Intention and barriers to use MOOCs: An investigation among the post graduate students in India

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Abstract

Massive Open Online Courses (MOOCs) have widely been acknowledged as a unified platform to reduce the digital divide and make education accessible to all. It also enables students' access to professors and educational contents sans spatial and institutional barriers. Despite several benefits, MOOCs' adoption and completion rate remain unimpressive, especially among developing countries. Using Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), we examine the key factors that influence the behavioral intention to use MOOCs among students in an Indian private university. The data from 412 postgraduate students were analyzed using Partial Least Squares-Structured Equation Modelling. The study identifies barriers to use MOOCs, in a university that has offered free MOOCs courses and certifications to the students. The study makes several theoretical contributions and offer adequate insights for higher education institutions to administer and integrate MOOCs in their curriculum.

Keywords Online learning · MOOCs · UTAUT2 · E-learning · Distance education

1 Introduction

Online learning through MOOCs platforms has been considered a revolutionary development in the education system, with scalable, seamless, and equitable access to courses from universities, anywhere in the world. The ubiquitous penetration of internet and mobile communication technologies has brought about disruptive, but desirable, transformations in the higher education landscape, by making it inclusive. India, after the USA, dominates the global growth in MOOCs' enrolments (Chauhan 2017). The Government of India (GoI) has been extensively promoting MOOCs,

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through its SWAYAM platform (GoI 2020). There is an exponential growth in the number of courses offered through MOOCs and the number of universities participating in these platforms, worldwide. As per a report by Shah (2018), over 900 universities around the world had offered 11.4 k courses on the various MOOCs platform, by the end of 2018. Several universities in India have entered into strategic partnerships with MOOCs platforms for providing content and certifications to the aspirants.

Though the number of learners on the MOOCs platforms have crossed 100 million, there is a fall in the number of new learners registering in MOOCs platforms (Shah 2018). The number of user growth has not been commensurate to the growth of MOOCs platforms. Ma and Lee (2018) point out that the widespread use of MOOCs is still lagging, especially in developing countries. Alraimi et al. (2015) find that MOOCs completion rate is low, and only 10% of registered users successfully complete the course requirements. It was also found that, after the transition from free models to paid models, the registration and completion of MOOCs has dwindled (Gardner and Brooks 2018).

As the number of MOOCs platforms and their contents are on the rise, there is a need to examine the factors that contribute to the intention to use MOOCs and barriers to the same. There is a gap in understanding user needs and usage levels among various user groups (Dhanarajan and Abeywardena 2013). Though a recent study (Tseng et al. 2019) has investigated teachers' level of adoption of MOOCs, students' perception, in this regard, remains unexplored. It is also necessary to understand the factors affecting acceptance and use of MOOCs, as learners are expected to be self-motivated and self-directed in their learning (Milligan et al. 2013). Henderikx et al. (2017) proposed that perspectives of MOOCs users should be examined, rather than merely looking at the completion rates. Zhenghao et al. (2015) posited that there is a lack of understanding of MOOCs' experiences in developing countries.

In this backdrop, this study aims to identify the factors influencing intention to use MOOCs among the students in an Indian private university using UTAUT2 (Unified Theory of Acceptance and Use of Technology2). The study also attempts to identify the barriers to use MOOCs among students in Indian universities. Results of the study intend to make four epistemological contributions. Firstly, this research intends to make a pioneering attempt to examine the effects of gender as a moderator on the theoretical relationships in UTAUT2, with respect to MOOCs adoption. Secondly, the study can identify the factors that influence the intention to use MOOCs in a developing country perspective. Thirdly, it can ascertain the barriers in using MOOCs, specifically among private university students India. Fourth, this is the first-ever study regarding Indian students' intention to use MOOCs, using the UTAUT2 framework.

2 Review of relevant literature

Open education resources (OER) are viewed as a means to provide access to quality and low cost higher education (Dhanarajan and Abeywardena 2013). The OERs refer to "educational resources that are freely available for use, reuse, adaptation and sharing" (UNESCO 2020). In India, the OER movement has been accelerated with Government of India developing guidelines for MOOCs (GoI 2020). MOOCs, though in a nascent

stage in India, have been transformational development for Indian students, that provides a complete experience of taking a course through a planned schedule, assessments, and interaction with peers.

3 Characteristics of MOOCs

MOOCs are courses that are characterized by a large number of student enrollment (Massive), free and open to the public (Open), and offered on web-based digital format (Online) (Gardner and Brooks 2018). They are flexible concerning the time of course completion (asynchronous) and have diverse types of participants with varied demographics and motivations to participate (Chuang and Ho 2016). These characteristics of MOOCs make the learning experience sufficiently different from e-learning (Gardner and Brooks 2018). They also provide a vast amount of behavioral data, which may be effectively used to improve the engagement and completion rates. Three key differences between MOOCs and traditional classroom courses are diverse student enrolment, high dropout rate compared to that of traditional courses, and lack of instructor presence or real-time support in MOOCs (Hew and Cheung 2014). The MOOCs allow participants to take the course with no penalty for failing to complete the course or obtaining a degree and certificate (Gardner and Brooks 2018).

4 Acceptance, motivation, intention to use and barriers to use MOOCs among students

A plethora of studies have examined the acceptance and motivation towards online learning, open education resources, and MOOCs among students. Understanding motivations to use MOOCs and factors that affect MOOCs acceptance is important to enhance usage and completion rates among the participants. One of the motivations for students to take up MOOCs has been to learn a new subject or gain more knowledge (Hew and Cheung 2014; Watted and Barak 2018). Watted and Barak (2018) found that university students were more interested in gaining knowledge and certifications, whereas general participants of MOOCs were more interested in research and professional development. Belanger et al. (2013) reported that students were motivated by fun and enjoyment to enroll in Duke University's first MOOC course. Watted and Barak (2018) posited education, career, and personal motivation for students to enroll in MOOCs. A few studies on MOOCs have focused on why the learners complete MOOCs (Wang and Baker 2015) and why they drop out (El Said 2016). Xing and Du (2019) have developed a model to predict dropouts in MOOCs, using behavioral data.

Researchers have explored continuance intention to use MOOCs. Tsai et al. (2018) found that three levels of learning interest (liking, enjoyment, and engagement) were positively related to continuance intention to use MOOCs. Perceived ease of use and perceived usefulness, mediated by satisfaction was found to have indirect effects on continuance intention to use K-MOOCs (Joo et al. 2018). Using the technology task fit model, Khan et al. (2018) surveyed 414 students in Pakistan and found that social recognition, perceived competence, and perceived relatedness have positive and significant effects on the behavioral intentions of the students. Zhou (2015) found that

attitudes towards MOOCs and perceived behavioral control were significant determinants of intentions to use them. Wu and Chen (2017) found that perceived usefulness and attitude influenced continuance intention to use MOOCs among Chinese students.

Ma and Lee (2018) found that Chinese students faced individual-level barriers, usage barriers, and value barriers to using MOOCs. Individual-level barriers included a lack of self-control and a negative attitude towards study. Usage barriers such as lack of internet access, resources, and lack of interaction with faculty were some of the concerns reported by the students. Value barriers included higher cost, lack of time, and lack of incentive to complete courses.

Even though there are many studies on MOOCs, very little empirical research has been undertaken on factors that influence participation in MOOCs (Zhou 2015). There is very little research using Extended Unified Theory of Technology Acceptance Model in the area of MOOCs, particularly in a developing nation like India. Therefore, we examine the initial acceptance and intention to use MOOCs using Indian students' sample, as MOOCs is relatively in the nascent development stage in the country.

5 Unified theory of user acceptance of technology (UTAUT)

Several theoretical frameworks explain individual and organizational acceptance and the use of information systems. UTAUT, proposed by Venkatesh et al. (2003), has been widely used in information systems literature (Williams et al. 2015) to explain user acceptance of the technology. The model explains user acceptance of technology using four constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions. The performance expectancy refers to the degree to which an individual believes that "using the system will help him or her to attain gains in job performance." Effort expectancy refers to the degree to which the user perceives "the system is easy to use." Social influence is defined as the degree to which an individual perceives that "others believe he or she should use the new system." Facilitating conditions refer to the degree to which an individual believes that "an organizational and technical infrastructure exists to support the use of the system." McKeown and Anderson (2016) used the UTAUT model to examine differences among postgraduate and undergraduate students' use of the Moodle e-learning platform and found that acceptance of the technology was higher among PG students.

The UTAUT model was extended and three additional constructs (hedonic motivation, price value, and habit) were incorporated in the UTAUT2 model (Venkatesh et al. 2012). UTAUT2 is believed to have better explanatory power compared to UTAUT (Venkatesh et al. 2012). Hedonic motivation is defined as the "fun derived from using technology." Price value refers to consumer's belief of "perceived value or benefits of using the technology, compared to the cost for using them." Habit is defined as the extent to which an "individual behavior can be activated unconsciously by stimulus cues." Though UTAUT has been extensively used and applied to a wide range of information systems studies (Williams et al. 2015), no research has examined UTAUT2 model's use and application in MOOCs among students, in the Indian context. Tseng et al. (2019) have used UTAUT2 to identify the level of adoption of MOOCs among university faculty in Taiwan.

6 Conceptual framework and research hypotheses

In the present study, based on the Extended Unified Theory of User Acceptance of Technology (UTAUT2) model, six factors, namely, performance expectancy, effort expectancy, hedonic motivation, social influence, facilitating conditions and habit were hypothesized to have a positive influence on behavioral intention to use MOOCs (Venkatesh et al. 2012). The conceptual model of the research is presented in Fig. 1.

The construct 'price value', proposed in the UTAUT2 model, was not included as the MOOCs platforms were freely available for the referent students.

H1: Performance expectancy has a positive influence on the behavioral intention to use MOOCs
H2: Effort expectancy has a positive influence on the behavioral intention to use MOOCs
H3: Social influence has a positive influence on the behavioral intention to use MOOCs
H4a: Facilitating conditions has a positive influence on the behavioral intention to use MOOCs
H5a: Hedonic motivation has a positive influence on the behavioral intention to use MOOCs
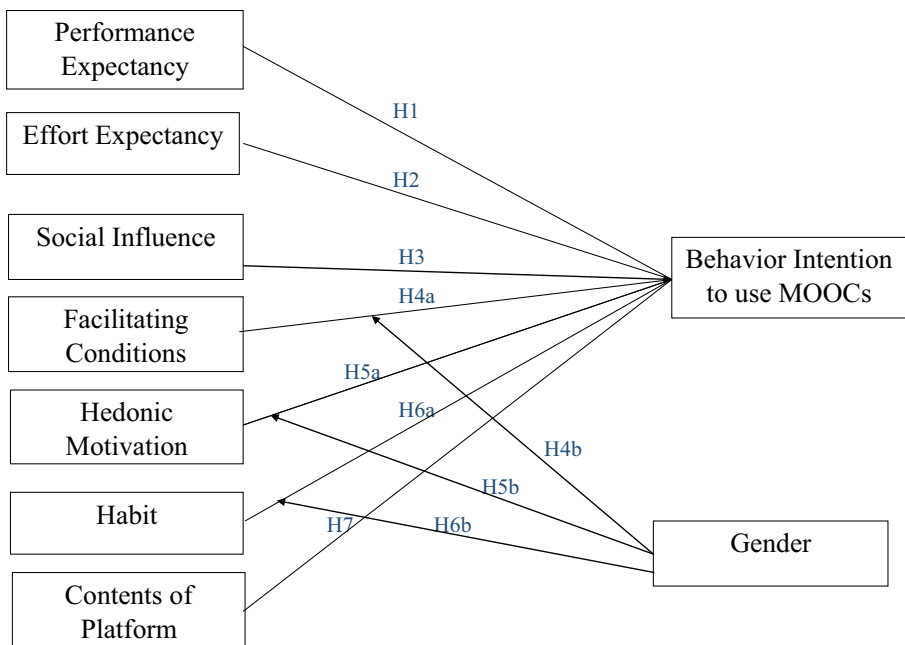H6a: Habit has a positive influence on the behavioral intention to use MOOCs

Fig. 1 Conceptual framework

6.1 Moderating effect of gender

The moderating effect of gender on behavioral intention to use MOOCs was examined for three constructs facilitating conditions, hedonic motivation, and habit, as proposed in the UTAUT2 model. Male users depend lesser on facilitating conditions when examining the use of new technology than female users (Venkatesh et al. 2012). Therefore, we hypothesize that.

> H4b: Facilitating conditions has a positive influence on the behavioral intention with the moderation of gender and specifically will have a high impact on female users.

Male users are found to have a greater tendency towards novelty seeking (Chau and Hui 1998). This is particularly applicable when the technology is new. Venkatesh et al. (2012) found that the impact of hedonic motivation is higher among young male users during the early use of new technology. Therefore, we propose that;

> H5b: Hedonic motivation has a positive influence on the behavioral intention with the moderating effect of gender and specifically will have a high impact on male users.

Information processing differs between male and female users. Women tend to put more emphasis on details and changes in the environment than men (Venkatesh et al. 2012). This characteristic in women results in weakening the effect of habit on intention or behavior for female users. Therefore, we propose that;

> H6b: Habit has a positive influence on the behavioral intention with a moderating effect of gender with high influence on male users.

7 Contents of the platform

In addition to the UTAUT2 model constructs, contents of the platform were hypothesized to influence intention to use MOOCs. Those who completed MOOCs were found to be more interested in the course content (Wang and Baker 2015). Hone and El Said (2016) posit that MOOCs' course content was a significant predictor of MOOCs retention. El Said (2016) found that course content and perceived value were significant in predicting MOOCs retention, in a study on undergraduate students in Egypt. Therefore, we hypothesize that if the students perceive value in the contents of the platform, they are more likely to use MOOCs. In the present study, we define 'contents of the platform' as the extent to which the learner believes that the platform provides content relevant to the learner.

> H7: Contents of the platform has a positive influence on the behavioral intention to use MOOCs.

8 Methodology

This empirical research used a quantitative method and a cross-sectional design to accomplish its goal. The study was conducted in an Indian private university that provided MOOCs courses, along with certifications, for free. It was, however, not mandatory for the students to undertake the courses. We construe that no-coercive choice paradigms would be more appropriate to examine the subjects' behavioral intentions to use. The university's student diversity is sufficient to represent Indian students' populace. Data was collected from the 412 postgraduate students who had enrolled for full-time programs from different disciplines in the university. An online survey was conducted during February 2019. A web link of online form was e-mailed to 2000 postgraduate students in Engineering, Management, and Health Sciences. A follow-up mail was sent to the students after 1 week as a reminder. The survey link was deactivated after 2 weeks. A total number of 412 usable responses were obtained, resulting in a 20% response rate. The sample included 47% male and 52% female students. The PG students were in the age group of 21–26 years and with no prior work experience. All the students, in the sample, reported having no prior experience in taking e-learning courses.

9 Measures

A pre-validated survey instrument, proposed in UTAUT2 model (Venkatesh et al. 2012), containing 27 items was used in the survey. All the measures in the UTAUT2 were modified to suit the context of MOOCs. The content of the platform was included as a new construct and was measured using a three-item scale. All the constructs were measured using a multi-item, seven-point Likert type scale (Venkatesh et al. 2012). The values ranged from 1 to 7, with strongly disagree coded as 1 and strongly agree coded as 7. Performance expectancy was measured using a four-item scale and was defined as the degree to which an individual believes that MOOCs are useful in gaining new skill sets. Effort expectancy was measured using a four-item scale and was defined as the degree of ease that is associated with the use of MOOCs platform. Social influence was measured using a three-item scale and defined as the degree to which the peers or faculty believe it is important to use the MOOCs platform. Facilitating conditions were measured on a four-item scale which measures the degree to which the student believes that the technical and the organizational infrastructure exist to support the use of MOOCs platform. The hedonic motivation was measured using a three-item scale and is defined as the pleasure or the fun factor that is experienced from using the MOOCs. One item in the construct (HM2) was excluded in the final analysis due to poor factor loading. Habit is the extent to which learners tend to perform the behavior automatically and was measured using a three-item scale. The dependent variable, behavioral intention to use MOOCs is defined as the perceived likelihood that a student engages in MOOCs and was measured using a three-item scale. The barriers to use MOOCs was presented as an open-ended question. The responses were coded based on themes and analyzed accordingly.

10 Analysis of results

Partial least square - structural equation model (PLS-SEM) was used to test the model. Smart PLS 3 software was used to test the model fit, its reliability and to validate the research hypotheses. The VIF values of all the constructs were observed to be below 4, which confirmed the absence of multi-collinearity among the variables considered.

The internal consistency and reliability of the measurement model and constructs in PLS-SEM models were measured using composite reliability and average variance extracted (AVE) scores. Composite reliability must be above 0.7 (Hair et al. 2017), to indicate that the items measure the factor that it is intended to measure. The AVE measures both convergent and divergent validity of the constructs. As per Höck et al. (2010), AVE should be greater than 0.5 to make a good construct. The composite reliabilities and average variance extracted values of the constructs used in the model are presented in Table 1. The results indicate that the scores are above the threshold value, indicating the reliability, convergent and divergent validity of the constructs.

In PLS-SEM, the fitness of the structural model is measured using SRMR. According to Hu and Bentler (1998), the SRMR value for a good model should be less than 0.08. The SRMR value for the model was found to be 0.055, indicating the robustness of the model. Hence it can be inferred that the construed theoretical relationship is reasonably consistent with the data set.

The structural model was tested using the bootstrapping test in Smart PLS. Each of the paths and their associated hypotheses were examined using t-statistic and the associated p-values. Table 2 summarizes the hypotheses and their associated inferences based on the bootstrapping test. The R^2 is another measure of the fitness of the model reported in bootstrapping, which in the present study, shows the ability of the model to assess the behavioral intention of students towards the usage of MOOCs. The R^2 value of 0.5 and above is considered to be a moderate model (Hair et al. 2017). In the study, R^2 was found to be 0.526, which implies that four significant factors are able to explain 52.6% of the variance in the intention to use MOOCs.

The analysis of the structural model indicates that habit is the most significant positive predictor of intention to use MOOCs among the referent students. This is followed by hedonic motivation, contents of the platform, and performance expectancy in the descending order of empirical significance. Gender was found to have a moderating effect on the relationship between hedonic motivation and behavioral intention. The effect of hedonic motivation was found higher among male participants. Male users were also found to have completed higher courses than the female users, on an average. Gender also moderated the relation between habit and behavioral intention to use MOOCs.

The other three constructs from the UTAUT2 framework, such as effort expectancy, social influence and facilitating conditions, appear to have no statistically significant influence upon the intention to use MOOCs in the current context of the study.

11 Barriers to use MOOCs

With respect to the barriers to use MOOCs, out of 412 students who responded 89 students had registered for MOOCs but could not even complete a single course.

Table 1 Measurement model reliability and validity results

	Indicators	Outer Loading	Internal Consistency/ Reliability	Convergent/Divergent Validity
			Composite Reliability (>0.7)	Average Variance Extracted (AVE) [>0.5]
Performance Expectancy	PE1	0.905		
	PE2	0.925		
	PE3	0.905	0.949	0.824
	PE4	0.895		
Effort Expectancy	EE1	0.869		
	EE2	0.931	0.949	0.822
	EE3	0.923		
	EE4	0.903		
Social Influence	SI1	0.857		
	SI2	0.938	0.933	0.823
	SI3	0.924		
Facilitating Conditions	FC1	0.868		
	FC2	0.885	0.91	0.716
	FC3	0.843		
	FC4	0.785		
	Facilitating Conditions * Gender	0.977		
Hedonic Motivation	HM1	0.944	0.926	0.863
	HM3	0.914		
	Hedonic Motivation * Gender	0.979		
Habit	HB1	0.896		
	HB2	0.887	0.899	0.748
	HB3	0.809		
	Habit * Gender	0.982		
Contents of Platform	CP1	0.941		
	CP2	0.939	0.946	0.854
	CP3	0.89		
Behavioral Intention	BI1	0.937	0.956	0.878
	BI2	0.929		
	BI3	0.944		

Around 130 students had completed one course and around 70 students did two courses. The number of students who successfully completed more than two courses was 123. Students reported time constraints, lesser effectiveness compared to traditional learning, technical barriers and monotonous as some of the barriers to low usage of MOOCs. Figure 2 shows the key barriers to use MOOCs.

Table 2 PLS-SEM results

Statement Of hypothesis	Result	P
H1: Performance expectancy has a positive influence towards the behavioral intention to use MOOCs	**Supported**	**0.006**
H2: Effort expectancy has a positive influence towards the behavioral intention to use MOOCs	Rejected	0.679
H3: Social influence has a positive influence towards the behavioral intention to use MOOCs	Rejected	0.483
H4a: Facilitating conditions has a positive influence on the behavioral intention to use MOOCs.	Rejected	0.104
H4b: Facilitating conditions has a positive influence on the behavioral intention with the moderation of gender and specifically will have high impact on female users.	Rejected	0.390
H5a: Hedonic motivation has a positive influence on the behavioral intention to use MOOCs	**Supported**	**0.002**
H5b: Hedonic motivation has a positive influence on the behavioral intention with the moderating effect of gender and specifically will have high impact on male users.	**Supported**	**0.013**
H6a: Habit has a positive influence on the behavioral intention to use MOOCs	**Supported**	**0.00**
H6b: Habit has a positive influence on the behavioral intention with a moderating effect of gender with high influence on male users.	**Supported**	**0.025**
H7: Contents of platform has a positive influence on the behavioral intention to use MOOCs	**Supported**	**0.003**

Around 41% of students reported that their regular academic schedules prevent them from engaging effectively into MOOCs, signaling their difficulty to manage time and unfavorable attitudes towards MOOCs.

12 Discussion

The MOOCs enable students to acquire new skill sets and certifications. Habit, being identified as the most significant predictor of the intention to use MOOCs, signals the self-efficacy of the respondents due to continuous use of the digital platforms. Our result is consistent with previous studies (Tsai et al. 2018), with respect to the fun and
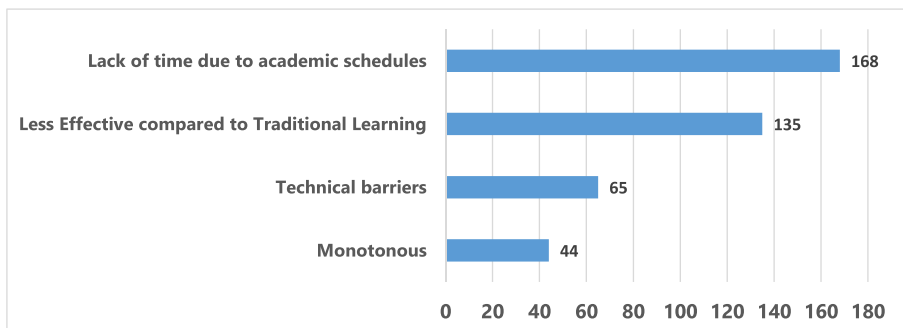
Fig. 2 Barriers to use MOOCs

enjoyment elements (hedonic motivation) in continuous intention to use MOOCs. Literature evidence is present regarding the role of content of platform as significant predictor of MOOCs' usage (Wang and Baker 2015; Hone and El Said 2016).

However, a previous study (Tseng et al. 2019), on faculty intention to use MOOCs, found no effect of hedonic motivation on the behavioral intention to adopt and use. The difference in the results may be due to the polarity in the perceived values of the stakeholders. The faculty may assign existential or use-value in the adoption of MOOCs, whereas students may be inclined more to its experiential value. Students are enthusiastic about MOOCs, being a new form of learning.

Contradicting the previous findings (Venkatesh et al. 2012; Tseng et al. 2019), effort expectancy, social influence and facilitating conditions did not have an influence on the behavioral intention to use MOOCs in the current context. This could be due to the sample in the study that is familiar with web-based technologies and has adequate resources to access the courses. It is also relevant to note that the sample profile of the study comprised of postgraduate students, whose cognitive level is high to make choices. The findings may differ from students from rural and remote areas with lesser access to the internet and experience with internet use, which need to be investigated before generalization of our results. It was found that students are interested to use MOOCs platforms with the average intention to use MOOCs to be 5.25 (on a scale of 7) with a standard deviation of 1.2. This result conveys an overtly higher level of intention to use MOOCs among the subjects.

Consistent with the previous research (Ma and Lee 2018), the current study has identified self-control and attitude as major individual barriers to the use of MOOCs. Xing and Du (2019) also have contended the role of behavioral dispositions in predicting the drop out possibility in MOOCs' adoption.

13 Theoretical contributions and managerial implications

The paper bestows four important contributions to the literature. First, it identifies the factors that influence the intention to use MOOCs in a developing country, using UTAUT2. Second, it also identifies the barriers faced by Indian private university students in using MOOCs. Third, this research makes a pioneering attempt to examine the effects of gender as a moderator on the theoretical relationships in UTAUT2, with respect to MOOCs adoption. Fourth, this is the first-ever study regarding Indian students' intention to use MOOCs, using the UTAUT2 framework.

The findings of the study provide useful insights into higher education institutions, planning to introduce MOOCs. There seems to be a high interest in undertaking MOOCs among Indian students for building skill sets. As it was found that performance expectancy and content of the platform influence intention to use, it can be inferred that learners consider the ability to increase skill sets and knowledge as one of the key factors of intention to use MOOCs. Hence, MOOCs must clearly indicate learning outcomes, skills that would be acquired, and content coverage of the course to attract learners to the course.

Due to time constraints and lack of faculty support in completing the course assignments, several students have not used MOOCs or left them incomplete. Therefore, MOOCs need to be integrated into the curriculum and the universities must

encourage blended learning through MOOCs in regular courses. Bralić and Divjak (2018) found blending MOOCs with a traditional course, that has specific learning outcomes, would enhance student motivation and increase MOOC's completion rate. Chamberlin and Parish (2011) found that students were more committed to finishing the course when credits are awarded for course completion. Our study also unfolds that students assign priority to their regular courses, which poses deterrence to the completion of MOOCs courses. Hence academic incentive (awarding credit) would be a suitable nudge to encourage the completion of MOOCs courses. This would also increase familiarity with the MOOCs course and would become a common practice and habit for the students.

Indian higher education institutions must encourage blended learning with clear learning outcomes and MOOCs must be embedded in the course, with a specific deadline to complete the course. After the completion of MOOCs, suitable assessments must be taken place to ensure timely completion of the course. Relevant MOOCs courses, identified by the faculty may be recommended to the students, for selected topics in the course, in addition to the classroom sessions. Blended learning would also facilitate interactions with faculty members, which is grossly absent in MOOCs. The role of faculty is critical in offering blended learning. Faculty must motivate students to inculcate the habit of self-directed learning. However, we do not overlook the finding of Ma and Lee (2018) which concedes that students tend to be reluctant to study in the classroom, due to lack of enthusiasm. MOOCs platforms may be an unpassable test without befitting rewards, in such cases.

Hedonic motivation was found to be another factor that influenced learners to use MOOCs. The institutions developing content for MOOCs need to create engaging and interesting experiences to the learners. While designing course content, it is important to use diverse multimedia and practical applications in order to create and sustain interest. It would make effective use of technology and remove the barriers of perceived monotony of traditional learning sessions. Higher education institutions need to set up an effective helpdesk to enable students to overcome technical issues.

Male students had a higher influence on hedonic motivation and habit on the intention to use. Institutions may consider this aspect while selecting student champions to promote MOOCs. Managers promoting MOOCs must emphasize the content, coverage and their platforms' benefits to students.

14 Limitations and conclusions

The study has a few limitations as well. Firstly, as the study was conducted focusing on free platforms, the impact of the price of the course on the intention to use MOOCs was not examined. Secondly, the study draws conclusions based on the intention to use and not the actual behavior of the participants and how they engage with MOOCs. Thirdly, the study was conducted in a large private university that has facilitated MOOCs free of cost and the use of ICT is comparatively high in its teaching and learning programs. The intention to use MOOCs might be higher in such facilitating conditions, than with otherwise. Hence, the generalizability of these results may be contestable. Future studies, with experimental design to capture the actual behavior of the users, are highly recommended.

El Said ([2016](#)) posited that MOOCs integrated with university programs would increase the likelihood of MOOCs completion. MOOCs have become a game-changer in education, making learning inclusive and global. Higher education institutions must find innovative ways to integrate MOOCs in their curriculum to enhance the learning experience of learners. In this era, where universities continually seek to bridge the gaps between industry and academia, MOOCs may provide easy means to incorporate complementary skill sets among the learners and make the learning pervasive and personalized.

Appendix 1: Measures

Performance Expectancy:
    PE1 - I find courses offered by MOOCs useful to build my career.
    PE2 - Doing courses on MOOCs enhances my knowledge on my subject interest.
    PE3 - MOOCs courses increase my academic productivity.
    PE4 - MOOCs make it easy for me to improvise my skill sets needed for my career.
    Effort Expectancy:
    EE1 - Learning how to Use MOOCs is easy to me.
    EE2 - I find MOOCs platform easy to access.
    EE3 - It is easy for me to become skillful at using MOOCs.
    EE4 - It is easy to understand the concepts on MOOCs.
    Social Influence:
    SI1 - People who are important to me think I should do MOOCs courses.
    SI2 - People who influence and assist me in my career think I should do MOOCs courses.
    SI3 - People whose opinion I value believe I should accomplish MOOCs certifications.
    Facilitating Conditions:
    FC1 - I have enough resources to do Courses on MOOCs.
    FC2 - I have the knowledge necessary to use MOOCs.
    FC3 - MOOCs website/app(s) is compatible with both PC and Mobile.
    FC4 - I easily get assistance from others when I face difficulties to access MOOCs.
    Hedonic Motivation:
    HM1 - Doing courses on MOOCs is fun.
    HM2 - Doing courses on MOOCs make me feel weariness. **(* Removed).**
    HM3 - I find MOOCs courses much entertaining to accomplish.
    Habit:
    HB1 - The use of MOOCs has become a habit for me.
    HB2 - I am addicted to learning via MOOCs.
    HB3 - I must use MOOCs.
    Contents of Platform:
    CP1 - MOOCs platform has enough content relevant to my area.
    CP2 - The courses on MOOCs cover all the concepts relevant to my area.
    CP3 - The contents on the MOOCs platform are good.

Behavioral Intention to use MOOCs:

BI1 - I intend to continue accomplishing courses on MOOCs in future.

BI2 - I will always try to use MOOC's throughout my career.

BI3 - I plan to continue doing more new courses through MOOCs.

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