Flow Experience and MOOC Acceptance: Mediating Role of MOOC Satisfaction

Shrikant Mulik[1]
Manjari Srivastava[2]
Nilay Yajnik[3]

Abstract

The primary purpose of this study is to examine the impact of flow experience on acceptance of Massive Open Online Courses (MOOC). It has also investigated whether MOOC satisfaction would mediate the relationship between flow experience and MOOC acceptance. The proposed research model was tested using a survey research method. Data was collected from 310 MOOC users using an online questionnaire and was analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results confirmed that flow experience impacts MOOC acceptance and MOOC satisfaction plays a mediating role in the relationship between flow experience and MOOC acceptance.

Keywords: *Massive Open Online Courses; MOOC; flow experience; MOOC satisfaction; MOOC acceptance; Partial Least Squares Structural Equation Modelling; PLS-SEM.*

1 Introduction

Massive Open Online Course (MOOC) is a new phenomenon in the education domain. It is being seen as a technological innovation that would disrupt the education domain. It could also be seen as a way to democratize education as the same education could be made available to the learner regardless of whether the learner is accessing the MOOC from Brooklyn (in New York City, USA) or from Borivali (in Mumbai, India).

1.1 Defining MOOC

In the year 2008, David Cormier coined the term, Massive Open Online Course to describe an online course titled 'Connectivism and Connected Knowledge' (Tirthali et al. 2014). The first word 'massive' typically refers to a large number of course participants though it may also refer to the capacity to enrol large numbers, or the capacity to obtain huge quantities of participant activity and performance data. While some MOOCs have reported the number of participants beyond a hundred thousand, a typical benchmark could be a thousand participants. To cater to this number of participants, which is larger than the number of participants in a traditional classroom, the MOOC needs to be designed accordingly.

There are some disagreements over the interpretation of the word 'open'. It typically means open access in a way that anyone with an internet connection can

1 *Research Scholar, NMIMS SBM, Mumbai, India*
2 *Associate Dean, NMIMS SBM, Navi Mumbai, India*
3 *Provost, Navrachana University, Vadodara, India*

access any MOOC without any pre-qualification or any entrance test. Many proponents of Open Educational Resources (OER) movement argue that MOOC should also provide open content with legally open licensing such as Creative Commons (CC). However, the majority of MOOCs today do not release the content with open licensing. A third interpretation of open is the use of open source software for offering MOOC. One of the MOOC providers, edX, has indeed made its platform software open source though other MOOC providers offer their courses with proprietary software.

There are virtually no disagreements when it comes to interpretation of the word 'online'. MOOCs are offered 100% online though some learners could form local study groups to have face-to-face meetings for discussion on the topics of the MOOC. MOOCs do offer discussion forums online, which can be used by learners from any corner of the world.

The word 'course' would differentiate MOOC from other educational resources such as YouTube videos, Wikipedia, or Open Educational Resources (OERs). The interpretation of the word 'course' is that the offering is bound by time with a definite start date and end date and organizes a (sometimes loose) sequence of activities and resources.

1.2 Characteristics of MOOC

MOOC is typically offered to an adult learner to complete in a specific time period. This period could be as short as one week and as long as 12 weeks though the typical length of a MOOC varies from four to six weeks. MOOC offers short pre-recorded videos for teaching. The length of these videos could range from 5 to 20 minutes while typical length of these videos is around 10 minutes. These videos are sometimes supplemented by online articles and external web pages. Assessment is done using auto-gradable quizzes and peer-reviewed assignments. To be auto-gradable, the quizzes typically contain multiple-choice questions. The peer-reviewed assignments are given along with the rubric so that participants can assess assignments submitted by their peers.

Online discussion forums are offered to facilitate interaction among faculty, teaching assistants, and students. Students can make use of these forums to ask questions or to share their comments. Some MOOCs emphasise on the participation in MOOC as it helps in building a sense of community among the participants. Given the massive enrolment to the course, the discussion forums used in the MOOC provide the facility to vote posts up or down, so that the most useful questions (with answers) and comments rise to the top of the list, and thus, the spam gets rejected by the community itself.

MOOCs are offered in a diverse range of subjects such as Architecture, Arts, Biology, Business Management, Chemistry, Computer Science, Data Analysis, Engineering, Humanities, Law, Medicine, Music, and Physics. Initially almost all MOOCs were available for free. However, gradually, the assessment and certification have become paid while the access to content is still free in majority of MOOCs. Some Universities have started recognizing the completion and certification of MOOC toward academic credit for their on-campus programs. As this trend continues, a few Universities have started offering official degree programs, purely as a collection of relevant MOOCs.

As MOOCs are largely delivered by Universities, majority of MOOCs are adapted from the undergraduate and post-graduate courses offered on campus of these Universities. Though they have open access without any pre-qualification criteria, the beneficiary needs to have basic competencies such as reading and writing in the language of MOOC plus must have high internet bandwidth to access the course.

While a high enrolment number is one of the key characteristics of MOOC, low retention rate or high dropout rate has also become associated with the MOOC. Though the completion rate is reported anywhere from 3% to 15%, a single digit completion rate seems to be a norm. While many point to this fact as a failure of MOOC, others insist that completion rate need not be a success metric for MOOC since it indicates freedom for learners on whether to pursue a particular course based on initial exploration.

While majority of MOOCs are taught by University faculty, they are provided on the platforms built and operated by third-party MOOC providers. There are more than 30 MOOC providers and the number seems to be only increasing. There are private enterprises such as Coursera, Udacity and Canvas Network. Many MOOC providers are supported by a university or a group of universities. For example, edX was launched by Harvard University and MIT, which were later joined by other universities from across the globe. The National Program on Technology Enhanced Learning (NPTEL) in India has been supported by Indian Institutes of Technology (IITs) and Indian Institute of Science (IISc). Similarly, eWant MOOC platform was launched by Taiwanese National Chiao Tung University. Governments are also supporting country-specific platforms to offer MOOCs. For example, the Mexican government has funded MexicoX, which has got more than 85% users from Mexico. Similarly, the Indian government is promoting the Study Webs of Active-learning for Young Aspiring Minds (SWAYAM) platform for providing MOOCs to Indian students and professionals.

MOOC offers many benefits over traditional education model as it can reach a number of students; it can provide high-quality course content at low or zero cost and can give unparalleled insights into human learning (Welsh and Dragusin 2013). Purely from a student perspective, MOOC offers an advantage over traditional lecture-based course due to its greater flexibility, customization, and accessibility, which results in structured self-paced learning –(Bruff et al. 2013). In spite of these benefits, MOOC suffers from certain weaknesses such as difficulty in authoritative assessment of written work utilizing critical thinking skills, reliable authentication for certification of students, and inability to provide frequent interaction between faculty and students (Welsh and Dragusin 2013).

1.3 Comparing MOOC with Other E-learning Alternatives

MOOC differs from other forms of e-learning such as Computer-Based Training (CBT), Learning Management System (LMS), or YouTube-based learning. Computer-Based Training (CBT) is typically standalone and is not offered openly on the Internet. It involves use of Compact Disc (CD) or DVD or pen drive to run learning lessons on a desktop for a logged-in user. LMS is typically used by instructors in many Universities and Corporate Learning & Development (L&D) departments to supplement online learning content with classroom-based sessions. Though LMS software such as Moodle and Blackboard can be used to offer MOOC, a typical use of LMS has been confined to the blended learning approach.

YouTube, which is one of the largest video sharing platforms, is increasingly being used as an e-learning platform. Many freelancer trainers and University faculty offer videos of their classroom sessions or sessions specifically recorded in studios on YouTube. A facility of setting up a channel and organizing videos in a playlist on that channel is effectively used by many teachers to offer a series of videos on topics ranging from English speaking to software testing to machine learning.

MOOC differs from these e-learning alternatives as it attempts to offer a complete learning experience fully online. It integrates various technologies such as online videos, online auto-gradable quizzes, and online discussion forums to provide a learning experience, which closely mimics a traditional classroom-based learning experience. While CBT provides digital teaching and assessment, it typically lacks the ability to connect learners with their peers or teachers. LMS is typically used by instructors to share class notes or to conduct online quizzes and tests. YouTube videos only provide one-way teaching but do not offer other aspects of learning experience such as assessment and interaction among teachers and students. MOOC offers key aspects of learning experience viz. teaching (instruction), assessment and interaction thus positioning itself as a viable alternative to traditional University courses offered in classrooms.

1.4 MOOC Adoption

MOOC got into the limelight in the year 2011 when one of the early MOOCs from Stanford University (a MOOC on Artificial Intelligence) attracted 160,000 students from across the globe out of which 23,000 finished it —(Kalyanaram 2018; Waldrop 2013). New York Times' declaration of the year 2012 as Year of MOOC '(Pappano 2012) further built up the hype around MOOC. Since those days, the number of MOOCs and MOOC users has increased significantly. Leading MOOC providers such as Coursera, edX, Udacity, and FutureLearn built legitimacy by partnering with hundreds of reputable, elite universities, and quickly grew to offer thousands of free courses that reached tens of millions of learners around the world ''''''(Thomas and Nedeva 2018). Though there are many MOOC providers, Coursera and edX, each having more than 10 million registered users, were reported to be the top two MOOC providers. While USA tops the list of countries for the number of MOOC users, the number of MOOC users is rising in countries like India, China and Brazil. As reported in January 2019 by a MOOC aggregator, Class Central, 101 million students enrolled in 11,400 courses offered by 900+ Universities in 2018 (Shah 2019).

Though the number of MOOC users currently exceeds 80 million (Shah 2018), the potential is even bigger at a global scale. There are over 3.5 billion Internet users, over 2.2 billion Facebook users, over 2 billion Android users, and over 1.3 billion YouTube users. Comparing the current number of MOOC users with these numbers can help us see the potential for MOOC adoption. In this context, it would be useful to identify the influencing factors for MOOC acceptance.

2 Literature Review

2.1 Influencing Factors for MOOC Adoption

Many researchers have investigated the influencing factors for MOOC acceptance. For example, Chang, Hung and Lin '''(2015) investigated the influence of learning styles on the learners' intentions to use MOOCs. Fang (2015) used Technology Acceptance Model 3 (TAM3) to examine the influencing factors for intention to use MOOC. In another study, MOOC course content was found to be a significant predictor of MOOC retention, with the relationship mediated by the effect of content on the perceived effectiveness of the course (Hone and El Said 2016). M. Zhou (2016) integrated the theory of planned behaviour (TPB) and the self-determination theory (SDT) as a research framework and found that attitude toward MOOCs and perceived behavioural control (PBC) were significant determinants of intention to use them. In a later study, Wu and Chen (2017) proposed and tested a unified model integrating the technology acceptance model (TAM), task fit technology (TTF) model, MOOCs features and social motivation to investigate continuance intention to use MOOCs. Khan et al. (2017) applied task-technology fit model, social motivation, and self-determination theory to predict the acceptance of MOOCs in a developing country. The present study intends to continue this exploration of factors influencing MOOC acceptance by examining the impact of flow experience and MOOC satisfaction.

2.2 MOOC Acceptance

Why do individuals accept a specific technology or technology system? Many research studies have been undertaken to find the answer to this question. A number of research studies have focused on assessing technology acceptance with 'intention to use' or 'actual use' as a dependent variable. The conceptual model in this stream of research identifies a set of independent variables that impact the intention to use, which may, in turn, impact actual use. Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT) and related models have established usage intention or behavioural intention as a predictor of behaviour i.e. usage '(Davis, Bagozzi, and Warshaw 1989; Lee, Kozar, and Larsen 2003; Venkatesh et al. 2003). In this study, MOOC acceptance is modelled as a behavioural intention to use MOOC and is defined as the degree to which a person has formulated conscious plans to use MOOC.

2.3 Flow Experience

Origins of the flow experience concept are in the studies about what motivates people to devote more time to certain activities such as sports and music than what would be expected based singularly on associated external rewards (de Manzano et al. 2010). Flow is defined as the state in which people are so involved in an activity that nothing else seems to matter; the experience itself is so enjoyable that people will do it even at great cost, for the sheer sake of doing it (Csikszentmihalyi 1990). The flow experience is also called 'being in the zone' by athletes, 'ecstasy' by religious mystics and 'aesthetic rapture' by musicians (Csíkszentmihály 1997). There are studies that have analysed the role of flow experience during different types of activities such as chess playing, piano playing, athletic sports, and learning '''(de Manzano et al. 2010; Clarke and Haworth 1994; Rathunde and Csikszentmihalyi 2005; Hamari et al. 2016). Similarly, many studies have examined the impact of flow experience on behavioural intention ––––'''(Liao 2006; Agarwal and Karahanna 2000; T. Zhou 2013a, 2013b, 2012; Lu, Zhou, and Wang 2009).

2.4 MOOC Satisfaction

Khalifa and Liu (2007) have recognized satisfaction as a post-evaluative judgment over a particular purchase and have identified three types of online shopping satisfaction viz. pre-purchase, at-purchase, and post-purchase satisfaction. In a similar way, three types of MOOC satisfaction can be identified as satisfaction in using content, satisfaction in getting assessed and satisfaction in interacting with peers and teachers. In MOOC, using content involves watching videos and reading online articles. Assessment in MOOC happens through online quizzes (typically auto-gradable using multiple-choice questions) and peer-reviewed assignments. Learners can interact with one another and with teachers or teaching assistants using online forums or in some cases, by means of video conferencing sessions using tools such as Google Hangout or Microsoft Skype. Thus, MOOC satisfaction becomes a formative construct and similar to the study by Ranaweera, Bansal, and McDougall (2008), it can be defined as the perception of a pleasurable fulfilment of a MOOC experience.

3 Research Model

Figure 1 shows the proposed research model. Studies have shown that flow experience has an impact on satisfaction in various contexts. Flow experience is found to have an impact on customer satisfaction in online financial services (Ding et al. 2010). It is also found to affect customer satisfaction in an online travel agency context (Hsu, Chang, and Chen 2012). Rose *et al. (2012)* and Bhattacharya & Srivastava (2018) have found that online shopping satisfaction was affected by flow experience. Similarly, Choi et al. (2016) have found that flow experience impacts the satisfaction of realistic performing arts. Based on this support from the literature, the following hypothesis is proposed.

H1: Flow Experience is positively associated with MOOC satisfaction.

MOOC acceptance indicates behavioural intention to use MOOC. Though no study has shown association between flow experience and behavioural intention to use MOOC, there are studies that have found impact of flow experience on intention to use distance learning system —— (Liao 2006), world wide web (Agarwal and Karahanna 2000), mobile TV –'(T. Zhou 2013a), instant messaging '(Lu, Zhou, and Wang 2009), mobile banking '(T. Zhou 2012) and mobile games (T. Zhou 2013b). Based on this support from the literature, the following hypothesis is proposed.

H2: Flow Experience is positively associated with MOOC acceptance.

Similarly, though no study has shown an association between MOOC satisfaction and MOOC acceptance, studies have shown the impact of satisfaction on behavioural intention in different contexts. For example, Khalifa & Liu (2007), Martin, Mortimer & Andrews (2015), and Bhattacharya & Srivastava (2018) have found the impact of online shopping satisfaction on online repurchase intention. Similarly, Ranaweera, Bansal and McDougall (2008) have found an association between website satisfaction and purchase intention. Based on this support from the literature, the following hypothesis is proposed.

H3: MOOC Satisfaction is positively associated with MOOC acceptance.

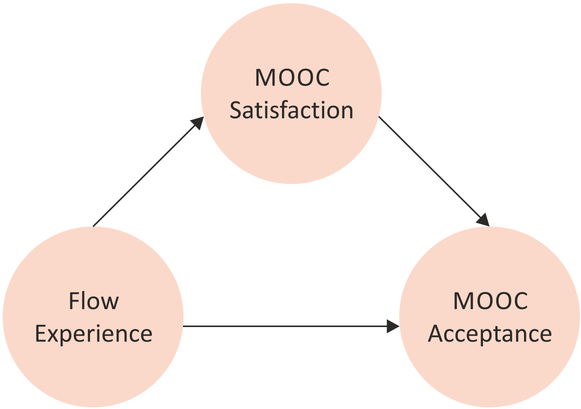


Figure 1: Proposed Research Model

4 Method

4.1 Data Collection

The study used an online questionnaire to collect data. A request to fill the questionnaire was sent to the professional network of the authors by email as well as by using social media tools viz. Facebook, LinkedIn, and WhatsApp. No incentive was offered for responding to the questionnaire. The questionnaire clearly mentioned that it is only applicable to the ones, who have used at least one MOOC. After cleansing, a total of 310 usable responses were obtained. Demographic details of the sample profile are provided in Table 1.

Table 1: Sample Profile

Demographic	Category	Number	Percentage
Gender	Male	226	72.90
	Female	84	27.10
Age	18-25	83	26.77
	26-40	107	34.52
	41-60	116	37.42
	60+	4	1.29
Occupation	Student	74	23.87
	Professional	236	76.13
Education	Diploma	4	1.29
	Graduation	96	30.97
	Post-graduation	185	59.68
	Doctoral	25	8.06

4.1 Questionnaire Design

A questionnaire was created by referring to scale items from extant literature. All items were measured on a 5-point Likert scale (from 'strongly disagree' to 'strongly agree'). The scale for MOOC acceptance was adapted from the scale of behavioural intention in (Venkatesh et al. 2003), in which it had Internal Consistency Reliability (ICR) greater than 0.70. Consistent to (Novak, Hoffman, and Yung 2000) and (Rose et al. 2012), flow experience was measured with a three-item scale following a narrative description of flow. Similar to (Khalifa and Liu 2007), different activities of MOOC use (i.e. using content, getting assessed and interacting with peers & teachers) were distinguished; hence, MOOC satisfaction was assessed as a formative, emergent construct formed with items based on these activities.

4.2 Model: SEM/PLS

Given the nature of research model, it is imperative to use second generation techniques instead of first generation techniques such as logistic or multiple regression method. The second generation techniques, often referred to as Structured Equation Model (SEM) are of two types: Covariance-based SEM (CB-SEM) and Partial Least Square SEM (PLS-SEM). There has been extensive literature –——'–''''—— (Joe F Hair, Ringle, and Sarstedt 2011; F. Hair Jr et al. 2014; Lowry and Gaskin 2014; Joseph F. Hair et al. 2019; Henseler, Hubona, and Ray 2016) that provides definitive guidance on when to choose one or the other.

CB-SEM is preferred when the objective is to test the theory or confirm the theory or to compare the alternate theories. It is particularly useful when the research needs a global goodness-of-fit (GOF) criterion. It is advised to be used when the model has non-recursive relationships.

The PLS-SEM is preferred over CB-SEM in the following cases:

- The model is complex with many constructs and many indicators.
- The model contains one or more formatively measured constructs.
- The sample size is small.
- The data are not normally distributed.

PLS-SEM has its own set of limitations. It cannot be used when the model contains causal loops or circular relationships between the latent variables. Since it does not have an adequate global goodness-of-fit measure, it is recommended not to be used for theory testing and confirmation. PLS-SEM also faces criticism for what is called as PLS-SEM bias. PLS-SEM bias refers to the PLS-SEM's property that structural model relationships are slightly underestimated while the relationships in the measurement models are slightly overestimated. This bias is reduced when the number of observations or the number of indicators per latent variables, or both, increases. This characteristic is commonly referred to as consistency at large. Hence, though PLS-SEM accommodates the use of single-item measures and small sample size, avoiding use of single-item measures for latent variables and having a sufficiently large sample size are recommended to reduce the PLS-SEM bias.

In the present study, the proposed research model contains MOOC satisfaction, which is a formatively measured construct. Though formative constructs can be accommodated in CB-SEM, it is considered to be much more difficult as against PLS-SEM, which readily incorporates formative constructs along with reflective constructs. Hence, in the present study, PLS-SEM is used instead of CB-SEM.

When it comes to the minimum sample size requirement in PLS-SEM, it is determined either by the often cited 10-times rule (Barclay, Higgins, and Thompson 1995) or by a more differentiated rule of thumb provided by (Cohen 1992). The 10-times rule indicates the minimum sample size to be 10 times of the larger of (1) the indicators on the most complex formative construct and (2) the largest number of antecedent constructs leading to an endogenous construct as predictors. In the proposed research model, the indicators on the most complex formative construct are three, while the largest number of antecedent constructs leading to an endogenous construct is two. Hence, the minimum sample size requirement is 30 as per the 10-times rule. On other hand, the table for sample size recommendation in PLS-SEM for a statistical power of 80% given in Joseph F. Hair et al. (2014), is based on Cohen (1992), indicating the minimum sample size requirement to be 59 for detecting minimum R^2 value of 0.25 for significance level of 5%. The same table provides minimum size requirement of 176 for detecting the minimum R^2 value of 0.10 for a significance level of 1%. The size of the sample used in this study is 310, which is more than either of these minimum sample size requirements.

As the number of observations is significantly more than the minimum sample size requirement and since the number of indicators is three for each latent variable, it is expected that PLS-SEM bias would be at a very low level.

There are many software tools available for using PLS-SEM such as PLS-Graph, VisualPLS, SmartPLS, and WarpPLS (Jha and Karn 2018). This research study used SmartPLS 2.0 M3 software.

5 Empirical Results

As a first step, the reflective measurement model was tested for reliability and validity. Composite Reliability (CR) values above the threshold value of 0.708 for all constructs indicated internal consistency reliability. Similarly, Average Variance Extracted (AVE) values above the threshold value of 0.50 for all constructs indicated convergent validity. Since both AVE and CR values were above their respective threshold values, all indicators were retained even though outer loadings were below 0.7 for few indicators, as suggested in Joseph F. Hair et al. (2014).

To test discriminant validity, cross-loadings of the indicators were examined. All indicators' outer loadings on the associated construct were found to be greater than all of their loadings on other constructs (i.e. the cross-loadings), thus indicating discriminant validity. We further tested for Fornell-Larcker criterion (Fornell and Larcker 1981), which is a more conservative approach to assessing discriminant validity (Joseph F. Hair et al. 2014). When tested, the square root of the AVE of each construct was found to be higher than its highest correlation with any other construct, thus indicating discriminant validity. The results of reliability and validity tests are shown in Table 2.

Table 2: Results of Reliability and Validity Tests

#	Construct	Item	Loadings
1	Flow Experience AVE = 0.6512 CR = 0.8441	Do you think you have ever experienced flow?	0.5843
		In general, how frequently would you say you have experienced ‘flow’ when you use MOOC?	0.899
		Most of the time that I have used the MOOC, I feel that I am in flow.	0.8966
2	MOOC Acceptance AVE = 0.6325 CR = 0.8366	I intend to use MOOCs in future.	0.8305
		I foresee that I would use MOOCs in the near future.	0.8571
		I plan to use MOOCs in six months.	0.6879

Next, we assessed the formative measurement model for collinearity issues. To do so, multiple regression analysis was performed using IBM SPSS to generate VIF and tolerance values. VIF values of all three indicators for MOOC satisfaction were found to be lower than 5 and their tolerance values were found to be higher than 0.2, indicating a lack of any collinearity issues. As the last step in assessing the formative measurement model, we examined values and significance of outer weights. The results are shown in Table 3. As the outer weight values of all three indicators were found to be significant, there was empirical support to retain these three indicators.

Table 3: Formative Measurement Model

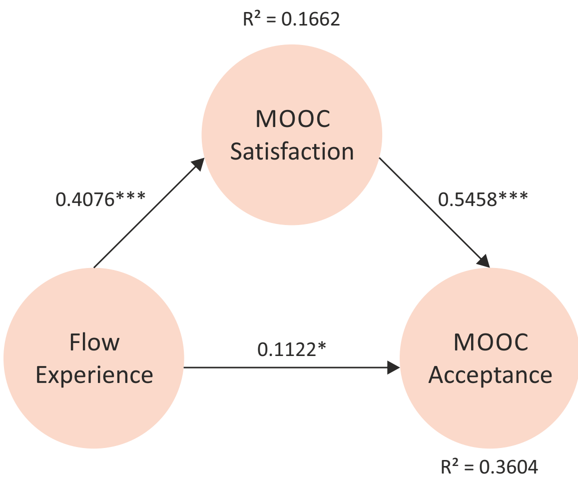
Formative Indicator	Tolerance (VIF)	Outer weight	t-value	Significance
I am satisfied with my experience of using educational content (videos, readings, etc.) in the MOOC.	0.822 (1.217)	0.5595	7.8724	Significant at 1 per cent level
I am satisfied with my experience of doing assignments/exercises in the MOOC.	0.780 (1.281)	0.3265	3.8723	Significant at 1 per cent level
I am satisfied with my experience of online discussions/interactions in the MOOC.	0.789 (1.268)	0.4186	5.2584	Significant at 1 per cent level

After evaluating reflective and formative measurement model, we began to analyse the structural model. The first step in doing so was to assess the structural model for collinearity issues. To do so, we used latent variable scores produced by SmartPLS, as input for collinearity assessment in IBM SPSS. We performed multiple regression analysis for all predictors of behavioural intention and found VIF values to be below the threshold value of 5. Thus, it indicated that collinearity among the predictor constructs is not an issue in the structural model.

Table 4 shows the results after running the PLS algorithm and bootstrapping procedure in SmartPLS software. The flow experience could explain the 17 per cent variance in MOOC satisfaction while it, along with MOOC satisfaction, could predict 36 per cent of the variance of MOOC acceptance. The path coefficient of MOOC satisfaction was found to be higher than that of flow experience thus indicating its higher impact on MOOC acceptance. Figure 2 shows the resultant model.

Table 4: Summary of Results

MOOC Satisfaction (R^2 = 0.1662)			
Predictors	Path Coefficient	t-value	Significance
Flow Experience	0.4076	7.2880	***
MOOC Acceptance (R^2 = 0.3604)			
Predictors	Path Coefficient		
MOOC Satisfaction	0.5458	11.9821	***
Flow Experience	0.1122	1.9509	*
*=p<0.1; **= p <0.5;***=p < 0.01; NS = Not Significant			



**=p<0.1, **=p<0.5, ***=p<0.01; NS= Not Significant*

Figure 2: Resultant Research Model

Then we began the testing of the mediating effect of MOOC satisfaction on the relationship between flow experience and MOOC acceptance by testing the conditions given in ‒Baron and Kenny (1986). We followed the approach given in Preacher and Hayes (2004, 2008), which is suitable for the PLS-SEM method as compared to Sobel (1982) test ——'‒(F. Hair Jr et al. 2014). As a first step, we assessed the significance of the direct effect of flow experience on MOOC acceptance in the absence of the mediator even though it is not a necessary condition (Zhao, Lynch, and Chen 2010). The significance test was conducted using the bootstrapping method. The relationship was found to be significant ($p < 0.01$) with a path coefficient of 0.3359 with corresponding t-value of 5.9009.

As a next step, the mediator was included in the model and the significance of the indirect effect was assessed. A necessary (but not sufficient) condition was the significance of the relationship between flow experience and MOOC satisfaction (0.4076) as well as between MOOC satisfaction and MOOC acceptance (0.5458). As both these relationships were found to be significant, the indirect effect was calculated to be 0.4076 X 0.5458 = 0.2225. To test its significance, bootstrapping procedure using 310 observations per subsample, 5000 subsamples and no sign changes was used. In a spreadsheet, indirect effect via the mediator was calculated as the product of direct effects between flow experience and MOOC satisfaction as well as between MOOC satisfaction and MOOC acceptance, for each of the 5000 subsamples. The standard deviation (which equals the standard error in bootstrapping) of 5000 indirect effect values was found to be 0.0351. The empirical t-value of 6.3435 was arrived at after dividing the original value (0.2225) by the bootstrapping standard error (0.0351). Hence, we could conclude that this relationship via the MOOC satisfaction mediator was significant ($p < 0.01$).

In the final step, we calculated the Variance Accounted For (VAF) that determines the size of the indirect effect in relation to the total effect. The direct effect of flow experience on MOOC acceptance had a value of 0.1122 while the indirect effect via MOOC satisfaction had a value of 0.2225. Thus, the total effect had a value of 0.1122 + 0.2225 = 0.3347. The VAF equals the direct effect divided by the total effect and had a value of 0.1122 / 0.3347 = 0.3352. That means 33.52 per cent of the effect of flow experience on MOOC acceptance was explained via the MOOC satisfaction mediator. Since the VAF is larger than 20 per cent but smaller than 80 per cent, this situation can be characterized as partial mediation.

6 Discussion

6.1 Interpretation of Findings

The study had two objectives; one, to examine the impact of flow experience on MOOC acceptance, and two, to examine the mediating role of MOOC satisfaction for the relationship between flow experience and MOOC acceptance. The data analysis found a significant relationship between flow experience and MOOC acceptance with a path coefficient of 0.1122. It is in line with the literature, which has reported an association between flow experience and behavioural intention in similar contexts——'''(Liao 2006; Agarwal and Karahanna 2000; T. Zhou 2013b, 2013a; Lu, Zhou, and Wang 2009; T. Zhou 2012).

The study also found a significant relationship between flow experience and MOOC satisfaction with a path coefficient of 0.4076 and a significant relationship between MOOC satisfaction and MOOC acceptance with a path coefficient of 0.5458. When tested for the mediation effect of MOOC satisfaction, it was found that MOOC satisfaction acts as the mediator for the relationship between flow experience and MOOC acceptance with 33.52 per cent VAF. This finding indicates that higher flow experience leads to higher MOOC satisfaction that further leads to higher intention to use MOOC. Similar results in different contexts were reported in Martin, Mortimer, and Andrews (2015); Rose et al. (2012); Choi et al. (2016); Hsu, Chang, and Chen (2012).

6.2 Research Limitations

This study suffers from certain limitations. One limitation arises due to the lack of probability sampling. Lack of access to large finite sampling frame such as registered users of all major MOOC providers made this study use snowball sampling, which is a non-probability sampling method. Future studies that have access to mailing lists of registered users of major MOOC providers can use probability sampling to test the model proposed in this study.

Another limitation arises as we assessed flow experience using a survey questionnaire. Csíkszentmihály (1997) had used the Experience Sampling Method (ESM) to assess flow experience. A digital version of this method was used by Chen (2000) to assess the flow experience of web users. Survey questionnaire may not yield good quality of data as compared to ESM for assessing flow experience but was used due to its feasibility for data collection. Future studies may choose to use online ESM instead of an online questionnaire to assess flow experience.

Finally, this study limited itself to examining intent to use MOOC and did not consider MOOC usage or MOOC completion. Future studies can make use of longitudinal study design to examine MOOC usage and MOOC completion.

6.3 Managerial Implications

This study would help MOOC providers such as SWAYAM in understanding influencers of intention to use MOOC. Higher intention to use MOOC would lead to higher MOOC enrolment, which is needed to make MOOC a viable alternative to traditional classroom-based courses. Based on the findings of this study, it is recommended that MOOC providers should develop the MOOC platform that would induce flow experience among its users. The gamification and use of immersive technologies such as augmented reality could help increase flow experience. The use of personalization techniques such as adaptive quizzing, flexible navigation of content and chatbots for quick clarification of doubts of learners could also help users gain flow experience. Investments in finding such innovative ways to provide flow experience to MOOC users will lead to their satisfaction, which will further lead to their intention to use MOOC.

It should be noted that not only MOOC providers but also MOOC teachers and learners will benefit from increasing MOOC adoption. With increasing MOOC adoption, MOOC teachers can reach a wider and global audience to share their wisdom. This is particularly helpful for teachers, who focus on niche areas and have difficulty in getting sufficient enrolments in a traditional university setup. The faculty who do not teach MOOC will also benefit, but in a different way. The teachers from small local universities can access MOOC to understand what is being offered by the elite University faculty and can enhance their own teaching methods and material. With growing adoption of MOOC, the individual learners will have access to larger number of courses in diverse subject areas. Thus, one can choose to enrol in a specific MOOC by choosing the most appropriate option from a large set of high-quality courses offered by top universities. Moreover, one can enrol in the courses, which are very niche in nature and are unlikely to be offered in local universities.

6.4 Applicability and Generalizability

The study has made a theoretical contribution by identifying MOOC satisfaction and flow experience as key determinants of MOOC acceptance. It has further established the mediating role of MOOC satisfaction for the relationship between flow experience and MOOC acceptance.

MOOC has the potential to democratize higher education (Kalyanaram 2018). With MOOC, higher education can be delivered 100% online without any requirements for setting up expensive infrastructure such as buildings and campuses. Many emerging economies such as India need to educate its increasing population but are constrained by the budgets. MOOC provides a 'close to silver bullet' to overcome this challenge.

Though the sample data was collected from India, the results of this study can be generalized to a wider population, which can access online resources. The sample, however, does not represent individuals, who do not have access to online resources. Emerging economies like India have many such individuals. The digital divide, as it is called, exists in India wherein a large section of population cannot access the internet. Hence, democratization of education by using MOOC has got the eradication of the digital divide as a pre-requisite. Increasing literacy levels, increasing electrification of all areas, and higher penetration of smart phones and mobile internet within India and elsewhere would help in reducing the digital divide.

In summary, with the identification of flow experience and MOOC satisfaction as key determintants of MOOC acceptance, this study has shown the way for democratization of education among online population in the emerging economies.

References

- Agarwal, Ritu, and Elena Karahanna. 2000. “Time Flies When You’re Having Fun: Cognitive Absorption and Beliefs about Information Technology Usage.” *MIS Quarterly* 24 (4): 665. https://doi.org/10.2307/3250951.
- Barclay, Donald, Christopher Higgins, and Ronald Thompson. 1995. “The Partial Least Squares (PLS) Approach to Causal Modeling: Personal Computer Adoption and Use as an Illustration.” *Technology Studies* 2 (2): 285–309. https://doi.org/10.1017/CBO9781107415324.004.
- Baron, Reuben M., and David A. Kenny. 1986. “The Moderator–Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations.” *Journal of Personality and Social Psychology* 51 (6): 1173–82. https://doi.org/10.1037/0022-3514.51.6.1173.
- Bhattacharya, Arijit, and Manjari Srivastava. 2018. “Antecedents of Online Shopping Experience/: An Empirical Study.” *NMIMS Management Review* XXXV (4): 12–30.
- Bruff, Derek O, Douglas H Fisher, Kathryn E McEwen, and Blaine E Smith. 2013. “Wrapping a MOOC: Student Perceptions of an Experiment in Blended Learning.” *MERLOT Journal of Online Learning and Teaching* 9 (2): 187–199.
- Chang, Ray I, Yu Hsin Hung, and Chun Fu Lin. 2015. “Survey of Learning Experiences and Influence of Learning Style Preferences on User Intentions Regarding MOOCs.” *British Journal of Educational Technology* 46 (3): 528–41. https://doi.org/10.1111/bjet.12275.
- Choi, Sangmin, Donghui Kim, Juhee Kang, Sungbae Kang, and Taesoo Moon. 2016. “The Influence of Flow and Satisfaction of Realistic Performing Art on Revisiting Intention” 126 (Business): 173–78. https://doi.org/10.14257/astl.2016.126.33.
- Clarke, Sharon G, and John T Haworth. 1994. “‘Flow’ Experience in the Daily Lives of Sixth-Form College Students.” *British Journal of Psychology* 85 (4): 511–23. https://doi.org/10.1111/j.2044-8295.1994.tb02538.x.
- Cohen, Jacob. 1992. “A Power Primer.” *Psychological Bulletin* 112 (1): 155–59. https://doi.org/10.1038/141613a0.
- Csíkszentmihály, M. 1997. “Finding Flow: The Psychology of Engagement with Everyday Life.” *Psychology Today*, 1–7.
- Csikszentmihalyi, Mihaly. 1990. *Flow: The Psychology of Optimal Performance*. *Optimal Experience: Psychological Studies of Flow in Consciousness*. New York: Harper and Row.
- Davis, Fred D., Richard P. Bagozzi, and Paul R. Warshaw. 1989. “User Acceptance of Computer Technology: A Comparison of Two Theoretical Models.” *Management Science* 35 (8): 982–1003. https://doi.org/10.2307/2632151.
- Ding, Xin David, Paul Jen-hwa Hu, Rohit Verma, and Don G Wardell. 2010. “The Impact of Service System Design and Flow Experience on Customer Satisfaction in Online Financial Services.” *Journal of Service Research* 13 (1): 96–110. https://doi.org/10.1177/1094670509350674.
- F. Hair Jr, Joe, Marko Sarstedt, Lucas Hopkins, and Volker G. Kuppelwieser. 2014. “Partial Least Squares Structural Equation Modeling (PLS-SEM).” *European Business Review* 26 (2): 106–21. https://doi.org/10.1108/EBR-10-2013-0128.

- Fang, Xu. 2015. "Research of the MOOC Study Behavior Influencing Factors." In *Proceedings of the 2015 3d International Conference on Advanced Information and Communication Technology for Education*, 11:18–22. Paris, France: Atlantis Press. https://doi.org/10.2991/icaicte-15.2015.5.
- Fornell, Claes, and David F. Larcker. 1981. "Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics." *Journal of Marketing Research* 18 (3): 382. https://doi.org/10.2307/3150980.
- Hair, Joe F, Christian M Ringle, and Marko Sarstedt. 2011. "PLS-SEM: Indeed a Silver Bullet." *The Journal of Marketing Theory and Practice* 19 (2): 139–52. https://doi.org/10.2753/MTP1069-6679190202.
- Hair, Joseph F., G Thomas. M Hufit, Christian Ringle M., and Marko. Sarstedt. 2014. *A Primer on Partial Least Squares Structural Equations Modeling (PLS-SEM)*. SAGE.
- Hair, Joseph F., Jeffrey J. Risher, Marko Sarstedt, and Christian M. Ringle. 2019. "When to Use and How to Report the Results of PLS-SEM." *European Business Review* 31 (1): 2–24. https://doi.org/10.1108/EBR-11-2018-0203.
- Hamari, Juho, David J Shernoff, Elizabeth Rowe, Brianno Coller, Jodi Asbell-Clarke, and Teon Edwards. 2016. "Challenging Games Help Students Learn: An Empirical Study on Engagement, Flow and Immersion in Game-Based Learning." *Computers in Human Behavior* 54 (JANUARY): 170–79. https://doi.org/10.1016/j.chb.2015.07.045.
- Henseler, Jörg, Geoffrey Hubona, and Pauline Ash Ray. 2016. *Using PLS Path Modeling in New Technology Research: Updated Guidelines*. *Industrial Management & Data Systems*. Vol. 116. https://doi.org/10.1108/IMDS-09-2015-0382.
- Hone, Kate S., and Ghada R. El Said. 2016. "Exploring the Factors Affecting MOOC Retention: A Survey Study." *Computers and Education* 98: 157–68. https://doi.org/10.1016/j.compedu.2016.03.016.
- Hsu, Chia Lin, Kuo Chien Chang, and Mu Chen Chen. 2012. "The Impact of Website Quality on Customer Satisfaction and Purchase Intention: Perceived Playfulness and Perceived Flow as Mediators." *Information Systems and E-Business Management* 10 (4): 549–70. https://doi.org/10.1007/s10257-011-0181-5.
- Jha, Pratibha, and Bhaskar Karn. 2018. "Knowledge-Based Supply Chain Practice: A Study on Indian Digital Selling Companies." *NMIMS Management Review* 36 (2): 45–59.
- Kalyanaram, Gurumurthy. 2018. "Democratization of High-Quality Education and Effective Learning." *NMIMS Management Review* XXXV (4): 6–11.
- Khalifa, Mohamed, and Vanessa Liu. 2007. "Online Consumer Retention: Contingent Effects of Online Shopping Habit and Online Shopping Experience." *European Journal of Information Systems* 16 (6): 780–92. https://doi.org/10.1057/palgrave.ejis.3000711.
- Khan, Ikram Ullah, Zahid Hameed, Yugang Yu, Tahir Islam, Zaryab Sheikh, and Safeer Ullah Khan. 2017. "Predicting the Acceptance of MOOCs in a Developing Country: Application of Task-Technology Fit Model, Social Motivation, and Self-Determination Theory." *Telematics and Informatics*, September. https://doi.org/10.1016/j.tele.2017.09.009.
- Lee, Younghwa, Kenneth A Kozar, and Kai R T Larsen. 2003. "The Technology Acceptance Model: Past, Present, and Future." *Communications of the Association for Information Systems* 12: 752–80. https://doi.org/10.1037/0011816.
- Liao, Li Fen. 2006. "A Flow Theory Perspective on Learner Motivation and Behavior in Distance Education." *Distance Education* 27 (1): 45–62. https://doi.org/10.1080/01587910600653215.

- Lowry, Paul Benjamin, and James Gaskin. 2014. "Partial Least Squares (PLS) Structural Equation Modeling (SEM) for Building and Testing Behavioral Causal Theory: When to Choose It and How to Use It." *IEEE Transactions on Professional Communication* 57 (2): 123–46. https://doi.org/10.1109/TPC.2014.2312452.
- Lu, Yaobin, Tao Zhou, and Bin Wang. 2009. "Exploring Chinese Users' Acceptance of Instant Messaging Using the Theory of Planned Behavior, the Technology Acceptance Model, and the Flow Theory." *Computers in Human Behavior* 25 (1): 29–39. https://doi.org/10.1016/j.chb.2008.06.002.
- Manzano, Orjan de, Töres Theorell, László Harmat, Fredrik Ullén, Örjan de Manzano, Töres Theorell, László Harmat, and Fredrik Ullén. 2010. "The Psychophysiology of Flow During Piano Playing." *Emotion (Washington, D.C.)* 10 (3): 301–11. https://doi.org/10.1037/a0018432.
- Martin, Jillian, Gary Mortimer, and Lynda Andrews. 2015. "Re-Examining Online Customer Experience to Include Purchase Frequency and Perceived Risk." *Journal of Retailing and Consumer Services* 25 (JULY): 81–95. https://doi.org/10.1016/j.jretconser.2015.03.008.
- Novak, Thomas P., Donna L. Hoffman, and Yiu-Fai Yung. 2000. "Measuring the Customer Experience in Online Environments: A Structural Modeling Approach." *Marketing Science* 19 (1): 22–42. https://doi.org/10.1287/mksc.19.1.22.15184.
- Pappano, Laura. 2012. "The Year of the MOOC." *The New York Times*, 1–7. http://www.edinaschools.org/cms/lib07/MN01909547/Centricity/Domain/272/The Year of the MOOC NY Times.pdf.
- Preacher, Kristopher J., and Andrew F. Hayes. 2004. "SPSS and SAS Procedures for Estimating Indirect Effects in Simple Mediation Models." *Behavior Research Methods, Instruments, and Computers* 36 (4): 717–31. https://doi.org/10.3758/BF03206553.
- ———. 2008. "Asymptotic and Resampling Strategies for Assessing and Comparing Indirect Effects in Multiple Mediator Models." *Behavior Research Methods* 40 (3): 879–91. https://doi.org/10.3758/BRM.40.3.879.
- Ranaweera, Chatura, Harvir Bansal, and Gordon McDougall. 2008. "Web Site Satisfaction and Purchase Intentions." *Managing Service Quality: An International Journal* 18 (4): 329–48. https://doi.org/10.1108/09604520810885590.
- Rathunde, Kevin, and Mihaly Csikszentmihalyi. 2005. "Middle School Students' Motivation and Quality of Experience: A Comparison of Montessori and Traditional School Environments." *American Journal of Education* 111 (3): 341–71. https://doi.org/10.1086/428885.
- Rose, Susan, Moira Clark, Phillip Samouel, and Neil Hair. 2012. "Online Customer Experience in E-Retailing: An Empirical Model of Antecedents and Outcomes." *Journal of Retailing* 88 (2): 308–22. https://doi.org/10.1016/j.jretai.2012.03.001.
- Shah, Dhawal. 2018. "By The Numbers: MOOCs in 2017." 2018. https://www.class-central.com/report/mooc-stats-2017/.
- ———. 2019. "2018 MOOC Roundup Series." 2019. https://www.class-central.com/report/tag/mooc-roundup-2018/.
- Sobel, Michael E. 1982. "Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models." *Sociological Methodology* 13 (1982): 290. https://doi.org/10.2307/270723.
- Thomas, Duncan A, and Maria Nedeva. 2018. "Broad Online Learning EdTech and USA Universities: Symbiotic Relationships in a Post-MOOC World." *Studies in Higher Education* 43 (10): 1730–49. https://doi.org/10.1080/03075079.2018.1520415.

- Tirthali, Devayani, D Ed, Fiona M Hollands, and Devayani Tirthali. 2014. "MOOCs/: Expectations and Reality."
- Venkatesh, Viswanath, Michael G Morris, Gordon B Davis, Fred D Davis, Davis, and Davis. 2003. "User Acceptance of Information Technology: Toward a Unified View." *MIS Quarterly* 27 (3): 425–78. https://doi.org/10.2307/30036540.
- Waldrop, M. Mitchell. 2013. "Online Learning: Campus 2.0." *Nature* 495 (7440): 160–63. https://doi.org/10.1038/495160a.
- Welsh, Dhb, and Mariana Dragusin. 2013. "The New Generation of Massive Open Online Course (MOOCS) and Entrepreneurship Education." *Small Business Institute® Journal* 9 (1): 51–65.
- Wu, Bing, and Xiaohui Chen. 2017. "Continuance Intention to Use MOOCs: Integrating the Technology Acceptance Model (TAM) and Task Technology Fit (TTF) Model." *Computers in Human Behavior* 67 (February): 221–32. https://doi.org/10.1016/j.chb.2016.10.028.
- Zhao, Xinshu, John G. Lynch, and Qimei Chen. 2010. "Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis." *Journal of Consumer Research* 37 (2): 197–206. https://doi.org/10.1086/651257.
- Zhou, Mingming. 2016. "Chinese University Students' Acceptance of MOOCs: A Self-Determination Perspective." *Computers & Education* 92–93 (January): 194–203. https://doi.org/10.1016/j.compedu.2015.10.012.
- Zhou, Tao. 2012. "Examining Mobile Banking User Adoption from the Perspectives of Trust and Flow Experience." *Information Technology and Management* 13 (1): 27–37. https://doi.org/10.1007/s10799-011-0111-8.
- ———. 2013a. "The Effect of Flow Experience on User Adoption of Mobile TV." *Behaviour & Information Technology* 32 (3): 263–72. https://doi.org/10.1080/0144929X.2011.650711.
- ———. 2013b. "Understanding the Effect of Flow on User Adoption of Mobile Games." *Personal and Ubiquitous Computing* 17: 741–48. https://doi.org/10.1007/s00779-012-0613-3.

Shrikant Mulik *is a research scholar at NMIMS SBM. He worked at L&T Infotech for 18 years before joining the academia. After working full-time for 18 months at NMIMS MPSTME, he has been serving as a visiting faculty in leading business schools. He is a social entrepreneur as his social enterprise (Vidyarjan Academy) works for the cause of enhancing employability of graduates. Shrikant's 10+ publications have earned over 370 citations as per Google Scholar. Shrikant has done his graduation in Computer Engineering from Mumbai University and post-graduation in Management from IIT Bombay. He can be reached at shrikant@iitbombay.org.*

Manjari Srivastava *is a Professor in Human Resource Management and Behavioural Sciences at NMIMS SBM. She has Masters in Psychology and holds Ph.D. in the area of Organizational Behaviour. With work experience of 18 years, Manjari is deeply involved in teaching, training, mentoring and research activities. Manjari has published vastly both in national and international journals, and has participated in various conferences both nationally and internationally. She has also published cases with Ivey Publishers Canada, one of the World's leading business case publishers. She can be reached at manjari.srivastava@nmims.edu.*

Nilay Yajnik *is Provost at Navrachana University, Vadodara, India. He has over 13 years of experience in IT industry with companies such as Wipro Infotech and Digital-HP. He has around 25 years of teaching experience. His teaching and research interests include information systems applications in business, ERP, IT strategy, innovation and e-business. He was Professor and Chairman of the Information Systems Area at NMIMS SBM. He is an Alumnus of the Harvard Business School's Global Colloquium on Participant Centered Learning held in Boston, USA. He can be reached at nilayyajnik@hotmail.com.*