education in rural parts and to increase the development and uptake of MOOCs by universities of India. Given the many advantages MOOCs provide, there is an urgent need to incorporate them into the educational system given India's rapid technological advancements and expansion of internet access. Despite being introduced in 2008, MOOC adoption in India didn't really take off until 2012. Nevertheless, MOOCs have not yet matured enough in India's blended learning landscape to be completely embraced by the country's mainstream educational system. MOOCs are not yet formally incorporated into instructional strategies. India still has a long way to go in this area, claim Chakravarty and Kaur (2016). These programs' efficacy and success largely depend on educators embracing them, which will inspire students to do the same, making them more effective than conventional educational systems and possibly transforming the field of education (Devgun, 2013). The widespread and affordable nature of MOOCs has the potential to revolutionize the current educational approaches in India if properly implemented. This study is being carried out in the Indian context because of the government's strong support for MOOCs and the need to comprehend the factors influencing their adoption for blended learning.

LITERATURE REVIEW

Most preceding investigations into MOOCs have predominantly focused on learner perspectives or the adoption of these courses through the lens of the TAM (Kulal *et al.*, 2025; Shao, 2018; Wu & Chen, 2017; Zhou, 2016; Yang & Su, 2017). Only a few research have additionally examined instructional tactics. There are numerous benefits of utilizing a blended approach with MOOC content, according to Ghadiri *et al.* (2013), who investigated the flipped teaching style. Similarly, Phatak (2015) outlined a blended MOOC paradigm to promote high-quality engineering education and discussed the role of teachers in implementing a "flipped classroom" teaching model. From the perspective of the teachers, this issue has only been the subject of a few research (Liyanagunawardena *et al.*, 2013). This is true even though teachers are essential to the adoption of MOOCs because they act as facilitators, interacting with students at every stage of the learning process. Additionally, they may have an impact on how students perceive MOOCs (Tseng *et al.*, 2019). The function of MOOCs in teachers' professional development has also been investigated by some researchers. For instance, because MOOCs are open, free, and flexible, Mabuan (2018) saw them as a useful and efficient tool for professional development. In a similar vein, Koukis and Jimoyiannis (2019) talked about how MOOCs can help teachers continue to advance their careers.

A number of studies have been conducted to establish the intentions of educators with regard to adopting technology in a teaching context- (a) Tseng *et al.* (2019) used the "Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2)" in the study to identify the factors affecting the adoption of MOOCs: price value, the facilitating conditions, and performance expectancy; (b) Wright (2014) utilized the efficacy theory and diffusion of innovation theory to explain the motivation behind online teaching; (c) Nikou and Economides (2019) examined the behaviour intentions of teachers to use the mobile-based assessment tools, thus facilitating a wider insight into the use of technology in the context of instruction and assessment; (d) Kujur *et al.* (2019) identified a positive and strong correlation between the adoption and the actual use of educational technologies by educators although it was not MOOC-centric; (e) Li and Wong (2019) presented case studies that reported the use of MOOCs at the campus level.

Technology Acceptance Model (TAM) (Davis, 1989) used for this investigation among the numerous acceptance models found in the literature for a number of reasons. First, TAM is a good model for this study because it incorporates important elements like perceived utility and perceived ease of use, relevant to how people behave when embracing the use of IT or information systems. Second, research on learners' and other users' acceptance of MOOCs has made extensive use of TAM (Hsu *et al.*, 2018; Wu & Chen, 2017). Scholars have slightly changed TAM in these studies by adding two elements that are specific to MOOCs: social influence and content quality. One of the main peculiarities of MOOCs in comparison with other ICT-based learning tools is that they are the opportunities to learn in groups, flexible access, different degrees of openness, and the delivery of high-quality content.

This study focuses on instructors' acceptance of MOOCs and considers current MOOCs rather than ones that were developed by the teachers. The researchers note, based on existing evidence, that MOOCs are typically used by teachers as a supplement to traditional classroom instruction to support successful blended learning, which includes flipped classrooms and other educational technology. Thus, the examination of MOOC adoption from the perspective of instructors becomes essential. In the Indian context, there is an apparent lack of serious empirical literature to examine the perception of MOOCs by instructors. This study is aimed at filling that gap. Although previous studies have used Technology Acceptance Model (TAM) to view MOOCs through the perspectives of learners, the present study uses TAM as the key model to investigate factors that determine the acceptance and use of MOOCs by instructors. The purpose of this paper is to examine the objectives of educators in Indian educational institutions regarding the usage of MOOCs for blended learning.

HYPOTHESES DEVELOPMENT

Technology Acceptance Model

Among the whole range of theories related to the process of adopting technology, TAM is often considered as one of the widely and highly used theory in studying the process of information systems acceptance by individuals. TAM is first used by Davis (1985) and basis of this theory is Theory of Reasoned Action proposed by Ajzen (1980); it focuses on two key predictors of system acceptance; perceived usefulness and ease of use. The model has been widely used in the research of educational technology. To use an example, Rubaai and Hashim (2019) examined the acceptance of MOOCs by lecturers to teach English as a second language. In the same way, Chan *et al.* (2018) investigated behavioural intentions to use cloud-based tools in MOOCs, which was based on Zhang *et al.* (2017) who applied TAM to investigate the implementation of e-learning. Moreover, another framework was used in conjunction with TAM as Wu and Chen (2017) examined the intention of learners to persist in using MOOCs.

Social Influence

It has been demonstrated that social influence is the key factor influencing the intentions of teachers to use MOOCs (Tseng *et al.*, 2019). It has an impact on their desire to keep using these courses as well (Wu & Chen, 2017). As a matter of fact, a survey of teachers in secondary schools to adopt digital learning environments by Pynoo *et al.* (2011) established that social influence was more significant than most of the other factors. Peer pressure has also been found to have a strong influence on the choices of people on new technologies (Rogers, 2003; Venkatesh *et al.*, 2003), and social networks have a powerful influence on the adoption of new information technologies (Hossain and de Silva, 2009). Learning is social by nature and necessitates peer interaction and support, claim Lee *et al.* (2017). In light of this, the researchers put forth the following theory:

H_1: Attitudes regarding MOOC use are positively impacted by social influence.

Perceived Usefulness

According to Davis (1989), employing systems or technology, like MOOCs, can improve task efficiency. Al-Shami *et al.* (2018) provided empirical evidence that the adoption of MOOCs is positively correlated with perceived usefulness.

Teo *et al.* (2008), building on the TAM framework, discovered that when analysing pre-service teachers' attitudes toward using computers in the classroom, perceived usefulness was a significant factor. Teo *et al.* (2019) found in a subsequent study that the intention to utilise Web 2.0 tools in teaching is directly influenced by perceived usefulness. Furthermore, a person's decision to enrol in a technical course is greatly influenced by the perceived advantages of the course (Ray *et al.*, 2019). The successful adoption of e-learning technologies has been largely attributed to perceived usefulness (Bhuasiri *et al.*, 2012). In light of this, the researchers put forth the following hypothesis:

H_2: Perceived usefulness has a positive impact on the attitude towards using MOOCs.

Perceived Ease of Use

According to Davis (1989) it means "the degree to which a user expects a system or technology to be effortless and simple to use." The perceived ease of use and perceived efficacy of a system are two essential components of TAM. The intention to continue using MOOCs depends on both perceived usefulness and ease of use, with perceived usefulness serving as a mediator for the influence of perceived ease of use (Wu & Chen, 2017). Numerous studies have examined the factors influencing the adoption of MOOCs, including those grounded in institutional theory. These studies' conclusions show a positive correlation between MOOC adoption and ease of use (Shami *et al.*, 2018; Hong *et al.*, 2009). When analysing pre-service teachers' attitudes toward using computers in the classroom, ease of use was found to be a significant determinant in addition to other factors (Teo *et al.*, 2008). Perceived usefulness can be influenced by perceived ease of use, according to research. In light of this, the Hypothesis is:

H_3: Perceived ease of use has positive impact on the attitude using MOOCs.

Content Quality

Researchers, MOOC creators, and academicians have frequently neglected the quality component of MOOC platforms. To help MOOC developers produce content that encourages more students to sign up for and finish courses, it is essential to comprehend these quality factors (Yang *et al.*, 2017). One important component of online learning and e-learning systems is the calibre of the courses or content (Molla & Licker, 2001). It has been demonstrated that the intention to use technology for teaching is significantly influenced by content knowledge (Teo *et al.*, 2019). Furthermore, studies show that a person's online behaviour is positively impacted by the Caliber of a course (Saeed *et al.*, 2003). Along with excellent learning resources from renowned universities collaborating with major online course platforms, MOOCs provide the convenience of flexible study schedules and locations. De Jong *et al.* (2020) provides recommendations for choosing and assessing content quality. Hence it hypothesized as under:

H_4: Content quality has positive impact on attitude towards using MOOCs.

Task Technology Fit (TTF)

It states that people will only embrace a technology if its features align with their tasks. When a technology is not properly matched with the work at hand, people cannot increase their performance, even though they may perceive it as helpful (Qashou, 2022). Because online learning technologies are often designed to enable users to efficiently complete a range of learning-related tasks, task-technology fit is crucial for examining online learning acceptability by integrating different viewpoints on the fit based on technology. One way to assess task technology fit is to consider how satisfied users are with how well a system's functionalities satisfy their needs (Goodhue *et al.*, 1995; Bere, 2018; Rahmi *et al.*, 2020). According to Hizam *et al.* (2021), the task-technology fit is the relationship between the functioning of the online technology system, personal capabilities, and task needs. It can be hypothesised as under:

H_5: Task Technology Fit has positive impact on teacher’s attitude towards MOOC.

Attitude and Intention to Adopt MOOCs

One of the best indicators of a person's intention to use technology is their attitude, a psychological construct (Teo & Zhou, 2014). According to Wu and Chen (2017), a person's attitude toward MOOCs indicates how they feel about using them, whether positively or negatively. When incorporating web technology into teaching practices, there is positive relationship between self-efficacy and attitudes toward web-based instruction (Lee and Tsai, 2010). Ajjan and Hartshorne (2008) found that faculty members' intentions to use Web 2.0 in the classroom are strongly predicted by their attitudes and perceived behavioural control. It follows that emphasizing the advantages of MOOCs, like improved learning opportunities, can help to promote a positive attitude toward them (Cha & Park, 2017). In light of this, the researchers suggest following hypothesis:

H_6: A positive attitude towards MOOCs impact intention to adopt MOOCs.

A conceptual research model is used to present the hypotheses derived from the literature review (Figure 2). The purpose of this suggested model is to investigate how instructors in higher education institutions (HEIs) plan to adopt MOOCs. As explained in the following sections of the paper, by hypothesis testing using structural equation modelling (SEM).

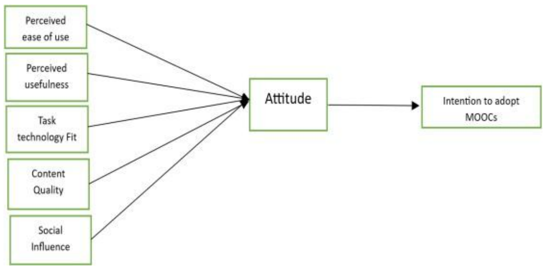

Figure 1: Conceptual Model

Source: Author's Own

RESEARCH METHODOLOGY

Sampling Design

Few studies were explicitly designed to collect responses from educators; therefore, the researchers created their own questionnaire based on previous, relevant studies (Wu & Zhang, 2014; Wu & Chen, 2017; Kim *et al.*, 2010). These studies served as the basis for the questions that were changed to fit the needs of this investigation. In order to address constructs that were not addressed by the adopted instruments, some additional questions were added to the survey instrument. The questionnaire is divided into two parts: the first part asks respondents about their demographics, and the second part has questions that measure the constructs of the proposed theoretical model. The responses are recorded for the observed variables of each construct using a five-point Likert scale, which goes from 1 (strongly disagree) to 5 (strongly agree). The first section contains four demographic questions, and the second section includes 21 questions to measure 6 constructs.

Data Collection and Sample Size

Teachers from higher education institutions (HEIs) in Gurugram division of Haryana, an urban area in Northen India, are the study's participants. The majority of the instructors are knowledgeable about MOOCs and instruct technical courses. Table 1 displays the profile of the responders. Teachers employed by Haryana educational institutions make up the target population, and respondents were chosen at random. There was no personal administration involved; data was gathered online using Google Forms. Although 312 responses were initially received, some of them were ambiguous or lacking information. 287 appropriate responses were ultimately included in the study and used for model evaluation after these invalid responses were eliminated.

DATA ANALYSIS

The relationship between independent factors that influence the adoption of MOOCs-like PEoU, PU, TTF, content quality, social influence is examined using PLS-SEM 4.0. The assumption of multivariate normality is not necessary for PLS-SEM since it is a non-parametric technique. The data's multivariate normality was evaluated using the WebPower analysis tool (Zhang & Yuan, 2018). PLS-SEM's greater predictive relevance over CB-SEM also played a role in the choice to employ it (Hair *et al.*, 2019). The Constant PLS algorithm in SmartPLS 4 software was used to calculate the model because it was made up of only reflective constructs (Becker *et al.*, 2023). By using a correction factor, PLS offers accurate estimates of construct correlations and indicator loadings in a common factor model (Dijkstra & Henseler, 2015).

EMPIRICAL RESULTS

Common Method Bias

Common method bias (CMB) was evaluated in the data prior to model estimation. Studies that use instruments with similar scales to measure latent variables may result in CMB. Instead of referring to the structural relationships within the model, it refers to bias introduced by the measurement technique. Full collinearity analysis was carried out because the variables in this study were assessed using a 5-point Likert scale. In this analysis, a random endogenous variable is compared to the constructs' inner VIF values. A possible Common Method Bias problem is indicated if any VIF is greater than 3.3 (Kock & Lynn, 2012). Factors like survey instructions that encourage respondents to provide answers in ways that are socially acceptable can lead to shared common variance (Kock, 2015). It can be said that there is no CMB issue because all of the inner VIF values for the variables in this investigation were less than 3.3.

Measurement Model Assessment

Besides testing the internal consistency, convergent and discriminant validity of the constructs, indicator reliability is also scrutinised during evaluation of the measurement model. At a loading level of 0.707 or more, the reliability of indicators is regarded to be reasonable as it has been reported by Chin (2010) and Hair *et al.* (2019). Composite reliability, which is very liberal in its threshold, and Cronbach, which is conservative in nature, are all used in measuring construct reliability. According to Dijkstra and Henseler (2015), the real construct reliability will be most appropriately reflected by the mid-value of these two measures, which is the value of Rho_a (PA). Additionally, Hair *et al.* (2022) state that construct reliability can be considered satisfactory if the estimates of reliability lie within the 0.70-0.95 interval. Hair *et al.* (2010) go on to posit that an average variance extracted (AVE) of a construct of one that is higher than one-half indicates convergent validity, and an AVE that is higher than 0.50 implies that the construct accounts for more than half of the variance in the measures of it. Discriminant validity is the ability of a construct in the structural model to be separated out of other latent variables. According to Henseler *et al.* (2015), the Heterotrait-Monotrait (HTMT) ratio is a more effective measure of discriminant validity compared to the previous Fornell- Larcker criterion (Fornell and Larcker, 1981). This analysis therefore takes the HTMT measure. In constructs of conceptual difference, when HTMT value is under 0.85, the constructs are said to have discriminant validity. The statistical significance of the deviation of the value of the statistic HTMT against the nominal value of 1.00 is determined using bootstrapping. The results of the reliability and convergent validity evaluation with factor loadings are provided in Table 2; Table 3 shows the findings of the discriminant validity evaluation based on the HTMT criterion. The results affirm that all the constructs in the model have the suggested reliability and validity standards.

Structural Model Assessment

The structural model's analysis started by looking at the inner VIF values in order to address any possible multicollinearity problems. All of the inner VIF values were less than 5 after checking the model variables for any notable multicollinearity issues (Hair *et al.,* 2017; James *et al.,* 2013). Coefficient of determination (R^2), applied to assess model's ability to explain the variance. The path coefficients were computed prior to using bootstrapping to test the significance of the structural relationships. Furthermore, each predictor construct's effect size (f^2) was calculated.

Table 5 displays the effect size (f^2), P- value and T-values, while Table 4 shows the explanatory power (R^2) with values greater than 0.25. The degree to which the independent variables affect the dependent ones is shown by the f^2 values. Cohen (1988, 2016) states that an effect size of 0.02 is small, 0.15 is medium, and 0.35 is large. Perceived usefulness on intention and perceived ease of use on perceived usefulness both show a sizable effect size. The PLS algorithm in SmartPLS 4 was used to test the model and evaluate the hypotheses. In order to assess the statistical significance of the coefficients, 10,000 subsamples were bootstrapped. Figure 2 shows the results of the model estimation with 6 hypotheses, and Table 5 displays the results of the structural model, including total effects. Significant direct coefficients were found for 4 hypotheses except H_2 and H_5. In terms of the intention to use MOOCs, the following hypotheses received significant support: H_1 ($\beta = 0.222$, $\rho = 0.003$), H_2 ($\beta = 0.406$, $\rho = 0.000$), H_3 ($\beta = 0.123$, $\rho = 0.015$), H_4 ($\beta = 0.106$, $\rho = 0.036$), H_6 ($\beta = 0.718$, $\rho = 0.000$). Hypotheses H_1, H_3, H_4, H_6 therefore empirically supported.

Table 1: Respondents Demographic Profile (N=287)

	Group	Frequency	Percentage
Gender	Male	129	44.98%
	Female	158	55.05%
Age	18-25	9	3.24%
	26-40	219	76.30%
	41-60	59	20.56%
Qualification	Post-graduation and NET	204	71.08%
	PG, NET and Ph.D.	80	27.87%
	Others	3	1.04%
District	Gurugram	101	35.9%
	Mahendragarh	96	33.45%
	Rewari	90	31.35%”

Source: Primary Data

Table 2: Validity and Reliability

	Factor Loadings	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
ATT	0.942	0.879	0.896	0.925	0.805
ATT1	0.853				
ATT2	0.895				
ATT3					
CQ	0.616	0.839	2.463	0.834	0.635
CQ1	0.984				
CQ2	0.747				
CQ3					
Intn	0.896	0.877	0.881	0.924	0.802
Intn1	0.904				
Intn2	0.887				
Intn3					
PEoU	0.879	0.866	0.868	0.918	0.789
PEoU1	0.902				
PEoU2	0.884				
PEoU3					
PU	0.822	0.856	0.900	0.898	0.687
PU1	0.857				
PU2	0.821				
PU3	0.815				
PU4					
SI	0.814	0.833	0.859	0.886	0.659
SI1	0.846				
SI2	0.821				
SI3	0.765				
SI4					
TTF	0.842	0.784	0.829	0.869	0.689
TTF1	0.762				
TTF2	0.882				
TTF3					

Notes: ATT = Attitude, CQ = Content Quality, Intn = Intention to Adopt MOOCs, PEoU = Perceived Ease of Use, PU= Perceived Usefulness, SI= Social Influence, TTF= Task Technology Fit

Source: Authors' Own

Table 3: HTMT Discriminant Reliability

	ATT	CQ	Intn	PEoU	PU	SI	TTF
ATT							
CQ	0.232						
Intn	0.688	0.349					
PEoU	0.586	0.346	0.645				
PU	0.262	0.522	0.324	0.657			
SI	0.544	0.243	0.703	0.598	0.267		
TTF	0.379	0.298	0.688	0.422	0.281	0.533	

Notes: ATT = Attitude, CQ = Content Quality, Intn = Intention to Adopt MOOCs, PEoU = Perceived Ease of Use, PU= Perceived Usefulness, SI= Social Influence, TTF= Task Technology Fit

Source: Authors' Own

Table 4: R Square

	R-Square	R-Square Adjusted
ATT	0.362	0.351
Intn	0.374	0.372

Notes: ATT= Attitude, Intn= Intention to Adopt MOOCs

Source: Authors' Own

Table 5: Path Coefficient and Hypothesis Testing

Hypothesis		Path Coefficients	Sample Mean (M)	F^2	T Statistics	P Values
H1	**SI →ATT**	0.239	0.242	0.057	3.250	0.001
H2	**PU → ATT**	-0.118	-0.109	0.013	1.754	0.080
H3	**PEoU →ATT**	0.376	0.368	0.111	4.767	0.000
H4	**CQ → ATT**	0.162	0.170	0.029	2.404	0.016
H5	**TTF → ATT**	0.071	0.070	0.006	1.371	0.170
H6	**ATT →Intn**	0.612	0.612	0.598	12.453	0.000

Notes: ATT = Attitude, CQ = Content Quality, Intn = Intention to Adopt MOOCs, PEoU = Perceived Ease of Use, PU= Perceived Usefulness, SI= Social Influence, TTF= Task Technology Fit

Source: Authors' Own

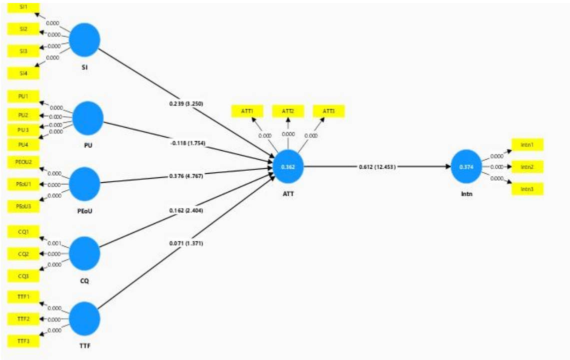

Figure 2: SEM Results

Source: PLS-SEM Output

DISCUSSION

Social influence has a significant impact on attitudes toward using MOOCs, as demonstrated in Figure 2 and Table 5, suggesting that other teachers' pedagogical approaches are important in a teaching environment. Attitudes regarding MOOC use are also strongly influenced by perceived ease of use. However, attitudes regarding the use of MOOCs are not significantly impacted by perceived usefulness. The attitude toward using MOOCs is significantly influenced by the quality of the content. Finally, though not the least, the hypothesis is supported by the empirical fact that attitudes towards MOOCs use have a strong impact on the intentions to use MOOCs in the context of blended learning. The joint effect of the perceived usefulness, perceived ease of use, content quality, and social influence explains 83 % of the variance in adoption intentions. However, as it has been mentioned above, not all of these antecedents have statistically significant impact on adoption intentions, and others do not.

Theoretical Implications

The current study is a critical evaluation of the current adoption of the Massive Open Online Courses (MOOCs) among faculty in the institution of higher learning (HEIs), and more so the institution of higher learning in India. To establish a profound theoretical basis of a proposed model, two additional constructs were incorporated into the canonical Technology Acceptance Model (TAM). Empirical analysis of the model supported the fact that the quality of MOOC content has a pronounced effect on the intention to adopt, which is in line with the previous empirical studies (Chauhan, 2017; Li *et al.*, 2012; Teo *et al.*, 2019; Yang *et al.*, 2017). Thus, the delivery of high-quality content becomes one of the key conditions of successful MOOC development. The research also supports the presence of antecedent research (Arima *et al.*, 2019; Pynoo *et al.*, 2011; Tseng *et al.*, 2019; Wu and Chen, 2017) as it proves that the social influence is a salient factor of the adoption intention. In addition, the findings show that positive attitudes toward MOOCs are developed based on their attitudes toward them being easy to use and this, in turn, influences future intentions to use these tools (Shami *et al.*, 2018; Hong *et al.*, 2009; Wu and Zhang, 2014; Wu and Chen, 2017). Interestingly, the teaching experience does not seem to have a strong influence on the intention of instructors to use MOOCs, which contradicts the previous assumptions according to which teaching experience could be the mediating variable in the decision to adopt MOOCs.

Practical Implications

The results of this research provide a definite and practical recommendation to higher education institutions (HEIs), policymakers and creators of MOOC platforms who wish to increase the level of faculty adoption of MOOCs in blended learning settings. Instead of viewing MOOCs as supplements, institutions can integrate them into the normal teaching processes.

First, social influence should be used by institutional leadership as it was found to be a powerful predictor of teacher’s attitudes. HEIs can implement it by designating MOOC champions or early-adopters of MOOCs in departments in formal capacities that have shown to successfully integrate MOOCs in the classroom. MOOC usage can be normalized and psychological resistance among reluctant faculty reduced by holding regular peer-led workshops, teaching showcases and internal communities of practice.

Second, perceived ease of use is important in determining attitudes and therefore institutions ought to offer practical technical education as opposed to general orientation. As an illustration, brief and practical training modules, which involve the incorporation of MOOC videos, quizzes and discussion forums into the current Learning Management Systems (LMS) can explicitly reduce the adoption barriers. Faculty in their initial semester of integrating MOOCs should be provided with dedicated instructional design and IT support units.

Third, the high importance of content quality means that the adoption of faculty is based not on quantity but on relevance and pedagogical fit.

MOOC repositories that are specific to the discipline should be curated by policymakers and academic administrators with high-quality courses being prioritized based on Indian curricula, learning outcomes and accreditation standards. Contextual fit can also be enhanced by incentivizing faculty to localize MOOC content.

Fourth, task technology fit was not significant but its practicality is of utmost importance. Institutions must promote faculty to use MOOCs selectively to tasks in which they can have the greatest value, such as teaching foundational theory, in a flipped classroom, remedial learning or a skill course, but not to directly replace courses. Lastly, policymakers can use these findings to implement as an institutional reward system, including the inclusion of MOOC-integrated courses in workload models, promotion policies, teaching performance prizes. These forms of institutional support indicate institutional commitment and turn MOOCs into a long-term pedagogical approach. In general, this paper indicates that the implementation of MOOCs can be successful only with a coordinated ecosystem strategy that consists of peer pressure, technical assistance, content moderation and institutional incentives instead of depending on the personal motivation of teachers.

LIMITATIONS AND FUTURE RECOMMENDATIONS

Although this research is comprehensive and wide-ranging, the researchers do not assert that it is exhaustive. The research has certain limitations. First of all, because it was carried out in Haryana, the results might not be generalizable to other areas. Results from a similar study with a national sample might be more broadly applicable. The gender gap in India's teaching workforce, which is also represented in the study's demographics, is another drawback. Future studies might concentrate on variations in MOOC adoption by gender. It would also be beneficial to investigate additional factors influencing teachers' adoption of MOOCs; a qualitative approach could be employed for this. Another possible line of inquiry is the use of probabilistic neural networks to predict student learning performance through MOOCs, as proposed by Arora and Saini (2013). Although this study focuses on the viewpoint of educators, study into the opinions of students and higher education administrations could also provide valuable information for future research.

REFERENCES

Ajjan, H., & Hartshorne, R. (2008). Investigating faculty decisions to adopt Web 2.0 technologies: Theory and empirical tests. *The Internet and Higher Education*, *11*(2), 71-80.

Ajzen, I. (1980). *Understanding attitudes and predicting social behavior.* Englewood cliffs. Prentice Hall.

Al-Atabi, M., & DeBoer, J. (2014). Teaching entrepreneurship using massive open online course (MOOC). *Technovation*, *34* (4), 261-264.

Al-Rahmi, A. M., Shamsuddin, A., & Alismaiel, O. A. (2020). Task-technology fit model: The factors affecting students' academic performance in higher education. *Universal Journal of Educational Research*, *8*(12), 6831-6843.

Al-Shami, S. A., Sedik, S., Rashid, N., & Hussin, H. (2018). An empirical analysis of MOOC adoption from the perspective of institutional theory. *Journal of Advanced Research in Dynamical and Control Systems*, *10*(6), 332-343.

Andersen, R., & Ponti, M. (2014). Participatory pedagogy in an open educational course: Challenges and opportunities. *Distance Education*, *35*(2), 234-249.

Arima, S., Miyakita, G., Yasui, M., & Okawa, K. (2019, October). *Enhancing educators' social presence in MOOCs: Design of daily video blog*. In 2019 IEEE Learning With MOOCS (LWMOOCS) (pp. 36-41). IEEE.

Arora, N., & Saini, J. R. (2013). A fuzzy probabilistic neural network for student's Academic performance prediction *International Journal of Innovative Research in Science, Engineering and Technology*, *2*(9), 4425-4432.

Becker, J. M., Cheah, J. H., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2023). PLS-SEM's most wanted guidance. *International Journal of Contemporary Hospitality Management*, *35*(1), 321-346.

Bere, A. (2018). Applying an extended task-technology fit for establishing determinants of mobile learning: An instant messaging initiative. *Journal of Information Systems Education*, *29*(4), 239-252.

Bhuasiri, W., Xaymoungkhoun, O., Zo, H., Rho, J. J., & Ciganek, A. P. (2012). Critical success factors for e-learning in devel- oping countries: A comparative analysis between ICT experts and faculty. *Computers and Education*, *58*(2), 843-855.

Bruff, D. O., Fisher, D. H., McEwen, K. E., & Smith, B. E. (2013). Wrapping a MOOC: Student perceptions of an experiment in blended learning. *Journal of Online Learning and Teaching*, *9*(2), 187-199.

Cha, S. B., & Park, S. Y. (2017). An analysis of structural relationships among university students' behavioral intention to use MOOC, major relevance, perceived usefulness, and acceptance attitude in agricultural science fields. *Journal of Agricultural Education and Human Resource Development*, *49*(3), 1-21.

Chakravarty, R., & Kaur, J. (2016). MOOCs in India: Yet to shine. *International Journal of Information Studies and Libraries*, *1*(1), 14-21.

Chan, M. M., Plata, R. B., Medina, J. A., Alario-Hoyos, C., Rizzardini, R. H., & De la Roca, M. (2018). Analysis of behavioral intention to Use cloud-based tools in a MOOC: A technology acceptance model approach. *Journal of Universal Computer Science*, *24*(8), 1072-1089.

Chauhan, J. (2017). An overview of MOOC in India. *International Journal of Computer Trends and Technology*, *49*(2), 111-120.

Chin, W.W. (2010). How to Write Up and Report PLS Analyses. In: Esposito Vinzi, V., Chin, W., Henseler, J., Wang, H. (eds) *Handbook of Partial Least Squares* (pp. 655-690). Springer

Chomal, V. S., & Saini, J. R. (2013). A study and analysis of Paradigm Shifts in education triggered by technology. *International Journal of Research in Economics and Social Sciences*, *3*(1), 14-28.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Routledge

Cohen, J. (2016). A power primer. In A. E. Kazdin (Ed.), *Methodological Issues and Strategies in Clinical Research* (4th ed., pp. 279-284). American Psychological Association.

Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results (Doctoral dissertation, Massachusetts Institute of Technology).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.

De Jong, P. G., Pickering, J. D., Hendriks, R. A., Swinnerton, B. J., Goshtasbpour, F., & Reinders, M. E. (2020). Twelve tips for integrating massive open online course content into classroom teaching. *Medical Teacher*, *42*(4), 393-397.

Devgun, P. (2013). Prospects for success of MOOC in higher education in India. *International Journal of Information and Computation Technology*, *3*(7), 641-646.

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly*, *39*(2), 297-316.

Evans, S., & Myrick, J. G. (2015). How MOOC instructors view the pedagogy and purposes of massive open online courses. *Distance Education*, *36*(3), 295-311.

Firmin, R., Schiorring, E., Whitmer, J., Willett, T., Collins, E. D., & Sujitparapitaya, S. (2014). Case study: Using MOOCs for conventional college coursework. *Distance Education*, *35*(2), 178-201.

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Garrison, D. R., & Kanuka, H. (2004). Blended learning: Uncovering its transformative potential in higher education. *Internet and Higher Education*, *7*(2), 95-105.

Ghadiri, K., Qayoumi, M. H., Junn, E., Hsu, P., & Sujitparapitaya, S. (2013). The transformative potential of blended learning using MIT edX's 6.002 x online MOOC content combined with student team-based learning in class. *Environment, 8*(14), 14-29.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS quarterly*, *19*(2), 213-236.

Hair, J. F., Hult, G., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squares structural modelling (PLS-SEM). *International Journal of Research & Method in Education*, *38*(2).

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 modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135.

Hizam, S. M., Akter, H., Sentosa, I., & Ahmed, W. (2021, March). Digital competency of educators in the virtual learning environment: A structural equation modeling analysis. In *IOP Conference Series: Earth and Environmental Science* (Vol. 704, No. 1, p. 012023). IOP Publishing.

Hong, J. Y., Suh, E. H., & Kim, S. J. (2009). Context-aware systems: A literature review and classification. *Expert Systems with Applications*, *36*(4), 8509-8522.

Hossain, L., & de Silva, A. (2009). Exploring user acceptance of technology using social networks. *The Journal of High Technology Management Research*, *20*(1), 1-18.

Hsu, J. Y., Chen, C. C., & Ting, P. F. (2018). Understanding MOOC continuance: An empirical examination of social support theory. *Interactive Learning Environments*, *26*(8), 1100-1118.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning.* (Vol. 112, p. 18). New York: Springer.

Joseph, A. M., & Nath, B. A. (2013). Integration of Massive Open Online Education (MOOC) System with in-Classroom Interaction and Assessment and Accreditation: An extensive report from a pilot study. In *Proceedings of the international conference on e-learning, e-business, enterprise information systems, and e-Government (EEE)* (p. 105). The Steering Committee of the World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp).

Kim, T., Suh, Y. K., Lee, G., & Choi, B. G. (2010). Modelling roles of task-technology fit and self-efficacy in hotel employees usage behaviours of hotel information systems. *International Journal of Tourism Research*, *12*(6), 709-725.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (ijec), 11*(4), 1-10.

Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems, 13*(7), 2.

Koukis, N., & Jimoyiannis, A. (2019). MOOCS for teacher professional development: Exploring teachers' perceptions and achievements. *Interactive Technology and Smart Education*, *16*(2), 74-91.

Kujur, S., Vinayagam, S. S., Awasthi, H. K., & Murthy, G. R. R. (2019). Study of factors influencing adoption of educational technology in teaching-learning process in agricultural universities in India. *International Journal of Education and Management Studies*, *9*(3), 164-168.

Kulal, A., MS, D., & Dinesh, S. (2025). Effectiveness of MOOCs on learning efficiency of students: a perception study. Journal of Research in Innovative Teaching & Learning, 18(1), 145-164.

Lee, C. S., Osop, H., Goh, D. H. L., & Kelni, G. (2017). Making sense of comments on YouTube educational videos: A self-directed learning perspective. *Online Information Review*, *41*(5), 1-17.

Lee, M. H., & Tsai, C. C. (2010). Exploring teachers' perceived self-efficacy and technological pedagogical content knowledge with respect to educational use of the World Wide Web. *Instructional Science*, *38*(1), 1-21.

Li, C. K., & Wong, T. M. (2019). Advancing teaching with massive open online courses: A review of case studies. *International Journal of Innovation and Learning*, *25*(2), 141-155.

Li, Y., Duan, Y., Fu, Z., & Alford, P. (2012). An empirical study on behavioral intention to reuse e-learning systems in rural China. *British Journal of Educational Technology*, *43*(6), 933-948.

Liyanagunawardena, T. R., Adams, A. A., & Williams, S. A. (2013). OOCs: A systematic study of the published literature 2008-2012. *The International Review of Research in Open and Distributed Learning*, *14*(3), 202-227.

Mabuan, R. A. (2018). Using blogs in teaching tertiary ESL writing. *English Review: Journal of English Education*, *6*(2), 1-10.

Molla, A., & Licker, P. (2001). E-commerce systems success: An attempt to extend and respecify the DeLone and McLean model of IS success. *Journal of Electronic Commerce Success*, *2*(4), 131-141.

Morris, N. P. (2014). In M. Baptista Nunes, M. McPherson, M. Baptista Nunes, & M. McPherson (Eds.), *How digital technologies, blended learning and MOOCs will impact the future of higher education*. IADIS Press.

Morris, N. P. (2014). *How Digital Technologies, Blended Learning and MOOCs Will Impact the Future of Higher Education*. International Association for the Development of the Information Society.

Nikou, S. A., & Economides, A. A. (2019). Factors that influence behavioral intention to use mobile-based assessment: A STEM teachers' perspective. *British Journal of Educational Technology*, *50*(2), 587-600.

Ospina-Delgado, J., García-Benau, M. A., & Zorio-Grima, A. (2016). Massive open online courses for IFRS education: A point of view of Spanish Accounting Educators. *Procedia-Social and Behavioral Sciences*, *228*, 356-361.

Phatak, D. B. (2014, September). *Adopting MOOCs for quality engineering education in India*. In Proceedings of the International Conference on Transformations in Engineering Education: ICTIEE 2014 (pp. 11-23). New Delhi: Springer India.

Pynoo, B., Devolder, P., Tondeur, J., Van Braak, J., Duyck, W., & Duyck, P. (2011). Predicting secondary school teachers' acceptance and use of a digital learning environment: A cross-sectional study. *Computers in Human Behavior*, *27*(1), 568-575.

Qashou, A. (2022). Obstacles to effective use of e-learning in higher education from the viewpoint of faculty members. *Turkish Online Journal of Distance Education*, *23*(1), 144-177.

Rao, P. N., Komaraiah, M., & Reddy, P. N. (2015). A case for MOOCs in Indian higher education system. *Journal of Engineering Education Transformations*, *29*(1), 15-25.

Ray, A., Bala, P. K., & Dasgupta, S. A. (2019). Role of authenticity and perceived benefits of online courses on technology based career choice in India: A modified technology adoption model based on career theory. *International Journal of Information Management*, *47*, 140-151.

Richter, S. L., & Krishnamurthi, M. (2014). Preparing faculty for teaching a MOOC: Recommendations from research and experience. *International Journal of Information and Education Technology*, *4*(5), 411-415.

Rogers, E. M. (2003). *Diffusion of innovations.* Free Press. New York.

Rubaai, N., & Hashim, H. (2019). Polytechnic ESL lecturers' acceptance of using massive open online course (MOOC) for teaching English as a second language (ESL). *International Journal of Innovative Technology and Exploring Engineering*, *8*(9), 114-121.

Ryan, L. (2013). *MOOCs - Massive Open Online Courses*. Retrieved March 20, 2020

Saeed, K. A., Hwang, Y., & Yi, M. Y. (2003). Toward an integrative framework for online Consumer behavior research: A meta-analysis approach. *Journal of End User Computing*, *15*(4), 1-26.

Sarnou, H., & Schug, D. (2025). Exploring the Challenges & Benefits of MOOCs as an Innovative Pedagogical Model in Higher Education. *SAR Journal (2619-9955)*, *8*(2).

Shao, Z. (2018). Examining the impact mechanism of social psychological motivations on individuals' continuance inten tion of MOOCs: The moderating effect of gender. *Internet Research*, *28*(1), 232-250.

Sharpe, R., Benfield, G., Roberts, G., & Francis, R. (2006). The undergraduate experience of blended e-learning: a review of UK literature and practice. The higher education academy, 4(2), 24-250.

Siemens, G. (2013, October 21). *What are MOOCs doing to open education*? Presented at Open Access Week. Retrieved July 7, 2015

Teo, T., & Zhou, M. (2014). Explaining the intention to use technology among university students: A structural equation modeling approach. *Journal of Computing in Higher Education*, *26*(2), 124-142.

Teo, T., Lee, C. B., & Chai, C. S. (2008). Understanding pre-service teachers' computer attitudes: Applying and extending the technology acceptance model. *Journal of Computer Assisted Learning*, *24*(2), 128-143.

Teo, T., Sang, G., Mei, B., & Hoi, C. K. W. (2019). Investigating pre-service teachers' acceptance of Web 2.0 technologies in their future teaching: A Chinese perspective. *Interactive Learning Environments*, *27*(4), 530-546.

Tseng, T. H., Lin, S., Wang, Y. S., & Liu, H. X. (2019). Investigating teachers' adoption of MOOCs: The perspective of UTAUT2. *Interactive Learning Environments*, *27*(1), 1-16.

UNDP India. (2016). *Human development report.* Oxford University Press.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478.

Wikipedia (2020). Massive Open Online Courses. Retrieved February 19, 2020

Wright, R. (2014). The Death of MOOCs has been greatly exaggerate. Retrieved February 18, 2020

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.

Wu, B., & Zhang, C. Y. (2014). Empirical study on continuance intentions towards ELearning 2.0 systems. *Behaviour & Information Technology*, *33*(10), 1027-1038.

Yang, H. H., & Su, C. H. (2017). Learner behaviour in a MOOC practice-oriented course: In empirical study integrating TAM and TPB. *The International Review of Research in Open and Distributed Learning*, *18*(5), 35-63.

Yang, M., Shao, Z., Liu, Q., & Liu, C. (2017). Understanding the quality factors that influence the continuance intention of students toward participation in MOOCs. *Educational Technology Research and Development*, *65*(5), 1195-1214.

Yuan, L. and Powell, S.J. (2013). MOOCs and open education: Implications for higher education. A white paper. JISC CETIS. Retrieved February 18, 2020

Zawacki-Richter, O., & Naidu, S. (2016). Mapping research trends from 35 years of publications in Distance Education. *Distance Education*, *37*(3), 245-269.

Zhang, M., Yin, S., Luo, M., & Yan, W. (2017). Learner control, user characteristics, platform difference, and their role in adoption intention for MOOC learning in China. *Australasian Journal of Educational Technology*, *33*(1), 114-133.

Zhang, Z., & Yuan, K. H. (2018). *Practical Statistical Power Analysis*. ISDSA Press, Granger, Indiana.

Zhou, M. (2016). Chinese university students' acceptance of MOOCs: A self-determination perspective. *Computers & Education*, 92, 194-203.