Examining Higher Education Students’ Intention of Adopting MOOCs: An Empirical Study

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ABSTRACT

Massive open online courses (MOOCs) have now become mainstream for learning in unprecedented situations, where traditional classroom learning is difficult to conduct. The aim of this study is to understand the factors that lead to the higher education students’ adoption of MOOCs and the barriers that prevent their use. This study proposes a theoretical model for measuring the higher education students’ intention to adopt MOOCs. The PLS-SEM approach was used to test the theoretical model developed for this study with a sample of 312 higher education students. The theoretical model explained 63.1% of the variance in the dependent variable of behavioral intention to use MOOCs. The findings identified that facilitating conditions, perceived usefulness, course flexibility, and job relevance are the factors—in order of their influence—that predict the higher education students’ perceived intention to use MOOCs. The findings of this study contribute to this existing body of knowledge of MOOC adoption.

KEYWORDS

Adoption, Behavioral Intention, Higher Education, MOOCs, TAM

INTRODUCTION

The Internet and the proliferation of computers and smartphones have enabled the digital learning process. E-learning is a process that allows for learning through the use of virtual technologies. Massive open online courses (MOOCs) represent an e-learning subset that enables any member of the learning community to enrol into any course they choose from any top university (Hone & El Said, 2016)—something that is not possible in the traditional learning environment. MOOCs have recently become one of the mainstream learning methodologies due to the situation caused by the Covid-19 pandemic in which formal classroom learning became unfeasible. The main MOOC features are massive scale and openness, which allow for the maximisation of learner access and interaction (Chen et al., 2018). With MOOCs’ help, learners can reskill or upskill in any of their interest areas, which advances their job competence. MOOCs deliver courses only through internet-based services and predefined content, such as video lectures and lecture materials (Wu & Chen, 2017). The assessment is based
on online quizzes, peer-reviewed assignments, and projects. MOOCs have become very popular in higher education due to their numerous benefits, which allow students to learn about any topic of their choice—thus enhancing their job opportunities without geographical constraints. They allow students and instructors to interact with the help of virtual classrooms across borders and irrespective of the participants’ diverse socioeconomic backgrounds (Khan et al., 2018). MOOCs have evolved from free to paid programs that focus on traditional higher education students to enhance their skills and fill the shortage gap in learning advanced topics (Lambert, 2020). They offer flexibility in learning and cut costs in education by offering options such as pay-as-you-go (Hone & El Said, 2016).

Many Ivy League universities offer postgraduate programs through MOOCs. The leading MOOC platform—Coursera—has 49 million users enrolled as of December 2019 in collaboration with more than 200 leading universities and companies, offering a total of 4,179 courses (Course, 2020). Similarly, edX, Udacity, FutureLearn, and Swayam are the other leading MOOC platforms in terms of the number of users enrolled and courses offered (Shah, 2019). Coursera, edX, Udacity, Edureka, Alison, Udemy, Pluralsight, Simplilearn, Miriadax, LinkedIn, Khan Academy, Skillshare, Jigsaw Academy, iVersity, intellipaat, FutureLearn, NovoEd, WizIQ, XuetangX, Federica, Linkstreet Learning, and Kadenze are the major players in the MOOCs market (MarketDigits, 2021). The government of India has initiated a MOOC platform called Swayam, which offers courses from school education to postgraduate studies to make quality education available to all social classes. According to Swayam’s data, there are 10 million students enrolled. The courses Swayam offers are integrated into India’s traditional higher-degree education, where students can transfer the credits that they acquire through Swayam to their regular degrees (ICEF, 2020). The University Grants Commission (UGC), India’s regulatory body for higher education, has authorized various universities and colleges to offer 40 percent of their total number of courses in a particular semester of multiple programs through Swayam.

MOOCs’ future looks bright in terms of massive content on a wide range of topics, a large number of participants from around the world, and market growth. MOOC providers must focus more on simulation-based teaching in the future and connect the number of enrolments to course completion and quality-based assessment. The current MOOC market was valued at USD 6845.4 million in 2020 and is expected to reach 18925.18 million by 2026, growing at an 18.13 percent CAGR (Mordor Intelligence, 2021). The majority of MOOCs learners go into the technology segments as per the Class Central such as artificial intelligence, machine learning, cyber security, and data analytics. According to a Class Central report, over 10,000 students are enrolled in online degree programs offered by leading universities such as Georgia Tech and the University of Illinois, which have partnered with top MOOC providers such as Udacity, edX, and Coursera (Mordor Intelligence, 2021).

The educational institutions and universities can take advantage of MOOC services in education, which are flexible, efficient, portable, word-class quality, reliable, and significantly more cost-cutting than traditional learning systems (Alshwaier et al., 2012). They allow for community-based learning through online discussion forums. The ability of many learners to join MOOCs is one of their advantages; however, many learners do so simply out of curiosity and fail to complete the course(s) they enrol in. Hence, the MOOC dropout rate is significantly higher than that of traditional classroom learning systems (Aparicio et al., 2019). Therefore, it is crucial to know what the barriers to MOOC adoption are. Students enrol into MOOCs to gain knowledge, but the rate of course completion is meagre (Huang et al., 2017). The success of MOOCs largely depends on the course completion rate and on the learners’ intention to continue using MOOCs (Aparicio et al., 2019; Wu & Chen, 2017).

In comparison with MOOC enrolment and participation rates in North America and Europe, participation in other parts of the world is limited, especially in Asian and African regions (Abdel-Maksoud, 2019). Although MOOCs offer diverse topics and encourage student equity (Lambert, 2020), studies related to MOOC adoption factors find that these new learning methodologies are limited, particularly in developing countries (Fianu et al., 2018; Khan et al., 2018; Ma & Lee, 2018; Trehan & Joshi, 2018). More studies are required to understand the learners’ intentions behind using MOOCs and complete the courses (Aharony & Bar-Ilan, 2016; Mendoza et al., 2017). Consequently,
the present study aims to address this research gap by studying the intention of adopting MOOCs in a developing country. The purpose of this research is to understand the factors that lead to the adoption of MOOCs and the barriers that prevent their use. To that end, this research develops a theoretical model based on the Technology Acceptance Model (TAM) framework. It then extends it with additional factors that predict students’ intention to use MOOCs.

LITERATURE REVIEW

A MOOC is defined as “an online course with the open of free and open registration, a publicly shared curriculum, and open-ended outcomes” (El-Hmoudova, 2014, p. 30). It can further be classified into two types: cMOOC (Liyanagunawardena et al., 2013) and xMOOC (El-Hmoudova, 2014; Wu & Chen, 2017). cMOOCs are defined as being “based upon connectivism pedagogy that uses interaction centred learning in complex information environments” (Wang et al., 2016, p. 684). xMOOCs are delivered with predefined curricula, video-based lectures, and assessments through quizzes, projects and feedback, as in the traditional classroom (El-Hmoudova, 2014). Learners joining xMOOCs can take assessments, complete credits, and earn certificates. In contrast, those who do not wish to complete the instructors’ assessments can continue learning and complete the course without obtaining a certificate. Prior studies have examined various MOOC aspects. Some studies have conducted extensive literature reviews of MOOC studies until the present (Al-Rahmi et al., 2019; Lambert, 2020; Liyanagunawardena et al., 2013), covering broad topics as MOOC research interests and socioeconomic barriers. One of the significant challenges of MOOCs is their tremendous dropout rate (Aparicio et al., 2019; El-Hmoudova, 2014). Learners show enthusiasm at the initial stage but lose interest when more tasks are required to complete the course (Sun et al., 2018). Hence, many studies have concentrated on the continuance intention to use MOOCs (Chen et al., 2018; Wu & Chen, 2017; Zhou, 2017). Studies have also discussed the MOOC retention rate (Hone & El Said, 2016). Hone & El Said (2016) identified that the content of MOOCs, perceived effectiveness, and instructor interaction are the predictors of retention. Another MOOC study explored whether participants’ country of origin and gender make any difference in learner outcomes (Gameel & Wilkins, 2019). Wang et al. (2019) studied herd behaviour in MOOC learning and identified that course difficulty and learner experience impact rational herding. Other studies concentrated on investigating MOOC success factors (Aparicio et al., 2019).

Understanding the factors that drive MOOC adoption and its barriers is of primary concern, leading to usage continuance and reduction in the dropout rate while increasing the MOOC acceptance and success rates. Past literature in this area conducted studies using qualitative and quantitative approaches and various theories and models. Some of the adoption factors that prior studies have identified for MOOCs are perceived usefulness/performance expectancy (Aharony & Bar-Ilan, 2016; Mendoza et al., 2017; Tao et al., 2019), perceived ease of use (Aharony & Bar-Ilan, 2016; Tao et al., 2019), perceived enjoyment (Tao et al., 2019), task–technology fit (Khan et al., 2018; Wu & Chen, 2017), reputation (Wu & Chen, 2017), social recognition (Wu & Chen, 2017; Khan et al., 2018), social influence (Wu & Chen, 2017), perceived relatedness (Khan et al., 2018), and perceived competence (Khan et al., 2018). Existing studies on MOOCs have identified specific adoption barriers, including facilitating conditions (Mendoza et al., 2017) and lack of accessibility (Ma & Lee, 2018a). Ma & Lee (2018b) identified barriers through the Innovation Resistance Theory (IRT) using focus group discussions, finding that usage, value, tradition, lack of self-control, attitude, lack of promotion, and economic circumstance were significant hindrances to using MOOCs.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

This study uses the Technology Acceptance Model (TAM) as its theoretical base for understanding the factors that lead to the adoption of MOOCs and the barriers that prevent their use. The TAM model
(Davis, 1989) describes the willingness of a consumer to use technology. The concept was derived from the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975). The main strength of this model is its parsimony—it can be used to assess the willingness to use any information technology/information system. According to TAM, perceived usefulness and perceived ease of use are the primary drivers for new technology adoption. Researchers have expanded the TAM model by adding additional constructs or integrating the model with other models by analysing mediators or defining the antecedents of perceived usefulness and perceived ease of use in predicting the intention to use a new information system. Prior studies related to MOOCs also used the TAM model to study adoption intention and usage. Aharony & Bar-Ilan (2016) used the TAM model to study the students’ perception of MOOCs in Israel and identified that perceived usefulness and perceived ease of use emerged as significant predictors. Another study (Tao et al., 2019) extended the TAM model to understand the students’ acceptance of MOOCs, and the results indicated that perceived usefulness, perceived ease of use, and perceived enjoyment were significantly influenced by behavioural intention. Prior studies mainly concentrated on utilitarian factors (Ma & Lee, 2018), perceived reputation (Wu & Chen, 2017), student motivational factors (Chaw & Tang, 2019; Luik et al., 2019), retention (North et al., 2014), and satisfaction (Abdel-Maksoud, 2019). However, additional factors also need to be considered for understanding MOOCs’ initial acceptance and the barriers that prevent students from continuing to use MOOCs.

This study proposes a theoretical model for measuring the higher education students’ adoption of MOOCs and the barriers that prevent their use. The study expands the TAM model by incorporating the following constructs: perceived usefulness, perceived ease of use, job relevance, compatibility, social influence, facilitating conditions, course flexibility, and the dependent variable of behavioral intention to adopt MOOC platforms. Apart from using the primary constructs of the TAM model, the theoretical model proposed here includes the utility factors of using MOOCs, the barriers of using MOOC systems, the social pressures, and the motivational aspects of using MOOCs. Furthermore, the proposed model integrates the following constructs: facilitating conditions, compatibility, job relevance, social influence, and course flexibility, which significantly influence the intention to adopt MOOCs. Prior studies of intention to use MOOCs have applied various theoretical frameworks, but a limited number of studies concentrated on integrating these factors into their adoption models (Khan et al., 2018).

**Behavioural Intention**

Fishbein & Ajzen (1975) defined behavioural intention as “the strength of one’s intention to perform a specified behaviour.” Specific theories, such as TRA (Fishbein & Ajzen, 1975), Theory of Planned Behavior (TPB) (Ajzen, 1991), and TAM (Davis, 1989), explain that behavioural intention influences actual behaviour. The relationship between the behavioural intention to use MOOCs is depicted in the theoretical model along with eight independent variables (Figure 1).

**Perceived Usefulness**

Perceived usefulness is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989). The main advantage of MOOCs is that it offers quality education from leading universities to everyone—something that is not normally affordable for many (Lu et al., 2019). MOOCs are helpful for people who wish to enhance their knowledge in their field or learn a new topic. Prior studies on the intention to use MOOCs also specified the importance of perceived usefulness (Shao, 2018; Wu & Chen, 2017). Hence, the following hypothesis is proposed:

H1: Perceived usefulness significantly influences the behavioural intention to use MOOCs.
Perceived Ease of Use

Perceived ease of use is defined as “the degree to which a person believes that using a particular system would be free of physical and mental effort” (Davis, 1989). Learning would be enjoyable and hassle-free if MOOC platforms are easy to use. More people would be motivated to use them if they can easily download video lectures, study materials, and interactive learning course interfaces. Prior studies also pointed out that perceived ease of use is a significant predictor of the intention to use MOOCs (Aharony & Bar-Ilan, 2016). Some studies also identified that perceived usefulness acts as a mediator between the perceived ease of use and the intention to use MOOCs (Wu & Chen, 2017). Hence, the following hypotheses are proposed:

H2: Perceived ease of use significantly influences the behavioural intention to use MOOCs.
H2a: Perceived ease of use significantly influenced the perceived usefulness of MOOCs.

Facilitating Conditions

Facilitating conditions are defined as “the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system” (Venkatesh et al., 2003). MOOC platforms require technological infrastructures, such as internet speed, computers, or mobile devices, to facilitate the courses they offer. Prior studies pointed out that adoption barriers, such as slow networks, lack of internet connectivity, and lack of support from the workplace might hinder the use of MOOCs (Mendoza et al., 2017). When sufficient resources are available for the use of MOOCs, more participants actively engage in learning. These resources include technological, organizational, and socioeconomic resources, and when learners are aware of them, they find it easier to use MOOCs. Hence, the following hypotheses are proposed:

H3: Facilitating conditions significantly influence the behavioural intention to use MOOC platforms.
H3a: Facilitating conditions improve the perceived ease of use of MOOC platforms.

Compatibility

Compatibility is defined as “the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters” (Rogers, 1995). Learners expect the operation of MOOC platforms to be similar to how they learn in a traditional classroom environment. They expect instructors to explain concepts and provide the assessments and feedback as they would in a regular classroom environment, leading to the ease of use of MOOC platforms. Prior studies also pointed out that MOOCs’ compatibility impacts the learners’ intention to use them (Singh & Panigrahi, 2018). Hence, the following hypotheses are proposed:

H4: Compatibility significantly influences the behavioural intention to use MOOC platforms.
H4a: Compatibility significantly influences the perceived ease of use of MOOC platforms.

Social Influence

Social influence refers to an individual’s perception of other people’s opinions about whether he or she should perform a particular behaviour (Venkatesh et al., 2003). It is derived from the well-known adoption theories of information systems. Those who join MOOCs certainly seek opinions from their peers and co-learners and review the feedback from the course. Prior studies also identified that social influence plays a significant role before enrolling in MOOCs because joining a MOOCs differs from traditional classroom enrolment (Chen et al., 2018; Zhou, 2017). Because anyone can
enrol in a MOOC, learners generally seek opinions from those who have already registered in the course, as well as from their friends and colleagues. Hence, the following hypothesis is proposed:

**H5:** Social influence significantly influences the behavioural intention to use MOOC platforms.

**Job Relevance**
Venkatesh and Davis (2000) defined job relevance as “an individual’s perception regarding the degree to which the target system is applicable to his or her job.” Learners who enrol in MOOCs look for career advancement and professional development (Sablina et al., 2018). Employers also understand MOOCs’ potential by associating with MOOC providers, recommending such training, and choosing the right talent. Hence, the following hypothesis is proposed:

**H6:** Job relevance significantly influences the behavioural intention to use MOOC platforms.

**Course Flexibility**
The learning flexibility offered by MOOCs plays a significant role for the learners who opt out of traditional learning and for the learners who would like to enhance their skills while doing their job. This flexibility is one of the highest-rated motivational factors—the aptness of learning while maintaining work and family responsibilities and learning on the go (Luik et al., 2019). Hence, the following hypothesis is proposed:

**H7:** Course flexibility significantly influences the behavioural intention to use MOOC platforms.

**METHODOLOGY**

**Variable Measurement**
The variables used in the theoretical model were measured using previously validated research items (Table 1). These elements were reworded following the context of the current study. This study used a 5-point Likert scale to measure items because this scale is widely used in marketing and social science research (Garland, 1991), where 1 is strongly opposed, and 5 is strongly supported. A total of 33 items were used in the questionnaire developed to measure and test the theoretical model.

To check the instrument’s applicability in the context of online learning acceptance, the developed questionnaire was presented to several academics and MOOC learners. A pre-test survey ensured the completeness and accuracy of the questionnaire by gathering responses from 15 MOOC users. The input received from both groups was integrated into the final questionnaire.

This analysis adopted a quantitative research approach, using a questionnaire to gather data. The sample was collected from higher education students in the management and information technology stream in Mumbai, India. The implemented sampling technique was convenience sampling. The work’s intent was explained to the respondents, and they were assured that their responses on the survey would only be used for this research study. Involvement in the survey was voluntary, and the respondents were free not to answer any question they did not wish to answer. Data collection was carried out through both online and offline methods. Data were collected through physical classroom questionnaire distribution, through which 215 filled survey forms were gathered. In addition, a Google form was created and sent to respondents’ emails, and 120 forms were collected through this online approach. A total of 312 questionnaires were usable from both methods, with a response rate of 62%. This sample size was considered to be robust (Hinkin, 1998).

Research-based surveys are subject to common method variance, where respondents fill out the survey questionnaire themselves (Podsakoff et al., 2003). Harman’s single-factor test was conducted
Table 1. Constructs and Their Sources

| Constructs                   | Items                                                                 | Source                      |
|------------------------------|-----------------------------------------------------------------------|-----------------------------|
| **Behavioural Intention (BI)** | BI1 Assuming I have access to a MOOCs system, I intend to use it.     | Venkatesh et al.(2012)      |
|                              | BI2 Given that I have access to a MOOCs system, I predict that I would use it. |                             |
|                              | BI3 I will frequently use a MOOCs system in the future.                |                             |
|                              | BI4 I will strongly recommend others to use a MOOCs system.             |                             |
| **Compatibility (Comp)**     | COMP1 Using the MOOCs system is not similar to something that I’ve done before. | Taylor & Todd (1995)        |
|                              | COMP2 MOOCs fits well with the way I like to manage my career.          |                             |
|                              | COMP3 I like to try new technology                                      |                             |
|                              | COMP4 MOOCs is compatible with my lifestyle.                            |                             |
|                              | COMP5 Using MOOCs fits into my working style.                           |                             |
| **Social Influence (SI)**    | SI1 People who influence my behaviour think that I should use MOOCs.   | Venkatesh et al. (2003)     |
|                              | SI2 People who are important to me think that I should use MOOCs.       |                             |
|                              | SI3 My top management supports using the MOOCs system.                  |                             |
| **Perceived Usefulness (PU)**| PU1 Using the MOOCs system would enhance my effectiveness in my course. | Venkatesh & Bala (2008)     |
|                              | PU2 Using the MOOCs system would improve my performance in the course.  |                             |
|                              | PU3 I would find the MOOCs system useful in the course.                 |                             |
|                              | PU4 Using the MOOCs system in the course would enhance my productivity. |                             |
| **Perceived Ease of Use (PEOU)** | PEOU1 It would be easy for me to become skilful at using MOOCs systems. | Venkatesh & Bala (2008)     |
|                              | PEOU2 Learning to operate MOOCs systems would be easy for me.           |                             |
|                              | PEOU3 I would find it easy to get a MOOCs system to do what I want it to do. |                             |
|                              | PEOU4 I would find MOOCs systems easy to use.                           |                             |
| **Facilitating Conditions (FC)** | FC1 I have the resources necessary to use the MOOCs system.            | Venkatesh et al. (2003)     |
|                              | FC2 I have enough Internet experience to use the MOOCs services.        |                             |
|                              | FC3 The current legal framework ensures risk-free and secured MOOCs services. |                             |
|                              | FC4 Learning to operate the MOOCs system is easy for me.                |                             |
|                              | FC5 It has made my learning more pleasure.                              |                             |
|                              | FC6 Using the MOOCs system is different from using other software I have used in the past. |                             |
| **Course Flexibility (CF)**  | CF1 Taking this class via the Internet allowed me to arrange my work for the class more effectively. | Arbaugh (2000)              |
|                              | CF2 Taking this class via the Internet allowed me to arrange my work schedule more effectively. |                             |
|                              | CF3 Taking this class via the Internet saved me a lot of time commuting to class. |                             |
|                              | CF4 Taking this class via the Internet allowed me to take a class I would otherwise have to miss. |                             |
|                              | CF5 Taking this class via the Internet allowed me to spend more time on non-related activities. |                             |
| **Job Relevance (JR)**       | JR1 In my job, usage of a MOOCs system is high.                        | Venkatesh & Davis (2000)    |
|                              | JR2 In my job, usage of a MOOCs system is relevant.                     |                             |
to analyse the prevalent bias of the process. The findings of the Harman single-factor test showed that several factors were derived from the factor analysis and that no single factor accounted for significant variability. The largest variance obtained for an individual construct was 13%. Therefore, common method variance was not a substantial issue in this analysis.

The Statistical Package for Social Sciences (SPSS) version 21.0 was used to process the data. Structural equation modelling (SEM) was used to evaluate the theoretical model used in this analysis. SEM tests the potential causal relationship between multiple variables simultaneously and calculates the strength of interrelationships between latent constructs. Path analysis models may be covariance-based SEM (CB-SEM) or partial least square SEM (PLS-SEM) (Hair et al., 2011). CB-SEM is more suitable for theory testing, whereas PLS-SEM is appropriate for modelling the conceptual relationships between latent constructs (Hair et al., 2011). Using Smart PLS 3 software (Ringle et al., 2015), PLS-SEM path modelling was used to calculate the structural and measurement paths of the theoretical model.

Results

The MOOC learner respondents (Table 2) were 68.3% male and 31.7% female. The majority of learners were 20 to 29 years of age. The majority of them had enrolled in 1 to 3 courses and had completed courses through the Coursera online learning platform.

PLS-SEM Model Assessment

PLS-SEM is more suitable for the theoretical design than for theory testing and is commonly used in marketing, information systems, and operational management disciplines (Hair et al., 2011). PLS-SEM can model latent structures with small and medium sample sizes and work well with data non-normality (Chin et al., 2003). This study used PLS-SEM and the two-step approach suggested by Anderson & Gerbing (1988). The measurement model was first analysed for reliability and validity, followed by a structural model to check the hypothesised causal relationship.

Measurement Model Analysis

In the PLS-SEM model, the first step was to assess the measurement model. The reliability of the latent constructs was assessed by computing Cronbach’s alpha and composite reliability (CR). The suggested cut-off value for both Cronbach’s alpha and composite reliability is above 0.70 (Hair et al., 2006). From Table 3, it is clear that all constructs with the cut-off value above 0.70 show that all items used in this study were sufficiently reliable. The indicator loadings of each construct were then evaluated. One item (COMP1) of latent construct compatibility, one item (FC6) of latent construct facilitating conditions, and two items (CF4, CF5) of latent construct course flexibility had outer loadings that were less than the cut-off value of 0.708 (Hair et al., 2019). As a result, these items were not used in subsequent PLS-SEM analyses. The initial questionnaire contained 33 items, 29 of which were used for further research. In this study, all of the remaining latent construct elements (Table 3) had factor loadings greater than the cut-off value of 0.708. (Hair et al., 2019).

The average variance extracted (AVE) was determined for testing the validity of the constructs. It is the complementary measure of composite reliability that reflects the overall variance in the indicators of the latent constructs (Hair et al., 2006). The AVE cut-off value is above 0.50 (Hair et al., 2006), and all constructs used in this analysis reached this cut-off value (Table 3).

Convergent and discriminant validity were estimated to determine the validity of the measurement model. The composite reliability and AVE of each construct were calculated to assess the converging validity of the measurement model. All measurements were above the cut-off value (Fornell & Larcker, 1981) for the measurement model (Table 4); thus, the convergent validity is proven for this analysis. To calculate discriminant validity, Henseler et al. (2015) proposed the HTMT (Heterotrait-Monotrait) criterion. HTMT is ‘defined as the mean value of the item correlations across constructs relative to the geometric mean of the average correlations for the items measuring the same construct’ (Sarstedt}
et al., 2019, p.8). The HTMT value of all constructs with other constructs was less than the threshold value of 0.85. (Henseler et al., 2015) (Table 4).

**Structural Model Analysis**

A non-parametric bootstrapping approach was used with 5,000 samples to evaluate the theoretical model. The structural model (Figure 1), the path coefficients, p-values, and bias-corrected confidence intervals are shown in Table 5. Path coefficients were significant for perceived usefulness, facilitating conditions, course flexibility, and job relevance (hypotheses H1, H3, H6, and H7) and significantly impacted the behavioural intention of using MOOCs. Perceived ease of use significantly impacted perceived usefulness, thus validating the H2a hypothesis. Facilitating conditions and the compatibility
greatly influenced perceived ease of use, consequently confirming hypotheses H3a and H4a. Nonetheless, perceived ease of use (hypothesis H2), compatibility (hypothesis H4), and social influence (hypothesis H5) did not influence the behavioural intention to use MOOCs.

The β coefficient indicates the effect of the independent variable in the theoretical model. Figure 1 indicates that perceived usefulness (β = 0.249, p = 0.000), facilitating conditions (β = 0.535, p = 0.000), job relevance (β = 0.089, p = 0.04), and course flexibility (β = 0.15, p = 0.026) were statistically significant. Among the independent variables, facilitating conditions had the highest

Table 3. Measurement model analysis

| Construct                     | Factor Loading | AVE   | Cronbach’s Alpha | Composite Reliability |
|-------------------------------|----------------|-------|-------------------|-----------------------|
| Behavioural Intention (BI)    |                |       |                   |                       |
|                               | 0.892          | 0.775 | 0.903             | 0.932                 |
|                               | 0.877          |       |                   |                       |
|                               | 0.877          |       |                   |                       |
|                               | 0.877          |       |                   |                       |
| Perceived Usefulness (PU)     |                |       |                   |                       |
|                               | 0.875          | 0.795 | 0.914             | 0.939                 |
|                               | 0.921          |       |                   |                       |
|                               | 0.886          |       |                   |                       |
|                               | 0.883          |       |                   |                       |
| Perceived Ease of Use (PEOU)  |                |       |                   |                       |
|                               | 0.746          | 0.628 | 0.802             | 0.871                 |
|                               | 0.836          |       |                   |                       |
|                               | 0.804          |       |                   |                       |
|                               | 0.781          |       |                   |                       |
| Facilitating Conditions (FC)  |                |       |                   |                       |
|                               | 0.767          | 0.608 | 0.84              | 0.886                 |
|                               | 0.763          |       |                   |                       |
|                               | 0.744          |       |                   |                       |
|                               | 0.831          |       |                   |                       |
|                               | 0.791          |       |                   |                       |
| Compatibility (COMP)          |                |       |                   |                       |
|                               | 0.846          | 0.724 | 0.871             | 0.913                 |
|                               | 0.754          |       |                   |                       |
|                               | 0.909          |       |                   |                       |
|                               | 0.886          |       |                   |                       |
| Job Relevance (JR)            |                |       |                   |                       |
|                               | 0.897          | 0.824 | 0.788             | 0.904                 |
|                               | 0.919          |       |                   |                       |
| Social Influence (SI)         |                |       |                   |                       |
|                               | 0.847          | 0.694 | 0.78              | 0.872                 |
|                               | 0.868          |       |                   |                       |
|                               | 0.782          |       |                   |                       |
| Course Flexibility (CF)       |                |       |                   |                       |
|                               | 0.901          | 0.794 | 0.871             | 0.92                  |
|                               | 0.873          |       |                   |                       |
|                               | 0.899          |       |                   |                       |
influence (\(\beta = 0.535\)) on the behavioural intention of MOOCs, followed by perceived usefulness (\(\beta = 0.249\)), course flexibility (\(\beta = 0.15\)), and job relevance (\(\beta = 0.089\)).

Perceived ease of use, compatibility and social influence was not statistically significant, suggesting that these variables did not directly impact the dependent variable of behavioural intention to use MOOCs. Regardless, perceived ease of use indirectly influenced the dependent variable of behavioural intention to use MOOCs through perceived usefulness.

The R\(^2\) value obtained during structural model analysis represents the total variance explained by the independent variables to the dependent variable. The R\(^2\) values obtained were 0.631, 0.355, and 0.469 for behavioural intention, perceived ease of use, and perceived usefulness. Together, perceived usefulness, facilitating conditions, job relevance, and course flexibility explained 63.1% of the variance on the dependent variable of behavioural intention to use MOOCs. Facilitating conditions and compatibility explained 35.5% of the variance on perceived ease of use. Perceived ease of use explained 46.9% of the variance on perceived usefulness.

Table 4. Discriminant Validity of Measured Items (HTMT)

| Constructs | BI  | CF   | COMP | FC  | JR  | PEOU | PU   | SI   |
|------------|-----|------|------|-----|-----|------|------|------|
| BI         |     |      |      |     |     |      |      |      |
| CF         | 0.636 |      |      |     |     |      |      |      |
| COMP       | 0.640 | 0.655 |      |     |     |      |      |      |
| FC         | 0.849 | 0.667 | 0.715 |     |     |      |      |      |
| JR         | 0.508 | 0.461 | 0.595 | 0.483 |     |      |      |      |
| PEOU       | 0.546 | 0.490 | 0.660 | 0.622 | 0.563 |      |      |      |
| PU         | 0.628 | 0.449 | 0.619 | 0.593 | 0.514 | 0.797 |      |      |
| SI         | 0.502 | 0.536 | 0.760 | 0.574 | 0.554 | 0.416 | 0.523 |      |

BI: Behavioural Intention; CF: Course Flexibility; COMP: Compatibility; FC: Facilitating Conditions; JR: Job Relevance; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; SI: Social Influence.

Table 5. Path coefficients

| Hypotheses | Path       | Path Coefficient | p-values | 2.5%  | 97.5%  | Result   |
|------------|------------|------------------|----------|-------|--------|----------|
| H1         | PU → BI    | 0.249***         | 0.000    | 0.148 | 0.366  | Accepted |
| H2         | PEOU → BI  | 0.155            | -0.238   | 0.023 |        | Rejected |
| H2a        | PEOU → PU  | 0.685***         | 0.000    | 0.592 | 0.757  | Accepted |
| H3         | FC → BI    | 0.535***         | 0.000    | 0.427 | 0.645  | Accepted |
| H3a        | FC → PEOU  | 0.288***         | 0.000    | 0.131 | 0.419  | Accepted |
| H4         | COMP → BI  | 0.49             | -0.095   | 0.181 |        | Rejected |
| H4a        | COMP → PEOU| 0.373***         | 0.000    | 0.225 | 0.542  | Accepted |
| H5         | SI → BI    | 0.363            | -0.157   | 0.047 |        | Rejected |
| H6         | JR → BI    | 0.089*           | 0.04     | 0.002 | 0.168  | Accepted |
| H7         | CF → BI    | 0.15*            | 0.026    | 0.027 | 0.289  | Accepted |

*p < 0.05; **p < 0.01; ***p < 0.001 Note: n.s: Not significant; *p<0.05; **p<0.01; ***p<0.001
Dotted line indicates non-significant path
The value of Stone-Geisser’s $Q^2$ (Geisser, 1975; Stone, 1974) was determined to cross-validate the model’s predictive validity by applying a blindfolding technique with an omission distance of seven. The $Q^2$ value obtained for the endogenous variables of behavioural intention, perceived usefulness, and perceived ease of use was 0.479, 0.367, and 0.216, respectively. They are greater than zero suggests the model’s predictive validity (Hair et al., 2011).

Discussion

The objective of this study was to understand the factors that lead to the higher education students’ adoption of MOOCs and the barriers that prevent their use. The study used the TAM theoretical framework and extended this model using additional constructs. The context of the study was India—a developing country—and the participants were higher education students. The findings of this study provide interesting insights into the existing literature on the adoption of MOOCs platforms.

First, the study identified that perceived usefulness, facilitating conditions, job relevance, and course flexibility are factors that predict higher education students’ perceived intention to use MOOCs. The theoretical model developed for this study explained 63.1% of the variance in the dependent variable of behavioural intention to use MOOCs. Among the identified factors, facilitating conditions were found to have the most substantial influence on the behavioural intention to use MOOCs, followed by perceived usefulness, course flexibility, and job relevance. While using MOOCs, learners identified that facilitating conditions constitute a significant barrier because MOOCs require internet infrastructure and digital devices. For a developing country like India, the broadband infrastructure still needs to be upgraded to have better internet connectivity and faster internet speed for the masses. For learners to use MOOCs, various technology resources are required to facilitate the learning process and complete courses. Another important finding of this study was that the facilitating conditions factor significantly influenced the perceived ease of using MOOCs. When sufficient resources are available for learners to enrol in MOOCs, this eases the process. Prior studies also corroborated this insight, indicating that technology barriers pose a significant hurdle in the adoption and continuous usage of MOOCs (Mendoza et al., 2017). Perceived usefulness emerged as the second most crucial
factor in this study. Learners perceived MOOCs as valuable because they have numerous benefits, such as providing access to quality education from leading universities worldwide at a lower cost and without geographical constraints. The main characteristics of MOOCs—being open to the masses and accessible online—allow any learner to get access to high-quality education, something that, in a developing country, lacks typically in the traditional learning environment. Existing studies also highlighted that perceived usefulness significantly influences learners when choosing a MOOC (Gupta, 2019). Another interesting finding of this study is that course flexibility has a significant influence on using MOOC platforms. The main reason for this could be virtual classrooms, where learners have the flexibility to learn at their convenience. Although MOOCs have a predefined schedule for course completion, learners can nevertheless still choose their timing, which is impossible in traditional classroom settings. According to the learners, this is one of the most significant benefits of MOOCs, and the resulting learning flexibility makes MOOCs so popular. Prior studies also pointed out that motivational factors, such as course flexibility, really engage students in learning through MOOCs (Luik et al., 2019). This study also found that job relevance has a significant influence on the behavioural intention to use MOOCs. From the perspective of the learners, the most appealing aspect of MOOCs is skill development. MOOCs increase the potential for professional advancement and job switching by providing knowledge and certificates. Past studies identified that MOOC learning has tangible outcomes, such as job relevance, which influences their adoption (Sablina et al., 2018).

Second, the study validated the theoretical model that was developed. The model extended the TAM theoretical framework by adding the following constructs: facilitating conditions, compatibility, job relevance, and course flexibility. The integrated model, which comprised perceived usefulness, facilitating conditions, course flexibility, and job relevance, explained 63.1% of the variance to predict the behavioural intention to use MOOCs. Perceived ease of use, compatibility, and social influence did not play a significant role in predicting the intention to use MOOCs. Learners perceived that the usefulness of a course was more important than the perceived ease of use when it came to the adoption of MOOCs. Learning is a process that requires effort, which might be why perceived ease of use is not significant; this is consistent with the findings of past studies (Fianu et al., 2018). Learners gave higher precedence to a new skill and topic acquisition than to whether a course is compatible with their existing learning methodologies. Social influence was not significant for using MOOCs in this study, perhaps because learning is considered an individual choice—in terms of area of specialisation and different skill requirements of each individual—which also leads to a variation in the learning resources. Furthermore, prior studies similarly pointed out that social influence could not influence an individual’s decision to adopt MOOCs (Fianu et al., 2018).

In this study, facilitating conditions and compatibility were the antecedents of perceived ease of use, which explained 35.5% of the variance. When MOOC learners have organisational and technological support, this increases their comfort of using MOOCs. Prior studies also highlighted that facilitating conditions and compatibility are significant antecedents to perceived ease of use when a learner receives support for both technological infrastructure and organisational support and can coordinate with their prior learning experiences, which makes their learning process easier (John, 2015; Teo & Zhou, 2014). The findings of this study are consistent with earlier studies that perceived ease of use to be the most significant predictor of perceived usefulness in comparison to other antecedents (Abdullah et al., 2016; Mohammadi, 2015).

Theoretical Implications

The main theoretical contribution of this study is that it extended the TAM model to understand further the learners’ behavioural intention to use MOOCs. This study is one among only a few studies that discuss MOOC adoption behaviour in a developing country. The theoretical model used in this study empirically proved that learners’ adoption of MOOCs includes the utility factors of using MOOCs, the barriers of using MOOC systems, the social pressures to join MOOCs, and the motivational aspects of using MOOCs. Hence, the present study bridges the gap by adding these constructs to the TAM
model. The resulting extended model has better predictive power to explain learners’ MOOC adoption behaviour. The majority of prior studies on MOOC adoption concentrated on North America and Europe, with limited participation from other parts of the world, especially from Asian and African regions (Abdel-Maksoud, 2019). This study was conducted in a different cultural and socioeconomic context, thus diversifying the insights found in the existing literature.

**Practical Implications**

This study’s findings have many practical implications. First, the factors that were found to be important in adopting MOOCs can be used as a guide by MOOC providers to increase enrolment and continuity of usage. Among the factors identified, facilitating conditions emerged as the most significant predictor. This shows that technological infrastructure and organisational support are required for using MOOCs. While designing and implementing MOOC platforms, the providers have to look into their digital infrastructures, such as network infrastructure, broadband connectivity, interface design, and ubiquitous devices to access the MOOCs. Lack of digital infrastructure is a significant barrier in the developing world. Learners enrol in MOOCs to enhance their professional careers—hence, organisations need to promote MOOCs. Furthermore, organisations should introduce various incentives and benefits to attract employees to use MOOCs to develop their skills further, and employers could use MOOCs for training purposes. The findings also revealed that learners place considerable importance on perceived usefulness and job relevance. To emphasise the usability of MOOCs, providers should develop promotional strategies to generate awareness among potential learners. For instance, MOOC providers could associate with universities and higher education providers through customised content and with the support of multiple native languages. Universities and educational institutions in developing countries could partner with leading universities worldwide to create educational content delivered through MOOCs. This would help learners from diverse economic backgrounds receive a quality education, which serves the purpose of massive open online courses. Another important finding that emerged and applied to MOOC providers is the significance of course flexibility. MOOC providers should provide flexible learning periods to learners so that, even though learners perhaps drop a course, they should be able to resume where they left off when/if they decide to re-join. This study also found that perceived ease of use has a significant significance on perceived usefulness. Thus, the platform developers who create MOOCs should develop straightforward, user-friendly interfaces. Another important finding of the study that applies to practitioners is the significance of compatibility and facilitating conditions to the perceived ease of using MOOCs. For compatibility, MOOC developers should design interfaces that are compatible with other user interfaces with which learners are familiar. This is important for both developers and providers—if learners’ experience of using MOOCs matches their experience with other existing systems they are familiar with, then usage will be increased. Similarly, if learners have appropriate resources for using MOOCs, then their ease of use is improved. Thus, various MOOC stakeholders should consider multiple aspects while offering MOOCs to learners. MOOC providers can use these results to provide MOOCs that would appeal to diversified learners, increase usage, and reduce the dropout rate.

**Limitations and Future Research**

The present study has several limitations that have the potential to be addressed by future research. The first limitation is that the sample was derived from only one higher education institution located in a metropolitan area. In contrast, future studies could sample both urban and rural populations and draw their samples from multiple institutions and universities. In
addition, this study used convenience sampling—thus, caution should be exercised when interpreting and generalising the findings. Future research could study various barriers that lead to dropping out of MOOCs and post-adoption of MOOCs. Finally, only a limited number of studies have addressed MOOC adoption behaviour in a developing country. Consequently, future research should focus more on theoretical frameworks and empirical findings in this understudied area.

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