Extending UTAUT Model to Examine MOOC Adoption

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

Abstract

The purpose of this study is to examine the adoption of Massive Open Online Courses (MOOC) by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) with an addition of Perceived Value construct. Data was collected from 310 individuals, who had enrolled in at least one MOOC offered by MOOC providers such as Coursera, edX and FutureLearn. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to test the reliability and validity of the data, and the hypothesized relationships. The results revealed that performance expectancy, effort expectancy, social influence, facilitating conditions and perceived value have a significant influence on intention to use MOOC. Together they predicted 49% of the variance in intention. The study makes a theoretical contribution by validating the extension of UTAUT in the context of MOOC adoption. It also has practical and policy implications.

Keywords: *Unified Theory of Acceptance and Use of Technology (UTAUT), Massive Open Online Courses (MOOC), Perceived Value, MOOC Adoption.*

[1] *Research Scholar, NMIMS School of Business Management, India*
[2] *Professor, NMIMS School of Business Management, India*
[3] *Director, Aditya Institute of Management Studies and Research, India*

Introduction

Massive Open Online Course (MOOC) is a new phenomenon in the education domain. It is an online course, which can be accessed over the internet using a desktop, a laptop or a smartphone. It is typically offered to an adult learner to complete in a specific time period such as six weeks. MOOC may or may not have a massive enrolment, but it is designed for the same. It offers videos for teaching. Assessment is done using auto-gradable quizzes and peer-reviewed assignments. Majority of MOOCs offer content for free while assessment and certification are offered for a fee.

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, which have launched MOOCs. 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 Technologies (IITs) and Indian Institute of Science. 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.

While MOOC can deliver high-quality content to a large number of students at a low cost and can provide insights into human learning, it also suffers from certain weaknesses. MOOC somewhat fails in offering an authoritative assessment of written work, reliable authentication for certification and frequent interaction of students with faculty (Welsh & Dragusin, 2013). Still, MOOC offers an advantage over traditional classroom-based courses due to more flexibility, customization and accessibility, which helps structured self-paced learning for students (Bruff, Fisher, McEwen, & Smith, 2013).

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 (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. Though there have been different opinions about the impact of MOOC on the traditional education system, the number of users have grown over a period of time. Class Central, a leading MOOC aggregator has reported the number of MOOC users to be around 78 million (Shah, 2018). At the same time, it has also pointed out that the growth in the number of MOOC users is slowing down. In this context, this research study attempts to explore the factors that would lead to higher enrolment figures for MOOC. It extends Unified Theory of Acceptance and Use of Technology (UTAUT) to identify the factors influencing MOOC adoption.

The paper is organized as follows. The next section discusses UTAUT, which serves as a theoretical foundation for this study. The third section develops the hypotheses for testing. The fourth section describes the method and results of hypothesis testing. The fifth section discusses the results and the final sixth section concludes the paper.

Theoretical Foundation

Why do individuals accept a specific technology? 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. Venkatesh et al. (2003) undertook a study to review and empirically compare the following eight key competing theoretical models from this stream of research.

1. Theory of Reasoned Action (TRA)
2. Technology Acceptance Model (TAM)
3. Motivational Model (MM)
4. Theory of Planned Behaviour (TPB)
5. Model combining the Technology Acceptance Model and the Theory of Planned Behaviour (C-TAM-TPB)
6. Model of PC Utilization (MPCU)
7. Innovation Diffusion Theory (IDT)
8. Social Cognitive Theory (SCT)

Before discussing UTAUT, it will be imperative to briefly review these models. The Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975) is the oldest model among these models. TRA examines beliefs within an individual to explain adoption behaviour. The core constructs in TRA are “behavioural intention”, “attitude toward behaviour” and “subjective norm”. The behavioural intention construct is expected to predict the performance of any voluntary act subject to two constraints – intent should not change prior to performance and the intention construct should correspond to the behavioural criterion in terms of action, target, context, time-frame and/or specificity (Sheppard, Hartwick, Warshaw, & Hartwick, 1988). Attitude toward behaviour refers to an individual's positive or negative feelings (evaluative affect) about performing the target behaviour. Finally, the subjective norm refers to the person's perception that most people who are important to him/her think he/she should or should not perform the behaviour in question.

Technology Acceptance Model (TAM) adapted TRA to explain computer usage behaviour. Published in 1986, TAM is considered to be the most influential and widely applied employed model in this field (Lee, Kozar, & Larsen, 2003). TAM postulates that two particular beliefs, Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are determinants for computer system acceptance behaviour (Davis, Bagozzi, & Warshaw, 1989). Perceived Usefulness refers to the prospective user's subjective probability that using a specific system will increase his or her job performance within an organizational context. Perceived Ease of Use, on the other hand, refers to the degree to which the prospective user expects the target system to be free of effort. TAM was later extended as TAM2, in which Subjective Norm, which is present in TRA, was added as a determinant of behavioural intention(Venkatesh & Davis, 2000).

Davis, Bagozzi & Warshaw (1992) applied motivational theory to understand new technology adoption and use. It proposed two determinants viz. Extrinsic Motivation and Intrinsic Motivation to understand technology adoption and use. Extrinsic motivation refers to the perception that users will want to perform an activity because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself, such as enhanced pay or promotions. On the other hand, intrinsic motivation refers to the perception that users will want to perform an activity for no apparent reinforcement other than the process of performing the activity per se.

Theory of Planned Behaviour (TPB) extended TRA by adding the construct of Perceived Behavioural Control as an additional determinant of intention and behaviour (Ajzen, 1991). Perceived Behavioural Control refers to the perceived ease or difficulty of performing the behaviour and it is assumed to reflect past experience as well as anticipated impediments and obstacles. Taylor & Todd (1995b) further decomposed attitude, subjective norm and perceived behavioural control into the underlying belief structure, to propose the Decomposed Theory of Planned Behaviour (DTPB). Another study (Taylor & Todd, 1995a) combined TAM and TPB to provide a hybrid model, which is referred to as the model combining the Technology Acceptance Model and the Theory of Planned Behaviour.

Thompson, Higgins & Howell (1991) adapted a competing theory of behaviour proposed by Triandis (1979) to examine utilization of the Personal Computer (PC). It found that social factors, complexity, job fit and long-term consequences have significant effects on PC use. Social factors refer to the individual's internalization of the reference groups' subjective culture and specific interpersonal agreements that the individual has made with others, in specific social situations. Complexity is defined as the degree to which an innovation is perceived as relatively difficult to understand and use. Job fit is defined as the extent to which an individual believes that using a PC can enhance the performance of his or her job. Finally, long-term consequences of use refer to outcomes that have a pay-off in the future, such as increasing the flexibility to change jobs or increasing the opportunities for more meaningful work.

Gary C. Moore and Izak Benbasat adapted Innovation Diffusion Theory (IDT) (Rogers, 1962) to develop an instrument to measure the various perceptions that an individual may have of adopting an information technology (IT) innovation (Moore & Benbasat, 1991). The eight core constructs in this instrument are Voluntariness of Use (the degree to which use of the innovation is perceived as being voluntary or of free will), Relative Advantage (the degree to which an innovation is perceived as being better than its precursor), Compatibility (the degree to which an innovation is perceived as being consistent with the existing values, needs and past experiences of potential adopters), Image (the degree to which use of an innovation is perceived to enhance one's image or status in one's social system), Ease of Use (the degree to which an individual believes that using a particular system would be free of physical and mental effort), Result Demonstrability (the tangibility of the results of using the innovation, including their observability and communicability), Visibility (the degree to which one can see others using the system in the organization), and Trialability (the degree to which an innovation may be experimented with before adoption). Agarwal & Prasad (1997) used this instrument to examine the use of technology and intention to continue such use in future. This instrument has also been used in conjunction with Theory of Planned Behaviour to examine the intention to adopt internet banking (Tan & Teo, 2000) and mobile banking (Püschel, Afonso Mazzon, & Mauro C. Hernandez, 2010).

Social Cognitive Theory (SCT) (Bandura, 1989) is a widely accepted theory of behaviour in Social Psychology and Industrial/Organizational Psychology. Compeau & Higgins (1995) applied and extended SCT to the context of computer utilization. They found that computer self-efficacy exerts a significant influence on individuals' expectations of the outcomes of using computers, their emotional reactions to computers (affect and anxiety), as well as their actual computer use. They also found that the encouragement of others in their workgroup as well as others' use of computers positively, influences the individual's self-efficacy and outcome expectations.

Venkatesh et al. (2003) empirically compared all these eight models and their extensions to formulate a unified model that integrates elements across the eight models and empirically validated the unified model. This unified model, shown in Figure 1, was named as Unified Theory of Acceptance and Use of Technology (UTAUT). While the eight contributing models could explain 17 to 53 percent of the variance in behavioural intention, UTAUT was found to perform much better with adjusted R^2 of 69 percent.

The UTAUT establishes three core determinants of Behavioural Intention - Performance Expectancy, Effort Expectancy and Social Influence. It further establishes Facilitating Conditions as a determinant of Use Behaviour. Behavioural Intention is also established as a determinant of Use Behaviour. Finally, gender, age, experience and voluntariness of use are shown to have a moderating effect on key relationships.

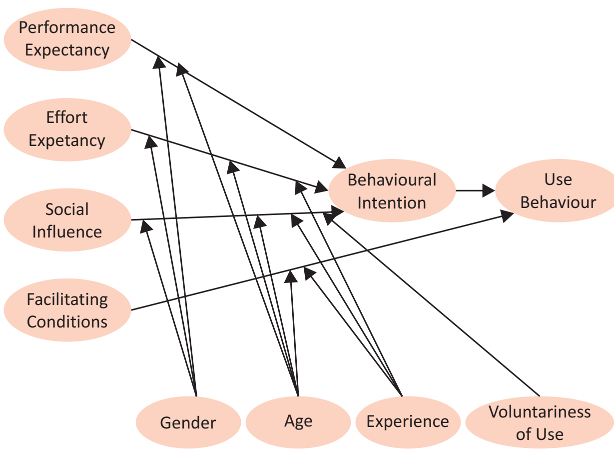

Figure 1: UTAUT

After its publication in the year 2003, UTAUT has been used in various research studies to examine adoption of technologies such as Internet banking (Abu-Shanab & Pearson, 2009), social media (Curtis et al., 2010), telemedicine (Hailemariam, Negash, & Musa, 2010), CRM systems (Pai & Tu, 2011), virtual communities of practice (Nistor, Baltes, & Schustek, 2012) and video-based learning (Mikalef, Pappas, & Giannakos, 2016). In a similar way, UTAUT can be used to examine MOOC adoption. It should also be noted that researchers have extended UTAUT when applying it in the specific contexts. Williams, Rana & Dwivedi (2015) performed a systematic review of 174 papers in which it was found that a number of external variables such as self-efficacy, attitude and trust were introduced to adapt UTAUT in specific contexts. In this study, the authors have proposed a research model by adding Perceived Value as an additional determinant of intention to use MOOC.

Why is it needed to add an additional determinant in the proposed model? It should be noted that UTAUT was originally developed to explain technology acceptance by employees of an organization. MOOC, on the other hand, is being used by consumers, who would need to spend their own time and money to use MOOC. Though MOOC content is typically available for free, one needs to spend a significant amount of time to use MOOC, which could have been used for some other purposes. In some cases, consumers would need to pay for the internet bandwidth and devices to use MOOC. Some consumers may also opt for certifications, for which they will need to pay. Perceived Value would capture the perception of MOOC users about the benefits received after spending their time and money. It is found to be a determinant of the behavioural intention in contexts such as online music purchase in Taiwan (Chu & Lu, 2007), online travel purchase in Spain (Bonsón Ponte, Carvajal-Trujillo, & Escobar-Rodríguez, 2015), online shopping in Taiwan (L. Y. Wu, Chen, Chen, & Cheng, 2014) and internet shopping in Korea (H.-W. Kim, Xu, & Gupta, 2012). In a similar way, perceived value is expected to be a significant factor in predicting the behavioural intention in the context of use of MOOC.

Hypotheses

The proposed research model is shown in Figure 2. Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Perceived Value are proposed to be determinants of Behavioural Intention. Since the cross-sectional approach is used over longitudinal approach, the scope of the research study is kept limited to assess intention to use MOOC rather than actual use of MOOC. Hence, only Behavioural Intention construct from UTAUT is being considered and the Use Behaviour construct is excluded. This is in line with the majority of UTAUT studies. As analyzed in (Williams et al., 2015), 135 out of 174 studies have chosen to use cross-sectional approach over longitudinal approach while using UTAUT. It should be noted that studies, which have assessed both behavioural intention and use behaviour using longitudinal approach have found behavioural intention as a predictor of use behaviour (Davis et al., 1989; Lee et al., 2003; Venkatesh et al., 2003). Behavioural Intention is defined in the present context as the degree to which a person has formulated conscious plans to use MOOC.

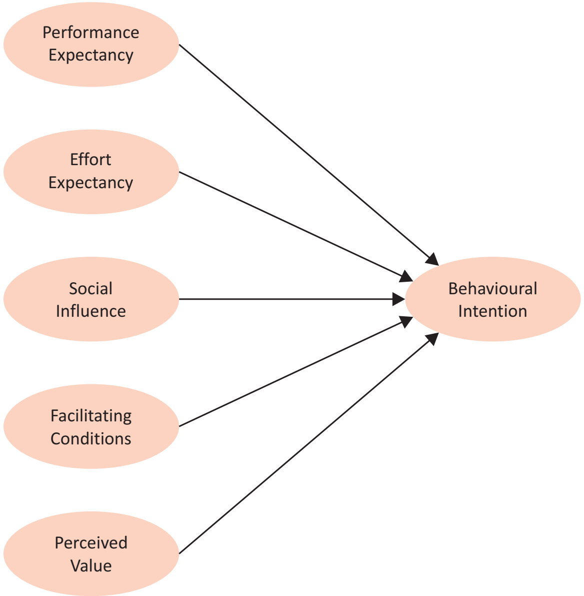

Figure 2: Proposed Research Model

Performance Expectancy

In UTAUT, performance expectancy is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance. The five constructs from the different models that capture this construct are Perceived Usefulness (TAM/TAM2 and C-TAM-TPB), Extrinsic Motivation (MM), Job Fit (MPCU), Relative Advantage (IDT) and Outcome Expectations (SCT).

As reported in Williams et al. (2015), out of 116 studies that examined the relationship between performance expectancy and behavioural intention, 93 studies (80%) found this relationship to be significant. The relationship between Performance Expectancy and Behavioural Intention is validated in various contexts such as adoption of Internet banking in Jordan (AbuShanab, Pearson, & Setterstorm, 2010), adoption of mobile devices/services in Finland (Carlsson, Carlsson, Hyvönen, Puhakainen, & Walden, 2006), adoption of world wide web for job seeking in South Africa (Pavon & Brown, 2010), registered nurses', certified nurse practitioners' and physician assistants' acceptance of electronic medical record (EMR) in the state of South Dakota of USA (Wills, El-Gayar, & Benett, 2008), and students' acceptance of online courses in the Sri Lankan State Universities (Wijewardene, Azam, & Khatibi, 2018).

We define performance expectancy as the degree to which an individual believes that using MOOC will help him or her to attain gains in job performance and propose the following hypothesis:

H1: Performance Expectancy has a positive impact on Behavioural Intention.

Effort Expectancy

Effort expectancy refers to the degree of ease associated with the use of the system. Three constructs from the existing models that pertain to this construct are Perceived Ease of Use (TAM/TAM2), Complexity (MPCU) and Ease of Use (IDT).

As described in Williams et al. (2015), 64 out of 110 studies (58%) have found a significant relationship between effort expectancy and behavioural intention. The relationship between Effort Expectancy and Behavioural Intention is found to be significant in numerous contexts such as intention to use hybrid media applications viz. code reading applications for camera phones (Louho & Kallioja, 2006), user acceptance of information technology in Canadian firms (Neufeld, Dong, & Higgins, 2007), adoption of digital libraries among university students in north-eastern USA (Nov & Ye, 2009), acceptance of CRM systems among staff members of four distribution service companies in Taiwan (Pai & Tu, 2011) and mobile banking adoption in Pakistan (Abbas, Hassan, Asif, Ahmed, & Haider, 2018).

In this study, effort expectancy refers to the degree of ease associated with the use of MOOC. Based on support from literature, the second hypothesis is as stated below:

H2: Effort Expectancy has a positive impact on Behavioural Intention.

Social Influence

Social influence is defined as the degree to which an individual perceives that others believe he or she should use the new system. Social influence as a direct determinant of behavioural intention is represented as Subjective Norm in TRA, TAM2, TPB/DTPB and C-TAM-TPB, Social Factors in MPCU, and Image in IDT.

Out of 115 studies that examined the relationship between social influence and behavioural intention, 86 studies (75%) found this relationship to be significant (Williams et al., 2015). The relationship between Social Influence and Behavioural Intention is found to be significant in many contexts such as adoption of e-government services in the state of Qatar (Al-Shafi & Weerakkody, 2009), user acceptance of e-Government services offered through kiosks in Taiwan (Hung, Wang, & Chou, 2007), adoption behaviour of mobile Internet users in Greece (Kourouthanassis, Georgiadis, Zamani, & Giaglis, 2010), adoption of a C2C auction site (Tao Bao) among students in China (Pahnila, Siponen, & Zheng, 2011) and adoption of Information Communication Technology (ICT) services among university library end-users in Uganda (Tibenderana, Ogao, Ikoja-Odongo, & Wokadala, 2010).

In the present context, social influence can be defined as the degree of importance an individual assigns to others' opinion on whether he or she should use MOOC. The third hypothesis is stated as below:

H3: Social Influence has a positive impact on Behavioural Intention.

Facilitating Conditions

Facilitating conditions are defined as the degree to which an individual believes that organizational and technical infrastructure exists to support the use of the system. This definition captures concepts embodied by three different constructs: Perceived Behavioural Control (TPB/DTPB, C-TAM-TPB), Facilitating Conditions (MPCU) and compatibility (IDT). Although original UTAUT did not consider Facilitating Conditions as a determinant of Behavioural Intention, it was proposed to be the one, in line with research studies that used or extended UTAUT in different contexts.

Williams et al. (2015) examined 48 studies that investigated the relationship between facilitating conditions and behavioural intention, and noted that 33 studies (69%) found this relationship to be significant. The relationship between Facilitating

Conditions and Behavioural Intention is found to be significant in several contexts such as adoption of e-file among US taxpayers (Schaupp & Hobbs, 2009), Internet Banking Adoption in Kuala Lumpur (Sok Foon & Chan Yin Fah, 2011), intention to use technology among school teachers in Singapore (Teo, 2011), adoption of mobile phones among undergraduate university students in South Africa (Biljon & Kotzé, 2008), and adoption behaviour of 3G mobile communication users in Taiwan (Y. L. Wu, Tao, & Yang, 2007).

We define facilitating conditions as the degree to which an individual believes that infrastructure exists to support the use of MOOC, and propose the following fourth hypothesis:

H4: Facilitating Conditions have a positive impact on Behavioural Intention.

Perceived Value

Zeithaml (1988) defined perceived value as the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given. It is found to have an influence on behavioural intention in different contexts. JC Sweeney, Soutar, & Johnson (1999) found it to have an impact on willingness to buy. Kuo, Wu, & Deng (2009) found perceived value to affect re-purchase intention in mobile value-added services, while Meng, Liang, & Yang (2011) found it to affect post-purchase behavioural intention of Taiwanese tourists. Y. H. Kim, Kim, & Wachter (2013) found that perceived value impacts mobile engagement intention. Cronin, Brady, & Hult (2000) reported that perceived value affects consumer behavioural intention in service environments. Similarly, perceived value is found to have an influence on the behavioural intention of heritage tourists (C.-F. Chen & Chen, 2010), and that of Taiwanese air passengers (C. F. Chen, 2008). Based on this support from literature, the following hypothesis is proposed:

H5: Perceived Value has a positive impact on Behavioural Intention.

Methodology

The study has used survey research method to test the hypotheses. This is in line with the majority of UTAUT studies that have used survey research method (Williams et al., 2015).

Data Collection

An online questionnaire was created and sent to members of the authors' professional network 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 persons, who have enrolled in 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

Instrument Development

There are many ways by which Perceived Value has been measured in the extant literature. Sánchez-Fernández & Iniesta-Bonillo (2007) have identified two main approaches to the operationalization of this construct. The first approach conceptualizes perceived value as a one-dimensional construct that can be measured by a self-reported set of items, which evaluates the consumer's perception of value. For example, Dodds, Monroe, & Grewal (1991) used a one-dimensional scale to measure perceived value for studying the effect of price, brand and store information on buyers' product evaluations. On the other hand, the second approach conceptualizes perceived value as a multi-dimensional construct that consists of several interrelated attributes to form a holistic representation of a complex phenomenon. For example, J Sweeney & Soutar (2001) have developed a 19-item scale, called PERVAL, that consists of four dimensions viz., Quality, Emotional Response, Price and Social. Similarly, James (2002) has developed a 25-item instrument measuring five dimensions of perceived value viz., Quality, Emotional Response, Monetary Price, Behavioural Price and Reputation. In this study, we have used a one-dimensional approach for assessing the perceived value with a three-item scale (Dodds et al., 1991).

The scale for constructs from UTAUT was adapted from Venkatesh et al. (2003) in which all these scales had Internal Consistency Reliability (ICR) greater than 0.70. The items were adapted for the present context. All items were measured on a 5-point Likert scale (from “strongly disagree” to “strongly agree”).

Data Analysis

The partial least squares technique of structural equation modelling (PLS-SEM) was used to test the reliability and validity of the data, and the study's hypothesized relationships or paths. SmartPLS 2.0 M3 software was used for data analysis.

As a first step, the measurement model was tested for reliability and validity. One indicator for the Facilitating Conditions construct was removed due to its poor loading. Table 2 shows the results of reliability and validity tests. Composite Reliability (CR) values above the threshold value of 0.708 for all constructs indicated internal consistency reliability. Similarly, 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 slightly below 0.7 for two indicators, as suggested in Hair, Hufit, Ringle M., & Sarstedt (2014).

Table 2: Results of Reliability and Validity Tests

Construct	Item	Loadings
Performance Expectancy AVE = 0.5231 CR = 0.8143	I find MOOC useful for my learning needs.	0.7320
	Using MOOC enables me to accomplish learning more quickly.	0.6964
	Using MOOC increases my productivity.	0.7241
	Using MOOC increases my chances of achieving things that are important to me.	0.7398
Effort Expectancy AVE = 0.5849 CR = 0.8491	I find MOOC easy to use.	0.7179
	My interaction with MOOC site is clear and understandable.	0.7685
	It is easy for me to become skilled at using MOOC.	0.7692
	Learning to use MOOC is easy for me.	0.8011
Social Influence AVE= 0.7697 CR = 0.9092	People, who influence my behaviour, think that I should use MOOC.	0.8259
	People, who are important to me, think that I should use MOOC.	0.9006
	People, whose opinions I value, prefer that I use MOOC.	0.9034
Facilitating Conditions AVE = 0.5645 CR = 0.7952	I have resources necessary to use MOOC.	0.7248
	I have the knowledge necessary to use MOOC.	0.7949
	MOOC is compatible with other technologies that I use.	0.7325
Perceived Value AVE = 0.6364 CR = 0.7952	MOOC is good value-for-money and efforts.	0.7708
	MOOC appears to be a good bargain.	0.7927
	I consider MOOC to be a good value.	0.8287
Behavioural Intention AVE = 0.6324 CR = 0.8364	I intend to use MOOCs in future.	0.8224
	I foresee that I will use MOOCs in the near future.	0.8659
	I plan to use MOOCs in six months.	0.6864

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 its loadings on other constructs (i.e. the cross-loadings), thus indicating discriminant validity. We further tested for Fornell-Larcker criterion (Fornell & Larcker, 1981), which is a more conservative approach to assessing discriminant validity (Hair et al., 2014). As per this criterion, the square root of the AVE of each construct should be higher than its highest correlation with any other construct. As shown in Table 3, the square root of the AVE of each construct is higher than its highest correlation with any other construct, thus indicating discriminant validity.

Table 3: Fornell-Larcker Criterion for Discriminant Validity

1.1	Effort Expectancy	Facilitating Conditions	Behavioural Intention	Performance Expectancy	Perceived Value	Social Influence
Effort Expectancy	**0.7648**	1.2	1.3	1.4	1.5	1.6
Facilitating Conditions	0.6993	**0.7513**	1.7	1.8	1.9	1.10
Behavioural Intention	0.6053	0.5722	**0.7952**	1.11	1.12	1.13
Performance Expectancy	0.7062	0.6456	0.6351	**0.7233**	1.14	1.15
Perceived Value	0.6433	0.5534	0.5652	0.6369	**0.7977**	1.16
Social Influence	0.2178	0.1439	0.2651	0.2875	0.2032	**0.8773**

After evaluating the measurement model, the first step in analyzing the structural model was to assess it for collinearity issues. To do so, latent variable scores produced by SmartPLS were used as input for collinearity assessment in IBM SPSS. After running multiple regression analysis for all predictors of Behavioural Intention, VIF values were found to be below the threshold value of 5, as shown in Table 4. Hence, it is concluded that collinearity among the predictor constructs is not an issue in the structural model.

Table 4 also shows the summary of results after running PLS algorithm, bootstrapping procedure and blindfolding procedure in SmartPLS software. The R2 value is found to be 0.492, which means 49.2% of the variance in Behavioural Intentions can be explained by this model. The path coefficients are significant for all relationships. The path coefficient for the relationship between performance expectancy and behavioural intention is bigger than other path coefficients indicating the prominent role of performance expectancy in influencing behavioural intention. Facilitating Conditions, Perceived Value, Effort Expectancy and Social Influence come second, third, fourth and fifth in prominence respectively.

Table 4: Summary of Results

Dependent Variable	Independent Variable	VIF	Path Coefficient	t Value	Significance
Behavioural Intention $R^2 = 0.492$	Performance Expectancy	2.497	0.2728	4.1906	Significant at 1% level
	Effort Expectancy	2.726	0.1573	2.3529	Significant at 5% level
	Social Influence	1.098	0.0917	1.9698	Significant at 5% level
	Facilitating Conditions	2.184	0.1766	2.3203	Significant at 5% level
	Perceived Value	1.944	0.1739	2.9506	Significant at 1% level

Based on these results, results of hypotheses testing are displayed in Table 5. The resultant research model is shown in Figure 3.

Table 5: Results of Hypotheses Testing

Hypothesis	Result
H1: Performance Expectancy has a positive impact on Behavio ural Intention.	Supported
H2: Effort Expectancy has a positive impact on Behavioural Intention.	Supported
H3: Social Influence has a positive impact on Behavio ural Intention.	Supported
H4: Facilitating Conditions ha ve a positive impact on Behavioural Intention.	Supported
H5: Perceived Value has a positive impact on Behavioural Intention.	Supported

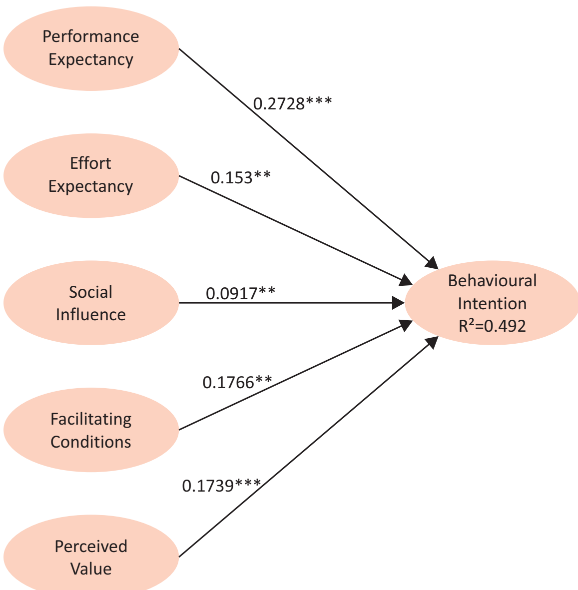

Figure 3: Resultant Model (=p<0.1; **= p < 0.5; ***=p < 0.01)*

Discussion

The purpose of the study is to examine the influencing factors of MOOC adoption. The UTAUT was chosen as the base model, which was extended to include Perceived Value that could influence the MOOC adoption. The endogenous variable in UTAUT is the Use Behaviour. However, due to its cross-sectional research design, this study has limited itself to examine the Behavioural Intention i.e. the intention to use MOOC instead of Use Behaviour i.e. the MOOC usage.

Interpretation of Findings

Consistent with UTAUT, the study hypothesized the impact of Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions on Behavioural Intention. The study found support for all four relationships. Among these four predictors, performance expectancy is found to be the most prominent predictor. This finding indicates that individuals strongly believe that using MOOC will help them to attain gains in job performance. This is very much in line with the literature. Based on analysis done by examining 149 studies, Williams et al. (2015) have found performance expectancy to be the most significant predictor of all four predictors of behavioural intention.

Facilitating conditions come second in prominence in this study, possibly due to sample profile. A significant relationship between facilitating conditions and behavioural intention means that the respondent believed that infrastructure exists to support their use of MOOC. Though we didn't ask for nationality or country of residence in our online questionnaire, the majority of respondents are expected to be from India, where infrastructure would play a key role in the acceptance of technology such as MOOC. Availability of resources such as good internet bandwidth and appropriate devices to access MOOC can't be taken for granted for all potential users of MOOC and hence, would be a determining factor for MOOC adoption.

Effort expectancy is also found to have an influencing role in the adoption of MOOC. This finding indicates that learners expect a good degree of ease associated with the use of MOOC. In other words, users would hesitate to use MOOC if they find it cumbersome to use. Finally, the influencing role of social influence indicates that opinions of others such as friends, colleagues, parents and teachers would matter when it comes to the decision of using MOOC.

The study also found support for perceived value as a determinant of behavioural intention. The perceived value construct is a widely used construct in retail marketing literature as it is found to be related to purchasing intention of consumers. The perceived value in the present context refers to the MOOC users' overall assessment of MOOC based on what is received in terms of learning and what is given in terms of efforts and money spent in using MOOC. The finding indicates that consumers would use MOOC only if they find MOOC more beneficial as compared to the cost incurred in using MOOC. This finding is again in line with literature that has examined the impact of the perceived value on behavioural intention.

Research Limitations

This study suffers from certain limitations. One limitation arises due to 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 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. Also, the sample profile was not very balanced. It was male dominated with about 73% of respondents being male. Also, the proportion of students as compared to professionals was only about 24%.

This study did not differentiate among MOOCs from different subject areas like social science, computer programming, philosophy, etc. Different results might be possible based on the subject area of the MOOC. One could argue that performance expectancy would not be a prominent factor for users of poetry-related MOOC as compared to the users of computer programming MOOC. Similarly, MOOCs were not distinguished based on their level of complexity (e.g. basic, intermediate and advanced).

Finally, this study limited itself to examining intention 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.

Theoretical Contribution

This study has affirmed the influencing role of UTAUT predictors in the context of MOOC adoption. Further, it has established perceived value as an external variable for adapting UTAUT in the consumer context in general and in the context of MOOC adoption in particular.

Practical Implications

This study would help existing and emerging MOOC providers 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 the traditional classroom-based course.

As performance expectancy is found to be a prominent determinant of MOOC acceptance, MOOC providers can focus either on designing MOOCs that would be useful for users or on emphasizing the usefulness of their MOOCs in their promotions, or both. They will also need to ensure high usability of MOOC so that users would find it easy to use. Similarly, MOOC providers can shape value perception of potential consumers of MOOCs by organizing promotional activities accordingly.

Policy Implications

The study has found facilitating conditions as a second prominent factor in influencing intention of the learner to use MOOC. Facilitating conditions indicate the degree to which an individual believes that infrastructure exists to support the use of MOOC. It means improving infrastructure would be critical for MOOC adoption. This implication is particularly important for developing countries like India, where MOOC can be used to deliver university education at a much higher scale without compromising the quality of education. These countries should increase their Internet bandwidth to enhance ease of access to MOOC.

What is perhaps more important is to bridge the digital divide so that MOOC can be adopted by all sections of the society. In the year 2013, Nowroozzadeh (2013) found that 83% of surveyed MOOC learners already had a two- or four-year post-secondary degree with 44.2% reporting education beyond a bachelor's degree. The same report mentioned that in Brazil, Russia, India, China and South Africa, almost 80% of MOOC learners come from the wealthiest and most well-educated 6% of the population. It means if the digital divide is not bridged, then MOOC would not be able to democratize education as expected.

Future Research

The study validated the extended UTAUT model to examine MOOC adoption. Though this model could explain 49% of the variance in intention to use MOOC, future research studies should explore additional constructs to explain more variance. It is also possible to explore the decomposition of the predictors to identify the underlying belief structure. One could also investigate the mediating effect of age, gender and experience on the key relationships in this model.

One of the limitations of this study is the lack of random sampling method. Future studies should attempt to make use of mailing lists of registered users of major MOOC providers as a sampling frame so as to use probability sampling method. A comparative study of MOOC learners from different countries could help enrich current understanding of MOOC adoption; it would also be useful for MOOC providers, who are offering their courses across the globe.

The model tested in this study could be tested separately for different MOOC subject categories such as Computer Science, Business, Social Science, etc. The understanding emerging from such study would help niche MOOC providers such as Kadenze, who are focusing on specific subject areas like music and art.

Finally, future research studies should examine MOOC completion and repeated use of MOOC beyond the intention to use MOOC. Such objectives would require longitudinal research design over a long period of time, but can give insights that would be useful for both MOOC providers and policymakers.

Conclusion

The study extended UTAUT to examine MOOC adoption. Since a cross-sectional research design was used, the intention to MOOC was examined instead of additionally examining MOOC usage. All four UTAUT predictors viz. Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions were tested in this study. The UTAUT was extended with Perceived Value as an additional predictor of behavioural intention for adapting UTAUT in the consumer context. The findings supported all factors as influencers for MOOC adoption. With these findings, this study makes a contribution to theory by means of a validated extension of UTAUT for consumer context in general and for MOOC adoption in particular. These findings would also help MOOC providers understand how they should develop and market their MOOCs more effectively. Finally, this study has policy implications as it indicates the need for improving infrastructure for increasing MOOC adoption for the democratization of education.

References

- Abbas, S. K., Hassan, H. A., Asif, J., Ahmed, B., & Haider, S. S. (2018). Integration of TTF, UTAUT, and ITM for Mobile Banking Adoption. *International Journal of Advanced Engineering, Management and Science*, *4*(5), 375–379. https://doi.org/10.22161/ijaems.4.5.6
- Abu-Shanab, E., & Pearson, M. (2009). Internet banking in Jordan: An Arabic instrument validation process. *International Arab Journal of Information Technology*, *6*(3), 235–244.
- AbuShanab, E., Pearson, M., & Setterstorm, A. (2010). Internet Banking and Customers' Acceptance in Jordan: The Unified Model's Perspective. *Communications of the Association for Information Systems*, *26*(Article 23), 493–524. https://doi.org/10.1073/pnas.0703993104
- Agarwal, R., & Prasad, J. (1997). The Role of Innovation Characteristics and Perceived Voluntariness in the Acceptance of Information Technologies. *Decision Sciences*, *28*(3), 557–582. https://doi.org/10.1111/j.1540-5915.1997.tb01322.x
- Ajzen, I. (1991). The theory of planned behavior. *Orgnizational Behavior and Human Decision Processes*, *50*, 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
- Al-Shafi, S., & Weerakkody, V. (2009). Understanding citizens' behavioural intention in the adoption of e-government services in the state of Qatar. *17th European Conference on Information Systems ECIS 2009*, 1618–1629. Retrieved from http://is2.lse.ac.uk/asp/aspecis/20090134.pdf
- Bandura, A. (1989). Social cognitive theory. In R. Vasta (Ed.), *Annals of child development. Vol. 6. Six theories of child development* (Vol. 6, pp. 1–60). Greenwich, CT: JAI Press.
- Biljon, J. Van, & Kotzé, P. (2008). Cultural Factors in a Mobile Phone Adoption and Usage Model. *Journal of Universal Computer Science*, *14*(16), 2650–2679. https://doi.org/10.3217/jucs-014-16-2650
- Bonsón Ponte, E., Carvajal-Trujillo, E., & Escobar-Rodríguez, T. (2015). Influence of trust and perceived value on the intention to purchase travel online: Integrating the effects of assurance on trust antecedents. *Tourism Management*, *47*, 286–302. https://doi.org/10.1016/j.tourman.2014.10.009
- Bruff, D. O., Fisher, D. H., McEwen, K. E., & Smith, B. E. (2013). Wrapping a MOOC: Student Perceptions of an Experiment in Blended Learning. *MERLOT Journal of Online Learning and Teaching*, *9*(2), 187–199.
- Carlsson, C., Carlsson, J., Hyvönen, K., Puhakainen, J., & Walden, P. (2006). Adoption of mobile devices/services - Searching for answers with the UTAUT. *Proceedings of the Annual Hawaii International Conference on System Sciences*, *6*(C), 1–10. https://doi.org/10.1109/HICSS.2006.38
- Chen, C.-F., & Chen, F.-S. (2010). Experience quality, perceived value, satisfaction and behavioral intentions for heritage tourists. *Tourism Management*, *31*(1), 29–35. https://doi.org/10.1016/j.tourman.2009.02.008
- Chen, C. F. (2008). Investigating structural relationships between service quality, perceived value, satisfaction, and behavioral intentions for air passengers: Evidence from Taiwan. *Transportation Research Part a-Policy and Practice*, *42*(4), 709–717. https://doi.org/10.1016/j.tra.2008.01.007
- Chu, C., & Lu, H. (2007). Factors influencing online music purchase intention in Taiwan. *Internet Research*, *17*(2), 139–155. https://doi.org/10.1108/10662240710737004
- Compeau, D., & Higgins, C. A. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. *MIS Quarterly*, *19*(2), 189–211.
- Cronin, J. J., Brady, M. K., & Hult, G. T. M. (2000). Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. *Journal of Retailing*, *76*(2), 193–218. https://doi.org/10.1016/S0022-4359(00)00028-2

- Curtis, L., Edwards, C., Fraser, K. L., Gudelsky, S., Holmquist, J., Thornton, K., & Sweetser, K. D. (2010). Adoption of social media for public relations by nonprofit organizations. *Public Relations Review*, *36*(1), 90–92. https://doi.org/10.1016/j.pubrev.2009.10.003
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: a Comparison of Two Theoretical Models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.2307/2632151
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace. *Journal of Applied Social Psychology*, *22*(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x
- Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of Price, Brand, and Store Information on Buyers' Product Evaluations. *Journal of Marketing Research*, *28*(3), 307. https://doi.org/10.2307/3172866
- Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior*. *Addison-Wesley Series in Social Psychology*. Addison-Wesley Pub. Co. https://doi.org/10.1016/j.ecolecon.2004.07.008
- Fornell, C., & Larcker, D. F. (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
- Hailemariam, G., Negash, S., & Musa, P. F. (2010). In search of Insights from Community of Practice and Use of Telemedicine in Low income Countries: The case of Ethiopia. *Amcis*, 276.
- Hair, J. F., Hufit, G. T. M., Ringle M., C., & Sarstedt, M. (2014). *A primer on partial least squares structural equations modeling (PLS-SEM)*. SAGE.
- Hung, Y., Wang, Y., & Chou, S.-C. T. (2007). User Acceptance of E-Government Services. *Proceedings of the PACIS 2007*, 1–8.
- James, F. (2002). Development of a multi-dimensional scale for measuring the perceived value of a service. *Journal of Leisure Research*, *34*(2), 119–134.
- Kalyanaram, G. (2018). Democratization of High-Quality Education and Effective Learning. *NMIMS Management Review*, *XXXV*(4), 6–11.
- Kim, H.-W., Xu, Y., & Gupta, S. (2012). Which is more important in Internet shopping, perceived price or trust? *Electronic Commerce Research and Applications*, *11*(3), 241–252. https://doi.org/10.1016/j.elerap.2011.06.003
- Kim, Y. H., Kim, D. J., & Wachter, K. (2013). A study of mobile user engagement (MoEN): Engagement motivations, perceived value, satisfaction, and continued engagement intention. *Decision Support Systems*, *56*(1), 361–370. https://doi.org/10.1016/j.dss.2013.07.002
- Kourouthanassis, P. E., Georgiadis, C. K., Zamani, E., & Giaglis, G. M. (2010). Explaining the Adoption of Mobile Internet Applications. *2010 Ninth International Conference on Mobile Business and 2010 Ninth Global Mobility Roundtable (ICMB-GMR)*, (2009), 148–153. https://doi.org/10.1109/ICMB-GMR.2010.70
- Kuo, Y. F., Wu, C. M., & Deng, W. J. (2009). The relationships among service quality, perceived value, customer satisfaction, and post-purchase intention in mobile value-added services. *Computers in Human Behavior*, *25*(4), 887–896. https://doi.org/10.1016/j.chb.2009.03.003
- Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The Technology Acceptance Model: Past, Present, and Future. *Communications of the Association for Information Systems*, *12*, 752–780. https://doi.org/10.1037/0011816
- Louho, R., & Kallioja, M. (2006). Factors affecting the use of hybrid media applications. *Graphic Arts in Finland*, *35*(3), 11–21. Retrieved from http://media.tkk.fi/GTTS/GAiF/GAiF_PDF/GAiF2006_3-2.pdf

- Meng, S., Liang, G., & Yang, S. (2011). The relationships of cruise image, perceived value, satisfaction, and post-purchase behavioral intention on Taiwanese tourists. *African Journal of Business Management*, *5*(1), 19–29. https://doi.org/10.5897/AJBM10.260
- Mikalef, P., Pappas, I. O., & Giannakos, M. (2016). An integrative adoption model of video-based learning. *International Journal of Information and Learning Technology*, *33*(4), 219–235. https://doi.org/10.1108/IJILT-01-2016-0007
- Moore, G. C., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Journal*, *2*(3), 192–222.
- Neufeld, D. J., Dong, L., & Higgins, C. (2007). Charismatic leadership and user acceptance of information technology. *European Journal of Information Systems*, *16*(4), 494–510. https://doi.org/10.1057/palgrave.ejis.3000682
- Nistor, N., Baltes, B., & Schustek, M. (2012). Knowledge sharing and educational technology acceptance in online academic communities of practice. *Campus-Wide Information Systems*, *29*(2), 108–116. https://doi.org/10.1108/10650741211212377
- Nov, O., & Ye, C. (2009). Resistance to change and the adoption of digital libraries: An integrative model. *Journal of the American Society for Information Science and Technology*, *60*(8), 1702–1708. https://doi.org/10.1002/asi.21068
- Nowroozzadeh, M. H. (2013). MOOCs taken by educated few. *Nature*, *503*(November), 342.
- Pahnila, S., Siponen, M., & Zheng, X. (2011). Integrating Habit into UTAUT: The Chinese eBay Case. *Pacific Asia Journal of the Association for Information Systems*, *3*(2), 1–30.
- Pai, J. C., & Tu, F. M. (2011). The acceptance and use of customer relationship management (CRM) systems: An empirical study of distribution service industry in Taiwan. *Expert Systems with Applications*, *38*(1), 579–584. https://doi.org/10.1016/j.eswa.2010.07.005
- Pappano, L. (2012). The Year of the MOOC. *The New York Times*, 1–7. Retrieved from http://www.edinaschools.org/cms/lib07/MN01909547/Centricity/Domain/272/The Year of the MOOC NY Times.pdf
- Pavon, F., & Brown, I. (2010). Factors influencing the adoption of the World Wide Web for job-seeking in South Africa. *SA Journal of Information Management*, *12*(1), 1–9. https://doi.org/10.4102/sajim.v12i1.443
- Püschel, J., Afonso Mazzon, J., & Mauro C. Hernandez, J. (2010). Mobile banking: proposition of an integrated adoption intention framework. *International Journal of Bank Marketing*, *28*(5), 389–409. https://doi.org/10.1108/02652321011064908
- Rogers, E. (1962). *Diffusion of Innovations*. New York: Macmillan.
- Sánchez-Fernández, R., & Iniesta-Bonillo, M. Á. (2007). The concept of perceived value: a systematic review of the research. *Marketing Theory*, *7*(4), 427–451. https://doi.org/10.1177/1470593107083165
- Schaupp, L. C., & Hobbs, J. (2009). E-File Adoption : A Study of U.S. Taxpayers' Intentions. In *Proceedings of the 42nd Hawaii International Conference on System Science* (pp. 1–10).
- Shah, D. (2018). By The Numbers: MOOCs in 2017. Retrieved April 10, 2018, from https://www.class-central.com/report/mooc-stats-2017/
- Sheppard, B. H., Hartwick, J. O. N., Warshaw, P. R., & Hartwick, J. O. N. (1988). The Theory of Reasoned Past Action : Meta-Analysis of with Modifications for Recommendations and. *Journal of Consumer Research*, *15*(3), 325–343. https://doi.org/10.1086/209170

- Sok Foon, Y., & Chan Yin Fah, B. (2011). Internet Banking Adoption in Kuala Lumpur: An Application of UTAUT Model. *International Journal of Business and Management*, *6*(4), 161–167. https://doi.org/10.5539/ijbm.v6n4p161
- Sweeney, J., & Soutar, G. (2001). Consumer perceived value: the development of a multiple item scale. *Journal of Retailing*, *77*(2), 203–220. https://doi.org/10.1016/S0022-4359(01)00041-0
- Sweeney, J., Soutar, G., & Johnson, L. (1999). The role of perceived risk in the quality value relationship: a study in a retail environment. *Journal of Retailing*, *75*(1), 77–105.
- Tan, M., & Teo, T. S. H. (2000). Factors Influencing the Adoption of Internet Banking. *Journal of the Association for Information Systems*, *1*(1), 1–44. https://doi.org/10.1016/j.elerap.2008.11.006
- Taylor, S., & Todd, P. (1995a). Assessing IT Usage: The Role of Prior Experience. *MIS Quarterly*, *19*(4), 561. https://doi.org/10.2307/249633
- Taylor, S., & Todd, P. A. (1995b). Understanding Information Technology Usage : A Test of Competing Models. *Information Systems Research*, *6*(2), 144–176.
- Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education*, *57*(4), 2432–2440. https://doi.org/10.1016/j.compedu.2011.06.008
- Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal Computing: Toward a Conceptual Model of Utilization. *MIS Quarterly*, *15*(1), 125. https://doi.org/10.2307/249443
- Tibenderana, P., Ogao, P., Ikoja-Odongo, J., & Wokadala, J. (2010). Measuring Levels of End-Users ' Acceptance and Use of Hybrid Library Services. *International Journal of Education and Development Using Information and Communication Technology (IJEDICT)*, *6*(2), 33–54. https://doi.org/10.5539/ass.v10n11p84
- Triandis, H. C. (1979). Values, attitudes, and interpersonal behavior. In *Nebraska Symposium on Motivation* (pp. 195–259).
- Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204.
- Venkatesh, V., Morris, M. G., Davis, G. B., Davis, F. D., Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540
- Waldrop, M. M. (2013). Online learning: Campus 2.0. *Nature*, *495*(7440), 160–163. https://doi.org/10.1038/495160a
- Welsh, D., & Dragusin, M. (2013). The New Generation of Massive Open Online Course (MOOCS) and Entrepreneurship Education. *Small Business Institute® Journal*, *9*(1), 51–65.
- Wijewardene, U. P., Azam, S. M. F., & Khatibi, A. (2018). Students ' Acceptance of Online Courses and Perceived Risk: A Study of UTAUT in the Sri Lankan State Universities. *International Journal of Advances in Scientific Research and Engineering*, *4*(1), 15–22.
- Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review. *Journal of Enterprise Information Management*, *28*(3), 443–488. https://doi.org/10.1108/JEIM-09-2014-0088
- Wills, M., El-Gayar, O., & Benett, D. (2008). Examining Healthcare Professionals' Acceptance of Electronic Medical Records Using UTAUT. *Issues in Information Systems*, *IX*(2), 396–401.
- Wu, L. Y., Chen, K. Y., Chen, P. Y., & Cheng, S. L. (2014). Perceived value, transaction cost, and repurchase-intention in online shopping: A relational exchange perspective. *Journal of Business Research*, *67*(1), 2768–2776. https://doi.org/10.1016/j.jbusres.2012.09.007

- Wu, Y. L., Tao, Y. H., & Yang, P. C. (2007). Using UTAUT to explore the behavior of 3G mobile communication users. *IEEM 2007: 2007 IEEE International Conference on Industrial Engineering and Engineering Management*, 199–203. https://doi.org/10.1109/IEEM.2007.4419179

- Zeithaml, V. A. (1988). Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence. *Journal of Marketing*, *52*(3), 2–22. https://doi.org/10.2307/1251446

Shrikant Mulik *is a research scholar at School of Business Management, SVKM's NMIMS University, Mumbai. He has 18 years of industry experience and two years of teaching experience. He has (co)authored nine academic publications, which have earned close to 300 citations as per Google Scholar. His research interests are in the areas of Technology Adoption, Services Computing and Technology for Education. His areas of interest in teaching include Digital Marketing, Technology Management, and Career Skills. 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 School of Business Management, SVKM's NMIMS University, Mumbai. 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 with 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 former Professor and Chairman of Information Systems Area at School of Business Management, SVKM's NMIMS University, Mumbai. He is currently Director at the Aditya Institute of Management Studies & Research (AIMSR), Mumbai. Dr. Yajnik is Ph.D. from Mumbai University, Master of Management Studies (MMS) from NMIMS (Mumbai University) and Master of Science (Technology) from BITS Pilani. He has participated in the HBS Global Colloquium on Participant-Centered Learning at the Harvard Business School, Boston, USA. He has published several papers at the national and international levels including in the Academy of Management Learning & Education (AMLE). He can be reached at nilayyajnik@hotmail.com*