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Can MOOC be a medium of lifelong learning? Examining the role of Perceived Reputation and Self-efficacy on Continuous Use Intention of MOOC

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Abstract

Many Higher Education Institutions in India have started to include Massive Open Online Course (MOOC) as a part of their curriculum. Yet little research has been done to understand the factors that affect the users' sustained interest to recurrently enroll and complete MOOC courses throughout their lifetime. A sample of 316 students from Higher Education Institutes in India participated in this survey. Partial Least Square Structural Equation Modeling (PLS-SEM) using smartPLS was employed to assess the structural model. The structural model used is a combination of constructs from technology acceptance theories namely perceived usefulness, perceived ease of use, attitude, facilitating condition and continuous use intention of MOOCs, with perceived reputation and MOOCs self-efficacy as external variables. The results not only proved the applicability of basic TAM constructs in understanding the behavioral intention of MOOCs but also the significance of external variables, particularly the role of perceived reputation in influencing the perceived usefulness of MOOCs.

KEYWORDS: Moocs, Perceived Reputation, Self-Efficacy, Technology Acceptance Model.

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1. Introduction

Technology has penetrated the lives of many individuals because of the sudden eruption of the COVID-19 pandemic, as a result of which people started to experience significant lifestyle changes. With the Internet and smartphones/computers becoming an integral part of life, working from home and education from home have become new norms. During the times of strict lockdown in India to curb the spread of COVID-19 infection, people had no choice but to head online, even for a minimal need. Thus, access to Information and Communication Technology (ICT) has become necessary and is no longer a luxury. At this juncture, online learning started gaining momentum among educational institutions due to its prolonged closure. The sudden transition to online learning during the pandemic has made students and the educational fraternity realize the importance of online learning platforms (Sun et al., 2020). Many students started enrolling in Massive Open Online Courses (MOOC) during the pandemic, which is evident in the surge in the enrollment rate by 25-30% (Shah, 2020). MOOC has the potential to lessen educational inequity. It is a boon for developing countries like India in particular, as access to quality education remains a distant dream for many. With multi-disciplinary skill sets being sought after by industry, graduate and post-graduate students started opting for specialized courses that may or may not be directly linked to their core area. MOOC is a model for providing learning content online to anyone with almost no limit on attendance. The model started becoming more widely used as it served as a platform to equip the student with a relevant skill set at a time and duration convenient to the student (Ansari & Biswal, 2023). The pandemic has become a major driving force of MOOC acceptance and use (Shen et al,

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2024; Brauweiler & Yerismpasheva, 2021; Jones & Sharma, 2020) and there has been a wide acceptance of MOOC among students of higher education institutions due to pandemic (AL-Nuaimi et al., 2022; Rasli et al., 2022; Haryati et al., 2021). This study is pivotal amidst increasing awareness of digital learning post-pandemic, and many higher education institutions started to adopt the online mode of education including flipped learning.

While online learning was gaining momentum even before the onset of the pandemic, and MOOC, in particular, was seeing a surge in enrollments, particularly from the US, India and the UK during the pandemic and particularly, India saw a whooping 7 times increase in MOOC enrolment (Chris & Martin, 2021), there was no significant improvement in the completion rates (Blackwell & Wiltrout, 2021). A study done in India showed that despite a massive increase in MOOC usage by Indian students due to covid19 pandemic, the dropout rates remained significantly higher (Dang et al., 2022). One of the challenges still faced by MOOC providers is its poor completion rate (Rekha et al., 2023; Romero-Rodríguez et al., 2020; Pursel et al.,2016; Cisel, 2014; Khalil & Ebner, 2014). In developing countries like India, the nominal fee to earn a certificate is often considered a financial barrier to taking MOOC courses (Blackwell & Wiltrout, 2021). The study also highlighted that the initial surge in MOOC enrollments did not sustain because of low motivational levels, and learning boredom due to lifestyle changes, making the retention of MOOC learners all the more difficult. Kizilcec et al. (2013) studied the pattern of MOOC learners in four countries, namely the US, UK, India and Russia. They found that most of the learners from India watched a couple of videos at the beginning of the course and did not intend to complete any MOOC course. Therefore, it has become crucial for educators to provide an online learning environment that can retain the learners' interest for MOOC to be successful in the long run.

With most of the past MOOC research focused on MOOC adoption, there is an urgent need to understand the poor completion rate (Meet & Kala, 2021). There is a paucity of studies focusing on MOOC dropouts and retention, while available such studies were mainly from the USA, South Korea and China (Goopio & Cheung, 2021; Khan et al., 2021). The ultimate success of a MOOC course depends on the completion rate and not on the number of participants (Rekha et al., 2023) and there is a dearth of MOOC-related studies based out of India (Rekha et al., 2023; Rasheed et al., 2019). Also, many past studies on online learning that were conducted among students of Higher Education Institutions (HEI) were in a mandatory environment, wherein students had to enroll in an online course as a part of their academic requirement. This research addresses the gap in the existing literature by focusing on factors affecting the continuous use intention of MOOCs among students of HEI in India in the context of the voluntary environment. In a voluntary environment, students enroll in MOOC courses out of self-interest and thirst to gain knowledge in the subject of their choice.

To understand what influences an individual to adopt and use MOOC, a recent systematic literature review by Badali et al. (2022) stated that the Technology Acceptance Model (TAM) is the second most widely used model. The model explains how beliefs such as ease of use, the usefulness of technology, and attitude towards using it affect one's intention to use it (Davis et al., 1989). TAM model can be integrated with other external variables to yield better results (Tao et al., 2019). Though many researchers started incorporating external variables into TAM for better predictive power, few studies have had factors related to MOOC's characteristics (Kim & Song, 2021). This study addresses the gap by integrating two external variables, namely Perceived Reputation (PR) and Self-Efficacy (SE).

Perceived reputation, a factor related to MOOC, refers to a set of user beliefs placed on the institutions, platforms and faculty offering MOOC courses. Many studies have shown a significant influence of a website's reputation on consumers' trust, subsequently leading to a prolonged commitment to the online platform (Casalo et al., 2007). As MOOC platforms are mostly partnered with reputed institutions worldwide, it becomes a deciding factor when choosing and enrolling in a MOOC course (Alraimi et al., 2015). Most MOOC researchers have overlooked this factor of reputation, which is considered an intrinsic trait of MOOC (Tella et al., 2021). Thus adding the external variable PR to the model would help in understanding how reputation influences the behavioral intention of MOOC users.

The second external variable used in the context of MOOC is self-efficacy, a factor related to MOOC users that refers to an individual's skills and confidence in using MOOC effortlessly. SE is seen as an essential factor in the successful completion of online courses (Punjani & Mahadevan, 2021). It is a critical variable to be considered in a developing country like India, where both the first-level digital divide (inequity in owning ICT) and the second-level digital divide (inequity in the ability to use ICT) are more pronounced. According to a study based on National Sample Survey Office (NSSO) data, only 25% of currently enrolled students in India in the age group between 5 and 35 years have access to the Internet, of which only 9% have a computer with Internet connection (Reddy A et al., 2021). A similar study using NSSO data also reveals that the computer and internet literacy rate in India is low (Rajam et al., 2021). Hence, the self-efficacy to use MOOC could act as an essential factor for MOOC to become a medium of choice for lifelong learning, particularly in India.

Thus, this study's main aim is to understand the structural relationship between perceived reputation, self-efficacy, and constructs from technology Acceptance theories to understand the factors that affect users' continuous use intention of MOOC. By throwing light on the significant factors that affect the sustained interest of MOOC learners, this study will inform educational policymakers to develop and design MOOC courses so that MOOCs may become an ideal medium of choice for lifelong learning.

2. Literature review

Even though India has the second-largest MOOC users, and many MOOC platforms and courses are developed in India, implementing such online learning platforms does not necessarily translate into efficient usage. Even in the case of Indian home-based MOOC platforms, of the total enrolled students, less than 1% of students went on to complete the course (Bordoloi et al., 2020). The success and effectiveness of MOOC usage depend solely on the educators and students, who are in turn influenced by various factors of society, organization and culture. It is of utmost importance to evaluate learners' perception of the factors that influence them not just to enroll but also to complete MOOC courses, which is of interest to this study.

2.1 MOOC in HEI

Past studies have shown that course completion is not the only reason a student enrolls on a MOOC course (Goopio & Cheung, 2021). Most enrolled users used the course material selectively if they found it helpful (Jacobsen, 2019). However, the success of MOOCs depends on the number of those who complete the course (completion rate) than those who merely enroll (Khan et al., 2021; Yang et al., 2017). The initial push to enroll in a course is not sustained throughout the course leading to increased dropout rates in many MOOC courses.

In the past decade, there has been a surge of MOOC models being opted by universities. They started offering short courses with specific schedules with online exams and providing a vocational degree/certificate to the candidates who completed the program. With the Internet reaching most of the population, MOOCs became a significant channel to empower people across different geographies with relevant skill sets. For the last ten years, we have seen the emergence of not-for-profit and for-profit MOOC providers from private sectors like Khan Academy, edX, Coursera, etc. In India, students can now earn a bachelor's degree by completing 40% of the program online via SWAYAM, India's official MOOC. The increasing demand for higher education in Asia makes MOOCs a viable choice (Goopio, 2021). The National Education Policy 2020 by the Government of India has a particular emphasis on the online mode of education as it has the potential to reach the neediest and underprivileged segment of people in India (Government of India, 2020).

2.2 Technology Acceptance Theories

There are several frameworks or models to understand the factors that influence user acceptance of technology, which include Technology Acceptance Model (TAM) by Davis, Theory of Reasoned action (TRA), Theory of Planned Behavior (TPB), Innovation Diffusion Theory (IDT), Motivational model, Unified Theory of Acceptance and Use of Technology (UTAUT), Social Cognitive Theory and to name a few.

TPB, TAM and UTAUT are the most widely used models. Past studies suggested incorporating the relevant constructs with TPB, TAM and UTAUT to understand better MOOC user behavior (Song et al., 2017; Tawafak et al., 2020; Meet & Kala, 2021). TAM is an extension of TRA, which predicts user acceptance of technology through intention measures. TAM was designed to predict the acceptance of computer-based technology (Davis et al., 1989). TAM includes two important constructs that impact the user acceptance of a particular technology; Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU is defined as "the degree to which a person believes that using a particular system would increase his/her job performance", and PEOU is defined as "the degree to which a person believes that using a system would require little effort" (Davis et al., 1989). It is vital to examine the role of PEOU in using MOOCs in developing countries, as the HEI are bringing a paradigm shift in traditional classroom teaching (Khan et al., 2021). PEOU and PU will affect the individual's attitude towards using MOOC, which leads to intention towards using it. Attitude (ATT) is defined as "the individual's positive or negative feelings towards a technology" (Davis et al., 1989). UTAUT is a combination of critical factors from eight theories/ models related to technology use, proposed by Venkatesh et al. (2003). The model has been used in different studies on technology acceptance and usage. The essential constructs of UTAUT are effort expectancy similar to PEOU, performance expectancy similar to PU, Social Influence and Facilitating Condition (Taherdoost, 2018). This study incorporates the variable Facilitating Condition (FC) from the UTAUT2 (Venkatesh et al., 2012), an extension of the UTAUT model. FC is defined as "the consumers' perceptions of the resources and support available to perform a behaviour" (Venkatesh et al., 2003).

Studies in the past focused on the adoption of e-learning and factors affecting the adoption intention of e-learning among students of HEI (El-Masri & Tarhini, 2017; Decman, 2015; Mohammadi, 2015; Park, 2009). However, only a few past studies have used an integrated model to understand the students' continuous use intention of MOOCs (Tao et al., 2019; Yang et al., 2017). Particularly in India, such studies are sparse. Hence, the present study addresses the gap by integrating constructs from TAM and UTAUT to study the individual's intention to continue using MOOC in a voluntary environment.

2.3 Conceptual framework and hypothesis development

Figure 1 explains the proposed research model, in which Continuance Use Intention (CUI) is a dependent variable. Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Attitude (ATT) from TAM are integrated with the Facilitating Condition (FC) of UTAUT2, with Perceived Reputation (PR) and Self-efficacy (SE) as external variables of TAM. The direction of influence of the constructs ATT, PU, PEOU AND FC on CUI is based on the theoretical models, namely TAM and UTAUT2. The direction of influence of external variables is explained in detail in the subsequent section.

2.4 Construct from TAM

A systematic literature review of MOOCs by Goopio and Cheung (2020) revealed that PEOU and PU positively affect continuance intention. Finally, ATT to Behavioral Intention (BI) is fundamental to TAM, which theorizes that the intention to use technology is based on an individual's positive attitude.

H1: Attitude towards using MOOCs positively influences an individual's continuous use intention of MOOCs.
H2: Perceived usefulness positively influences an individual's attitude toward using MOOCs.
H3: Perceived ease of use positively influences an individual's attitude toward using MOOCs.
H4: Perceived ease of use has a positive influence on perceived usefulness.

2.5 Constructs from UTAUT2

Access to digital infrastructure comes at the forefront of using digital learning tools seamlessly. In India, the digital divide is a pertinent issue, and access to the Internet is still meagre among a large population (Rajam et al., 2021). Given the prevailing status of ICT infrastructure in India, the construct facilitating condition plays a significant role in the continuous use intention of MOOCs by users. Thus, facilitating conditions plays a vital role in the practical usage of MOOCs by users.

H5: Facilitating condition positively influences an individual's continuous use intention of MOOC.

2.6 External Variables

The study uses two MOOC-related characteristics namely self-efficacy, which is a MOOC user factor and perceived reputation, a factor related to MOOC, to know how well they add as antecedents to TAM constructs in understanding users' continuous intention in using MOOCs.

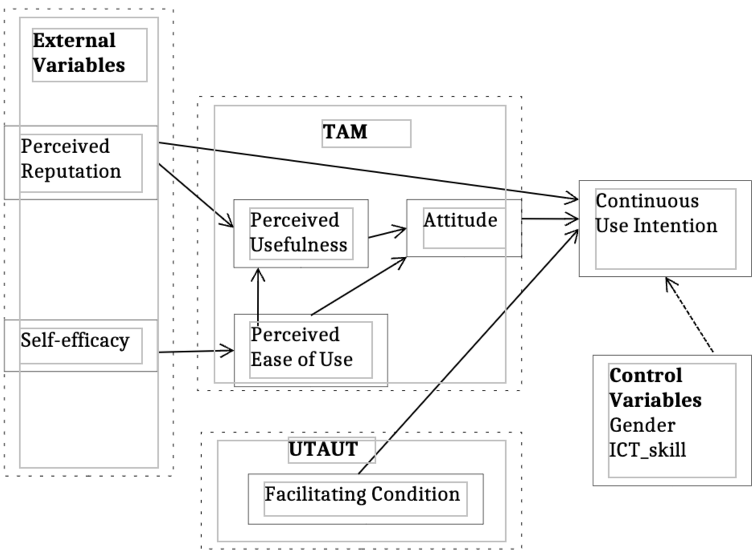

Figure 1 - Research Model. Integrating the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with self-efficacy and perceived reputation as external variables.

Self-efficacy

Self-efficacy is drawn from Bandura's Social Cognitive Theory (Bandura, 1986). It is defined as an individual's ability to perform a specific task to yield the desired outcome. Prior studies showed that computer self-efficacy indirectly influenced behavioral intention to use technology via perceived ease of use (Roca et al., 2006; Venkatesh & Davis, 1996). Individuals having higher self-efficacy are often highly motivated, goal-oriented and self-regulated learners (Lee et al., 2020). In a voluntary environment, self-regulated learning is the key to successful online learning (Cho & Shen, 2013). Also, self-efficacy is the critical determinant of MOOC completers. Individuals exhibiting higher self-efficacy are more inclined to complete the MOOC course (Kuo et al., 2021; Barak et al., 2016). Hence, we postulate the following hypothesis:

H6: Self-efficacy positively influences an individual's perceived ease of use of MOOCs.

Perceived Reputation

An organization's reputation positively affects customer retention in service sectors (Milan et al., 2015). Reputation has been a variable of interest in many industries (Cioppi et al., 2019). In the context of MOOC, the reputation of the course provider is the key to retaining learners' interest (Khan et al., 2018). According to Fombrun and Van Riel (1997), reputation is defined as a "collective representation of a firm's past actions and results that describes the firm's ability to deliver valued outcomes to multiple stakeholders". Renowned and elite Western universities offer most MOOC courses hosted on platforms such as Coursera, edX, etc. (Rambe & Moeti, 2017). The fact that MOOC courses are being offered by reputed institutions worldwide is a significant reason for students from developing countries to enroll in such courses. Like in any other product/service sector where the reputation of a firm drives repeated purchases, in the context of MOOC, reputation could drive sustained usage among individuals. Also, there is a dearth of research looking at reputation as a MOOC feature in influencing the behavioral intention of learners, particularly in the Indian context. Studies by Wu and Chen (2017), Huanhuan and Xu (2015), and Alraimi et al. (2015) showed perceived reputation as a significant predictor of MOOC use intention. This study differs from the above studies in that reputation is used as an external variable in the integrated TAM model and is also hypothesized to influence CUI directly and indirectly via PU, particularly in the Indian context.

H7: Perceived reputation positively influences an individual's perceived usefulness of MOOC.

H8: Perceived reputation positively influences an individual's continuous use intention of MOOCs.

Control Variables

The control variables used in the research model are level of ICT skill and gender. Demographic variables, including gender and level of ICT skill, were examined in past studies to know how they impacted learners' MOOC behavior (Greene et al., 2015; Kaveri et al., 2015; Dillahunt et al.,2014). ICT skill is the extent to which an individual is good at using ICT and has four levels: elementary, limited, professional and expert.

3. Methods

The study uses a survey method to test the hypothesis developed. Questionnaire development and data collection are discussed subsequently.

3.1 Questionnaire development

We employed a questionnaire survey that has two sections. The first section is related to demographic profiles such as gender, place of study, etc. of the participants. The second section corresponds to items measuring constructs used in the research model. Each item is measured using a five-point Likert scale, with 1 being "strongly disagree" and 5 being "strongly agree". The appendix shows the items under each construct used in the research model.

3.2 Data collection

The target participants of this study are undergraduate and postgraduate students of Higher education Institutions from Chennai (Metro) and Coimbatore (semi-metro) cities in India. Chennai and Coimbatore are cities located in the state of Tamil Nadu, India. According to the AISHE 2019-20 report, Tamil Nadu is one of the top 5 states with the highest number of student enrollment in higher education. A purposive sampling method was employed, and the interested participants were given the questionnaire. Participants were briefed about the survey, and data was collected only from those who had either enrolled or completed a MOOC course in a voluntary environment. With a 95% confidence interval and a 5% margin of error, the sample size estimated was 384. However, out of 466 responses received, only 316 were complete responses and considered for further analysis.

3.3 Data analysis

Data analysis involves two components: Confirmatory Factor Analysis (CFA) explained in the section confirmatory factor analysis and Structural Equation Modeling (SEM) explained in the section structural model and hypothesis testing. Partial Least Square Structural Equation Modeling (PLS-SEM), a widely used tool in Information System (IS) literature, is used to analyze data. PLS-SEM is best suited for performing both exploratory and confirmatory factor analysis as it does not have any assumptions about the data distribution and works well even with a small sample size (Hair et al., 2017). However, we used the recently introduced Consistent Partial Least Square (PLSc) estimation using SmartPLS due to the following reasons: (1) It is more robust than the traditional PLS-SEM; (2) The estimations of PLSc are almost similar to CB-SEM result; (3) Constructs are reflective (Dash and Paul, 2021; Cheah et al., 2018).

Reliability, convergent, and discriminant validity are assessed for CFA with the PLSc method. According to Hair et al. (2017), construct reliability and convergent validity: CR >=0.70, Average Variance Extracted (AVE) for CV >=0.50 and item factor loading >0.70. Discriminant Validity (DV) is assessed using the consistent PLS-based Heterotrait-Monotrait (HTMT) method proposed by Henseler et al. (2015). According to this method, the correlation of items is measured simultaneously within the same construct and across the constructs. A predefined threshold of 0.85, as Kline suggested, and the HTMT values should be lower than the threshold value (HTMT 0.85) to achieve discriminant validity (Kline, 2011). The hypothesis and relationship between the constructs in the study are tested using PLS-SEM. The metric for validating the proposed model includes the R^2 value.

4. Results

4.1 Descriptive summary

Table 1 shows the descriptive summary. About 45% of the respondents were female, and 55% were male students. Those studying in the metro region comprise 29%, and those from the semi-metro constitute about 71%. ICT skills are limited for 49% of the total respondents, 39% were professional, 6% exhibited elementary-level ICT skills, and 5% were ICT experts.

4.2 Confirmatory Factor Analysis

Reliability and Convergent validity

Table 2 shows Cronbach’s Alpha score to measure reliability. As mentioned earlier, the score should be greater than 0.70. Convergent validity is measured using three criteria put forward by Fornell and Larcker: item loading, Composite Reliability (CR) and Average Variance Extracted (AVE), as shown in Table 2. Cronbach’s alpha and Convergent Validity of all the constructs met the required criteria and were deemed adequate.

Discriminant Validity

Discriminant validity refers to the extent to which a given construct differs from another. Prior researches show that the HTMT method is preferable to the Fornell-Larcker method (Ramayah et al., 2017; Henseler et al., 2015) due to the bias effect suffered by the consistent PLS-based Fornell-Larcker method (Afthanorhan et al., 2021). Hence, this study uses HTMT to assess DV. Table 3 presents the HTMT values of each construct, which is less than HTMT0.85, thus satisfying the Discriminant Validity criterion.

4.3 Structural model and hypothesis testing

The consistent PLS technique is used to assess the structural model and estimate the path coefficient and significance of the proposed hypothesis. Figure 2 shows the path coefficients and corresponding level of significance. The variance of the dependent variable is also shown in Figure 2. The R square value quantifies the amount of variance in the dependent variable as explained by the independent variables. The R-square value of the dependent variable, CUI, is 68.5%, which is highly acceptable and 50.3% for the construct attitude. Perceived ease of use and Perceived reputation together account for 59.4% variance in Perceived Usefulness, while self-efficacy accounts for 46.1% variance in PEOU.

Table 4 shows the proposed hypothesis's indirect, direct, and total effects. The results show that attitude is the strongest predictor (β = 0.718) of continuous use intention of MOOC, which implies that students who have a positive attitude towards using MOOC tend to use it persistently. In turn, attitude is affected directly by perceived usefulness (β = 0.448) and perceived ease of use (β = 0.309). Thus, hypotheses 1-4 related to TAM constructs are all supported. Facilitating condition, a construct from UTAUT added to the model does not affect the continuous use intention of MOOCs, rejecting hypothesis H5. The facilitating condition talks about available resources and support in using MOOCs.

Table 1 - Descriptive summary.

Variables		*Frequency*	*%*
Gender	Female	141	44.62
	Male	175	55.38
Place of Study	Metro	91	28.80
	Semi-Metro	225	71.20
ICT_Skill	Elementary	20	6.33
	Limited	156	49.37
	Professional	124	39.24
	Expert	16	5.06

Table 2 - Reliability and convergent validity.

Construct	*Item code*	*Item loading*	*AVE*	*CR*	*Cronbach's α*
Perceived Usefulness	PU1	0.843	0.633	0.873	0.874
	PU2	0.779			
	PU3	0.769			
	PU4	0.792			
Perceived Ease of Use	PEOU1	0.780	0.689	0.869	0.869
	PEOU2	0.845			
	PEOU3	0.865			
Attitude	ATT1	0.805	0.655	0.850	0.850
	ATT2	0.783			
	ATT3	0.838			
Continuous Use Intention	CUI1	0.731	0.520	0.812	0.812
	CUI2	0.744			
	CUI3	0.707			
	CUI4	0.703			
Facilitating Condition	FC1	0.755	0.526	0.769	0.770
	FC2	0.682			
	FC3	0.738			
Perceived Reputation	PR1	0.749	0.588	0.851	0.851
	PR2	0.797			
	PR3	0.740			
	PR4	0.781			
Self-efficacy	SE1	0.734	0.532	0.773	0.773
	SE2	0.723			
	SE3	0.731			

Table 3 - Discriminant validity (HTMT ratio).

	ATT	CUI	FC	PEOU	PR	PU	SE
ATT							
CUI	0.824						
FC	0.794	0.682					
PEOU	0.647	0.623	0.579				
PR	0.654	0.586	0.522	0.559			
PU	0.681	0.644	0.600	0.759	0.540		
SE	0.782	0.691	0.779	0.680	0.654	0.627	

Table 4 - Summary of the direct and indirect effects of the proposed hypothesis.

H#	*Proposed relationship*	*Indirect effect*	*Direct effect*	*Total effect*	*Results*
H1	ATT (+) -> CUI	-	0.718^{***}	0.718	Supported
H2	PU (+) -> ATT	-	0.448^{***}	0.448	Supported
H3	PEOU (+) -> ATT	0.298^{***}	0.309^{**}	0.607	Supported
H4	PEOU (+) -> PU	-	0.667^{***}	0.667	Supported
H5	FC (+) -> CUI	-	0.062	0.062	Not Supported
H6	SE (+) -> PEOU	-	0.680^{***}	0.680	Supported
H7	PR (+) -> PU	-	0.167^{*}	0.167	Supported
H8	PR (+) -> CUI	0.054	0.077	0.131	Not Supported

The external variables added to the TAM model are self-efficacy and perceived reputation. Self-efficacy directly affects perceived ease of use (β = 0.680) and indirectly affects attitude (β = 0.413) positively. Those who perceive that they are capable of using MOOCs tend to feel comfortable in using MOOCs and also show a positive attitude towards using them, supporting hypotheses 6 and 7. Perceived reputation positively affects perceived usefulness (β = 0.167). However, its relationship with continuous use intention is insignificant, supporting H8 (β = 0.131) and rejecting hypothesis H9, respectively. Students who think that MOOC courses are offered by prestigious universities and taught by well-qualified professors from such universities tend to perceive MOOCs to be very useful, but the same does not lead to continuous use intention. The control variables used in the model, namely gender and ICT skill, came out to be insignificant.

5. Discussions and Conclusion

Students' continuous use intention of MOOC is the main emphasis of this study. The study uses TAM as the underlying theoretical model with two external variables, namely perceived reputation and self-efficacy and includes constructs from the UTAUT model to understand the factors that affect the continuous use intention of MOOCs.

The study also includes two control variables, namely gender and ICT skills.

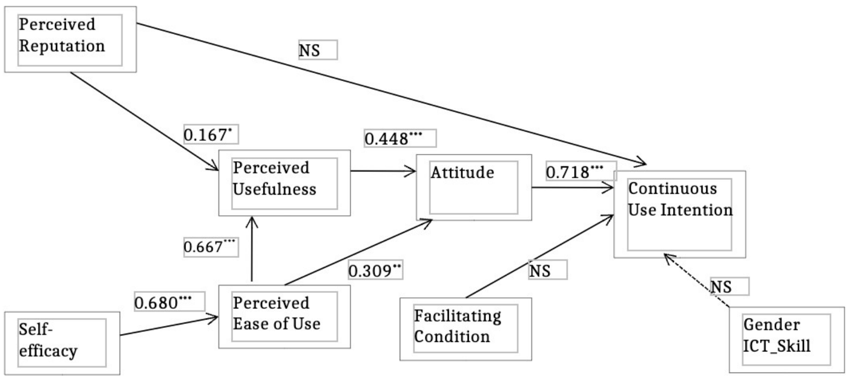

Figure 2 - Structural model analysis.
Note: path coefficient and T-test are significant at: *P<0.05, **P<0.01, ***P<0.001, NS-Not Significant

The model could explain 69% of the variance in explaining the continuous use intention of MOOCs with the attitude of MOOC users being the strongest predictor of continuous MOOC usage and is consistent with past studies (Wang et al., 2022; Cheon et al.,2012; Park, 2009). This is in line with similar researches done in India to study the adoption intention using the TAM model, which showed the positive effect of attitude on intention to adopt MOOCs (Virani et al., 2023; Singh, A. et al., 2021).

As with many prior studies, perceived usefulness and perceived ease of use are the strongest determinants of attitude, and perceived ease of use affects attitude through perceived usefulness (Saleh et al., 2022; Decman, 2015; Cheon et al., 2012; Park, 2009), reinforcing the applicability of the basic TAM model in understanding the factors affecting continued use intention of MOOC in a voluntary environment, among students of HEI in India. In a cross-country study between India and Italy, Indians rely more on the perceived usefulness of a technology which in turn affects its continuous use intention (Chauhan et al., 2021). The results prove that if the users believe that using MOOCs would add value to building their careers, they will develop a positive attitude towards using it persistently. MOOC designers should not overlook the factor “user-friendliness” and its role in MOOC usage. The course modules’ design should allow MOOC users to use its features with little effort. The facilitating condition, a construct from UTAUT2 added to the model, does not affect the continuous use intention of MOOCs. The facilitating condition is found to be insignificant in affecting MOOC usage. A possible reason could be the nature of respondents, who are HEI students and it is presumed that they have adequate supporting resources to access MOOC courses. As Venkatesh et al. (2012) described, facilitating condition and its relationship with behavioral intention to use technology is greatly influenced by the environment where the individual uses it.

The study reveals the importance of the external variables integrated with the model in affecting the continuous use intention of MOOCs. Self-efficacy, an intrinsic motivational factor, directly affects perceived ease of use, and attitude indirectly through PEOU and is consistent with a study by Chahal & Rani (2022) on e-learning acceptance by students of higher education institutions in India. This result is also in line with a study by Badali et al. (2022) that showed motivation is one of the most critical factors affecting MOOC retention, and self-efficacy is considered an intrinsic motivational factor (Park, 2009). Those who feel skilled at using MOOC use it with little effort, which in turn influences them to be lifelong users of MOOC.

Perceived reputation affects perceived usefulness positively, aligning with the studies by Huanhuan and Xu (2015) and Wu and Chen (2017). MOOC users are more influenced by reputed institutions and faculty offering MOOC courses. In other words, students from developing countries are particularly attracted to MOOCs because reputed institutions offer the vast majority of courses on MOOCs. The caveat here is that although perceived reputation affects perceived usefulness, it does not significantly impact the continuous use intention of MOOCs. Hence, perceived reputation could initially be a critical factor for attracting first-time users to register for MOOC courses (Gupta & Maurya, 2020); it may not be enough to drive them through course completion and sustained usage.

Implications

The inference from the study provides some valuable suggestions for policymakers in the field of education and MOOC content providers to shape the professional lives of students. In addition to providing the best quality content, MOOC providers should form tie-ups with reputed companies for course content creation, similar to what many universities do. This activity will put continuous positive pressure on MOOCs to provide content relevant to the industry and help enhance perceived reputation among prospective students. As given in the study model, this will positively affect the perceived usefulness of MOOCs, which will be mutually beneficial to both students and content providers. Students get rewarded significantly in their place of work because of acquiring the required skill set, and the MOOC will increase the perceived reputation quotient, which will increase enrollment.

The major thrust will be on the education policy. Self-efficacy, perceived ease of use and overall attitude towards MOOC can be influenced from the high school/college level by providing essential knowledge for all students. This can make them feel at ease when using information technology platforms. Additionally, some of the courses can be taught in a hybrid manner with explanations in the school/college and follow-up activities based on online content. This intervention will help boost the attitude toward completing MOOCs, as students may not feel different when enrolling for MOOCs where everything is online. Also, the habituation to this hybrid environment from the school level will have a system-driven positive influence on the self-efficacy of students, as group activities are known to motivate team members to rise to the occasion.

To corroborate the implications given in this study, policymakers can carry out research (data from other geographies also) to understand the influence of the hybrid model of curriculum (part offline and party online) on the self-efficacy of the students and, in addition, on the attitude of those who had enrolled in MOOC in those geographies. MOOC content providers can also engage in peer research surveys to understand the proportion of users who complete vs who enrol among peer groups, the strategies that are being followed by successful content providers (based on the response from students), etc. This will make the industry more competitive, resulting in developing better quality content and devising strategies that make the content more engaging. Also, the results help the content providers understand the gaps between perceived use and reputation among peers and may help them act upon these to enhance them.

Limitations and Future Research

The inference from this study is from a state with relatively higher enrollment in education. Similar surveys have to be conducted in different geographies with different precedence w.r.t education like north, west, east and northeastern part of India to include the demographic and cultural factors. Also, the place of study can be extended to rural to get the complete demography. The result may further strengthen the hypothesis and open up new areas regarding control factors that must be considered.

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Appendix - Survey items

Constructs	*Items*	*Measures*	*References*
Attitude	ATT1	Learning through MOOC is a good idea	Park (2009)
	ATT2	Learning through MOOC is a wise idea	
	ATT3	I am positive towards using MOOC	
Facilitating Condition	FC1	I have adequate resources to use MOOC	Venkatesh et al.(2003)
	FC2	I can get help from others when I have difficulties using MOOC	
	FC3	I have knowledge necessary to use MOOC	
Perceived Usefulness	PU1	MOOC helps me to be self-reliable	Chiu & Wang (2008)
	PU2	MOOC improves my learning performance	Bhattacherjee (2001)
	PU3	MOOC improves my learning effectiveness	Bhattacherjee (2001)
	PU4	I find MOOCs to be useful to me	Roca, Chiu, & Martínez (2006)
Perceived Ease of Use	PEOU1	MOOC is easy to use	DeLone & McLean (2003)
	PEOU2	It is easy to become skillful in using MOOC	Wu and Zhang (2014)
	PEOU3	Interaction with MOOC is clear and understandable	Wu and Zhang (2014)
Perceived Reputation	PR1	MOOC courses are offered by reputed universities	Munisamy, Jaafar, & Nagaraj (2014); Wu & Chen (2017)
	PR2	MOOC partners (Coursera, edX, etc) - universities have good reputation	
	PR3	Professors from reputed universities teach MOOC courses	
	PR4	Good reputation of MOOCs platform offers courses I am interested in.	
Self-efficacy	SE1	I am confident in using MOOC	Liaw (2008)
	SE2	I feel confident in operating MOOC functionalities	
	SE3	I am confident using MOOC course contents	
Continuous Use Intention	CUI1	I intend to continue using MOOC in the future	Alraimi et al.(2015)
	CUI2	I will continue using MOOC in future	
	CUI3	I will strongly recommend MOOC for others to use it	
	CUI4	I will keep using MOOC as regularly as I do now	