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Exploring factors affecting the adoption of MOOC in Generation Z using extended UTAUT2 model

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Abstract

The advent of Internet heralded the rise of scalable educational technology dubbed as massive open online course (MOOC). Easy to use, access, economical as well as flexible, provide students lot of freedom and the advantage of self-paced learning. Despite all these merits, MOOC adoption is low in the higher educational institutions (HEIs) of India. The aim of this study is to explore the factors affecting the behavioural intention to adopt MOOCs among Generation Z (Gen Z) enrolled in the Indian HEIs. The study uses the extended UTAUT2 model with additional constructs of language competency and teacher influence to explore MOOC adoption among the Gen Z. Using online survey, data of 483 students was collected from HEIs of India using stratified random sampling and analysed using partial least square-structure equation modelling (PLS-SEM) technique. The results establish the general applicability of UTAUT2 model in context of MOOC in Indian settings with explanatory power of 69.9% and highlights the positive influence of price value, hedonic motivation, facilitating conditions, performance expectancy and effort expectancy on MOOC adoption. However, the constructs of social influence, habit, language competency, and teacher influence unexpectedly do not have an impact on Behavioural Intention of Gen Z towards MOOC adoption. Based on the research findings, study implications and future directions of the research have been suggested.

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1 Introduction

The internet has influenced almost every aspect of our daily life including education. It has transformed the way we used to attain education from the close confines of a traditional classroom to now scalable and innovative medium in modern education named MOOC which is accessible from any place in the world using an internet connection and a mobile device (Albelbisi et al., 2021a; Ma & Lee, 2019). Online classrooms are not only complementing the traditional classrooms but are also making the students learn from lectures designed, curated and delivered by the world's best professors teaching in the best universities of the world accessible to large population almost free of cost (Al-Adwan, 2020; Albelbisi et al., 2021b; Deng et al., 2019; Ma & Lee, 2019). MOOCs are considered to be a good medium for encouraging lifelong learning which is one of the important goals of Sustainable Development Goals (SDG4) listed by United Nations for achievement by member countries by 2030 (Lambert, 2020; Meet & Kala, 2021). The COVID-19 pandemic made online learning a necessity for many especially school and college students to the working professionals (Anand Shankar Raja and Kallarakal, 2020; Altalhi, 2021). Growing substantially in number in the last few years, MOOCs have attracted thousands of users across nations (Larionova et al., 2018; Classcentral.com, 2020; Altalhi, 2021).

The majority of present generation MOOC learners belongs to Gen Z – defined as individuals born between 1995 and 2010 (Francis & Hoefel, 2018). Born in the digital era, Gen Z is the first generation whose life hinges on technology and modern technological solutions are all the part of their living ecosystem (Larionova et al., 2018). It is important to note that Gen Z also known as digital natives are highly technology-driven; thus, deploying digital means to engage and teach them assumes significant importance. In India, government owned MOOC platform viz. SWAYAM has a registered user base of 16 million (Classcentral.com, 2020) and the country has a world's largest population of 500 million people in the age bracket of 5–24 years, providing huge opportunity to the education sector to further grow and evolve (IBEF, 2021). To accommodate rise in number of students in the HEIs of India, country needs to have at least another 800 new universities and 40,000 new colleges by 2030 (Thestatesman.com, 2019). India's higher education Gross Enrolment Ratio (GER) in 2019–20 stood at 27.1%, which is calculated for 18–23 years of age group and is way below the GER of many developed and developing nations (AISHE, 2019–20) which calls for massive thrust on education sector (Christensen & Alcorn, 2013). This imminent requirement has given researchers an area to study and explore as how online education through MOOCs can be furthered and what are the factors influencing MOOC adoption. The reasons for choosing Gen Z as a subject of study on MOOC adoption are majorly three. Firstly, MOOC offerings resonates well with the likings of Gen Z of convenience, comfort, quality and quick access (Larionova et al., 2018). Secondly, it is also to be studied that how Gen Z who have been brought up in the digital world adopt to the new virtual learning environment other than the traditional classrooms in achieving their educational and vocational goals (Szabó

et al., 2021) and Thirdly, in India the higher education GER exit 2019–2020 is at 27.1 calculated on the age group of 18–23 years (AISHE, 2019–20), which falls in the age bracket of Gen Z.

In the extant literature, many research has investigated MOOCs adoption by students in general (Al-Adwan, 2021; Al-Adwan & Khdour, 2020; Wan et al., 2020; Fianu et al., 2018). However, to the best of the authors' knowledge, this is the first study that targets the adoption of MOOCs by Gen Z students, particularly in India. Given that a considerable percentage (27.1%) of students in the Indian higher education belongs to Gen Z students, the finding of this study would be very useful to guide the efforts toward a successful adoption of MOOCs in India. Furthermore, Christensen and Alcorn (2013) in their study revealed that HEIs must acknowledge imbalance in demand and supply in affordable quality of higher education and they should actively participate in creating and curating MOOC in Indian-language especially on subjects in demand catering to Indian students from diverse cultural and geographical backgrounds. Similar findings are echoed by Aldahdouh and Osório (2016) and Connolly (2016) highlighting the significance of language proficiency in MOOC participation and suggested that students enrol in only those MOOCs which are available in their language. Garcia Mendoza et al. (2017) highlighted the need to examine the impact of language competency on MOOC adoption as communication plays a vital role in every form of learning be it online or offline; learners have a better learning outcomes in their native language (UNESCO, 2016). Similarly need was felt to evaluate teachers' or instructors' characteristics and influence on learning processes and outcomes of MOOC participants (Littlejohn et al., 2020). Teacher's influence refers to the role of a teacher in motivating and directing a student to use MOOC for his better understanding and knowledge of the subject. Teacher has a positive influence on the offline and online learning activities of a student and teacher's prior exposure to MOOC as a student or creator, comfort and ease of handling education technology, and teaching experience could be a possible influencer besides promoting positive attitude towards MOOC learning (Garrison, 2000; Tseng et al., 2019; Jung & Lee, 2020).

Realizing the potential of MOOC to disrupt the education sector, and the dearth of research in the area of MOOC adoption in Indian context (Virani et al, 2020), particularly among the students pursuing higher education in Indian Universities and Institutes has motivated the scholar to undertake this research with Gen Z as a subject of study and language competency and teacher influence as an additional constructs positively impacting MOOC adoption.

2 Literature review and hypotheses development

Over a past decade, educational technology is gaining much attention, interest and reviews and is becoming a part of learning mechanism for millions of learners across the world (Albelbisi et al., 2021a; Ma & Lee, 2019). MOOCs are evolving and emerging as a cost efficient, and an attractive way to bridge the current and huge gap in the country's education system (UNESCO, 2016; Al-Adwan, 2020). Many research in the field of technology adoption resulted into theory and model

development which further have explained organizations' and individuals' intention to use technological innovations, which have their origins in information systems, psychology, sociology and anthropology (Venkatesh & Davis, 2000; Davis, 1989; Venkatesh et al., 2003). The theoretical models in this field of research identifies certain independent variables that positively or negatively influence the dependent variable of intention to use and which in turn, may impact actual use of the technology. Literature review revealed that UTAUT is one of the well-researched and widely applied theory for explaining technology adoption and usage majorly on the premises of it being a result of synthesis of as many as eight theories (Williams et al., 2015). Four constructs of the UTAUT namely performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) were tested and applicability of it is shown to significantly influence behavioural intention (BI) of the learners in e-learning settings (Dečman, 2015; Rosaline and Wesley, 2017; Fianu et al., 2018; Persada et al., 2019). The extended version of UTAUT namely UTAUT2 model has been applied and validated by researchers on varied technologies however not much research has happened on validating UTAUT 2 in the educational context (Mittal et al, 2021). Only limited studies have validated UTAUT2 in the educational settings (Mittal et al., 2021; Tseng et al., 2019), therefore, contemplating inconsistency in generalization of research available, more research is necessitated to validate UTAUT2 as a theoretical framework (Khalid et al., 2021). A study by Venkatesh (2012)demanded the extension of UTAUT2 to enhance the explanatory power in other consumer technology use. Based on the suggestion and previous research (Littlejohn et al., 2020; Radovan & Kristl, 2017; Tseng et al., 2019), we carried out our study in two parts. Firstly, we test to validate the influence of existing UTAUT2 constructs on Gen Z Behavioural Intention to adopt MOOC in the Indian settings. Second, we extended UTAUT2 by incorporating the additional two constructs of language competency (Deng et al., 2019; Jung & lee, 2020) and teachers' influence (Chang et al., 2015; Pynoo et al., 2011; Tseng et al., 2019) which is believed to have a significant influence on Gen Z Behavioural Intention to adopt MOOCs.

It is important to note that the original UTAUT includes moderators (gender, age, and experience). These moderators are not examined in this study for several reasons. Eliminating the moderating variables results in generating more simplified models that can be employed to test the direct relationships between the constructs (Dwivedi et al., 2017, 2020). Additionally, excluding the moderators contributes significantly to building models that could be utilized in any context (Rana et al., 2017). Finally, moderators may not influence on the use and adoption context (Dwivedi et al., 2019).

An individual adopts a technology only when he feels that the use of technology will enhance their performance. Existing studies on technology adoption have highlighted the significant influence of PE on the BI to adopt e-learning (Dečman, 2015; Fianu et al., 2018; Jambulingam, 2013; Persada et al., 2019). During the Pandemic, PE was found to be major reason to adopt online teaching and learning owning to its usefulness (Kala & Chaubey, 2022; Mittal et al, 2021). In this study, it is assumed that the techno-savvy Gen Z studying in HEIs and confined to their homes to prevent the further outbreak of the COVID-19 pandemic may consider MOOCs to enhance

their knowledge and skill and subsequently their employability in the professional world. Therefore, it was hypothesized that**:**

H1. Performance expectancy influences Gen Z Behavioural Intention to adopt MOOC.

Another variable in UTAUT is effort expectancy which is similar to ease of use (TAM) defined as innovation perceived to be used or handled with ease and without much efforts (Davis, 1989). Previous researches have emphasized on the positive impact of effort expectancy on BI to adopt new technology (Venkatesh et al., 2003). A study by Al-Adwan (2020) reveal the positive influence of perceived ease of use which is a variable of effort expectancy on user's BI towards MOOC. It is perceived that Gen Z who's innate familiarity with digital devices and online world (Weinswig, 2016) may find MOOC usage easy. Hence, it was hypothesized that:

H2. Effort Expectancy influences Gen Z Behavioural Intention to adopt MOOC.

Social influence is defined as ways and means in which people adjust or change their behaviour to conform to the societal norms and it has an influence on an individual when it comes to technology usage (Venkatesh et al., 2003) and is also corroborated by previous studies on technology adoption (Tseng et al., 2019). Study reveal that the young generation rely on family, friends and peers opinion when it comes to digital learning (Rosaline and Wesley, 2017; Persada et al., 2019). Hence, it was hypothesized that:

H3. Social influence influences Gen Z Behavioural Intention to adopt MOOC.

Facilitating conditions (FC) refers to consumers' schema of availability of necessary resources and support ecosystem to do a task (Brown & Venkatesh, 2005; Venkatesh et al., 2003). Researchers reveal that FC influence BI and use behaviour of the learners (Chang et al., 2019; Kala & Chaubey, 2022; Persada et al., 2019). Taking cognizance of this, it is projected that FC influence the BI towards MOOC adoption. Hence, we hypothesized that.

H4. Facilitating conditions influences the Behavioural Intention of Gen Z to adopt MOOC.

Hedonic motivation (HM) is defined as degree of fun, pleasure and enjoyment derived using a technology (Brown & Venkatesh, 2005). The online technology adoption depends on the pleasure an individual derive from it (Yang et al., 2012). HM is an antecedent of BI to adopt online and internet based technologies such as learning management software, mobile learning, e-learning, digital social media, mobile banking etc. (Baptista & Oliveira, 2015; Moorthy et al., 2019; Raman & Don, 2013). Previous studies have found HM as a significant predictor of BI to adopt technology (El-Masri & Tarhini, 2017; Moghavvemi et al., 2017). Digitization and social media fuelled peer pressure has encouraged Gen Z to value experiences

more than any other generations do and to lead a turbo charged, interesting, fun, experience-rich lives. Gen Z's innate familiarity with the technological products and services affirm that they will be at forefront of adopting all the new online consumer technologies (Weinswig, 2016). Hence, it was hypothesized that:

H5. Hedonic motivation influences Gen Z Behavioural Intention to adopt MOOC.

The price value (PV) is described as an individual users' cognitive barter between the perceived benefits derived by using a technology and the money spent on using it (Venkatesh, 2012). The direct connect between PV and BI have been proved by previous studies on online learning (Raman & Don, 2013; Tseng et al., 2019). It is assumed that Gen Z perceive the benefits offered by MOOCs are more than the money spent as they get an access to online education from instructors teaching in one of the world's best universities free or at a subsidized cost enhancing knowledge and skill resulting in improved employability quotient. Hence, it was hypothesized that:

H6. Price Value influences Gen Z Behavioural Intention to adopt MOOC.

Habit (HT) is explained as exhibiting behaviour in an auto mode as a result of learning (Limayem et al., 2015). HT is found to have a positive influence on BI and use behaviour (Venkatesh, 2012). Previous investigations affirmed the positive influence of HT on internet based technologies (El-Masri & Tarhini, 2017; Gupta & Dogra, 2017). In this study, it is expected that Gen Z by virtue of innate familiarity with internet devices and technologies (Weinswig, 2016) have a conditioned behaviour towards using the technology which may influence their intention to adopt MOOCs. The influence of habit on student's use of MOOC is not studied especially in educational settings of India. Hence, it was hypothesized that:

H7. Habit influences Gen Z Behavioural Intention to adopt MOOC.

Language competency refers to students' knowledge and proficiency in language in which online learning is being conducted. In information systems research, language has been found to influence technology acceptance (Deng et al., 2019). In the developing countries, language has a strong influence on students opting for MOOCs (Aldahdouh & Osório, 2016; Anand Shankar Raja and Kallarakal, 2020). Previous studies have highlighted the need of establishing the influence of language on online education (Deng et al., 2019; Jung & lee, 2020). Contemplating different languages spoken widely in India, it is important to establish the significance and the influence of language competency towards MOOC adoption (Christensen & Alcorn, 2013) and also given the ubiquity of non-native English MOOC learners it is expected that the language competencies influences the BI of Gen Z towards MOOC adoption. Hence, it was hypothesized that:

H8. Language competency influences Gen Z Behavioural Intention to use MOOC.

Teacher's influence refers to the role of a teacher in motivating and encouraging a student to use online learning tools for his better understanding and knowledge of the subject. It is found that teachers who are regarded as important social agents and nation builders have a positive influence on students' mental makeup and behaviour and their independent use of technology for learning (Huang et al., 2019; Hoi & Mu, 2021; Al-Adwan et al., 2021a) and also as a key reason of participants enrolling in MOOC and promoting positive attitude towards MOOC learning (Chang et al., 2015; Jung & Lee, 2020; Tseng et al., 2019). Students consider teachers as their mentors and given the emergent need to adopt blended learning made mandatory by the COVID 19 there is a need to re-consider the changing role of teachers from sage on the stage to the facilitator on the side who can influence the learning strategies and processes adopted by learners and the subsequent outcomes (Littlejohn et al., 2020) (Fig. 1). Hence, it was hypothesized that:

H9. Teacher influence influences Gen Z Behavioural Intention to use MOOC.

3 Research methodology

The study adopted quantitative research approach to create and test the conceptual framework (Rodrigues et al., 2021). Recent review papers by Alemayehu and Chen (2021) and Meet and Kala (2021) found that the quantitative research approach was extensively used in MOOC research. Furthermore, constructs of the UTAUT model and the PLS-SEM technique for examining relationships among constructs were widely used in MOOC adoption. Accordingly, the quantitative approach using the UTAUT model and PLS-SEM was employed in this study. At first, literature review was undertaken to figure out gap in research followed by development of a research instrument viz. survey questionnaire. Similar to most of UTAUT-based research in the field of
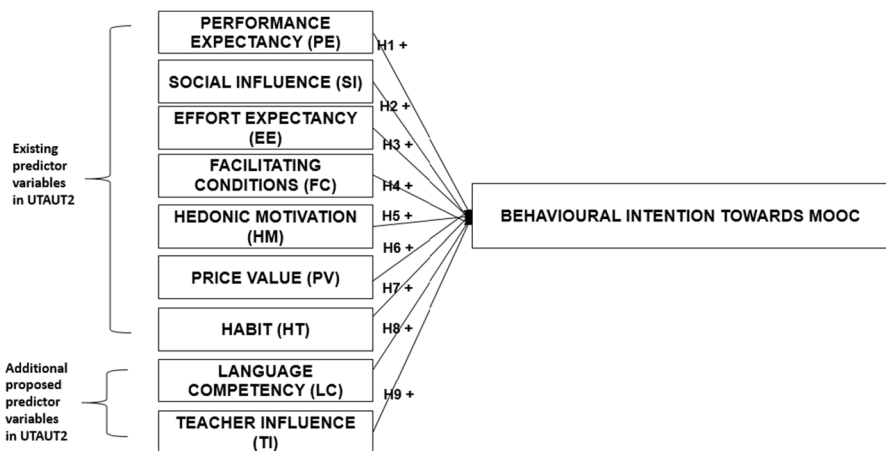

Fig. 1 Conceptual Framework

Table 1 Type of University in Northern India

Types of University	Private	State	Central	Deemed	IOE*	IONR*	Total
University (In No.s)	160	124	19	37	7	21	368
Respondent (In No.s)	179	158	57	51	12	26	483

*IOE—Institution of eminence

*IONR—Institution of national repute

Table 2 Demographic Profile (n = 483)

Demographic	Characteristics	Frequency	Percentage
Age	20 and less	155	32.1
	21–25	328	67.9
Education	Undergraduate	269	55.7
	Postgraduate	214	44.3
Gender	Male	240	49.7
	Female	243	50.3

educational technology adoption (Al-Adwan et al., 2018a, 2018b, 2021b), and particularly UTAUT-MOOCs research (Fianu et al., 2018; Wan et al., 2020), this study used survey questionnaire as the main data collection method to validate the research model. The items for the constructs of PE, EE, SI, FC, and BI referred to as UTAUT constructs were adapted from the research of Venkatesh et al. (2003) and modified in context of MOOCs. The items measuring HT, HM and PV were adapted from Venkatesh (2012) and modified in context of MOOCs. Similarly, the language competency and teacher influence items were adapted from the research work of Barak et al. (2015) and Sebastianelli et al. (2015) respectively and modified into the MOOC context. The items on the scale were meant for the students to specify their degree of agreement on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A committee of experts comprising three academicians, two research scholars, and two industry experts working with MOOC providers vetted the questionnaire and finalized it. Later, a pilot survey was conducted on a sample of 100 students (excluded in the full-scale survey) of Indian HEIs who completed MOOCs. The Cronbach alpha of 0.953 added to the reliability of pilot study and paved way for full-scale survey which was completed over a period of 14 weeks during June–September 2021.The primary data of 483 students were collected from Gen Z respondents from various HEIs (Table 1) in Northern cities of India using stratified random sampling (Alraimi et al., 2015; Altalhi, 2021; Fianu et al., 2020; Šumak & Šorgo, 2016).

Demographic details of the sampled students are shown in Table 2.

4 Data analysis

Table 2 shows the demographic details of the sampled Gen Z participants. Of the total, 32.1% of the participants were in the age group of less than 20 and 67.9% were in 21–25 years. 55.7% of participants were pursuing undergraduate and 44.3% were pursuing postgraduate. 49.7% were male and 50.3% were female.

4.1 Measurement model

The partial least squares (PLS) method was used for primary data analysis and validate the conceptual framework. PLS has the capability to evaluate the measurement model and the structural model simultaneously (Hair et al., 2014). In comparison to the covariance-based structural equation modeling (CB-SEM), PLS-SEM is chosen for data analysis as it works well on both, small and large sample sizes, and has no restriction on normal distribution (Chin, 1998). PLS-SEM is considered to be adequate and accurate for validating explanatory power and appraising complex models (Hair et al., 2014). For the given reasons, PLS is deemed fit for analysis. SmartPLS 3.0 software (Ringle et al., 2015) is used for analysis.

In the measurement model, properties of reliability and validity of the constructs were calculated. Each construct's internal consistency and item reliability was assessed by Chronbach alpha (α), Composite Reliability (CR) and Average Variance Extracted (AVE). Reliability indicators suggest that the values for Cronbach's α, composite Reliability (CR) should be higher than 0.7, and the critical value for AVE should be higher that 0.5 (Fornell & Larcker, 1981). As depicted in Table 3, high level of reliability and internal consistency of all the constructs were established as the value of Cronbach's α was above 0.7 (Nunnally, 1978). CR values more than the threshold of 0.7 confirms the level of reliability and internal consistency of all the constructs. Convergent validity was measured by evaluating factors loading of each construct. The convergent validity for all constructs was verified on account of AVE values were found to be greater than the threshold value of 0.5 (Hair et al., 2014) barring construct TI having a borderline AVE value of 0.472. Discriminant validity (DV) measures the degree of difference between one construct with another and two of the prominent measure of assessing it were the Fornell and Larcker (1981) criterion and the HTMT (heterotrait-monotrait ratio) criterion (Henseler et al., 2015). Discriminant validity was achieved when the squared root of each construct's AVE was greater than any correlations with other constructs (Fornell & Larcker, 1981). As seen in Table 4, DV criteria was met.

The HTMT measures similarity between predictor variables. If the HTMT is less than one, DV is considered as established (Henseler et al., 2015). Table 5 confirms that all HTMT values are well within the cut-off value. Thus, the results of these tests indicates that discriminant validity was verified.

Table 3 Construct Operationalization

Variable & Construct	Mean	SD	Factor Loading	VIF
Performance Expectancy (PE) (α = 0.870, CR = 0.911, AVE = 0.720)				
PE1 I find Online Courses (MOOCs) useful in my studies	3.894	0.914	0.850	2.230
PE2 Online Courses (MOOCs) increases my chances of achieving knowledge that is important to me	3.986	0.929	0.878	2.664
PE3 Online Courses (MOOCs) enables me to accomplish my task more quickly	3.648	0.978	0.833	1.917
PE4 Online Courses (MOOCs) increases my productivity (It adds to my knowledge)	3.890	0.947	0.833	2.106
Effort Expectancy (PE) (α = 0.868, CR = 0.919, AVE = 0.790)				
EE1 How to use Online Courses (MOOCs) is easy for me	3.650	1.124	0.867	2.118
EE2 My interaction with Online Courses (MOOCs) is clear and understandable	3.600	1.011	0.903	2.427
EE3 I find Online Courses (MOOCs) easy to use	3.851	1.004	0.897	2.309
Social Influence (SI) (α = 0.884, CR = 0.928, AVE = 0.812)				
SI1 People who are important to me think that I should use Massive Open Online Courses (MOOCs)	3.658	1.000	0.886	2.388
SI2 People who influence my behavior think that I should use Massive Open Online Courses (MOOCs)	3.609	1.023	0.912	2.638
SI3 People whose opinions that I value prefer that I use Massive Open Online Courses (MOOCs)	3.602	1.005	0.905	2.518
Facilitating Condition (FC) (α = 0.723, CR = 0.833, AVE = 0.565)				
FC1 I have the resources necessary to use Online Courses (MOOCs)	3.834	1.161	0.749	1.379
FC2 I have the knowledge necessary to use Massive Open Online Courses (MOOCs)	3.536	1.059	0.868	2.690
FC3 Online Courses (MOOCs) is compatible with other technologies (Mobile/Laptops/Tablets) I use	3.710	1.029	0.845	2.485
FC4 I can get help from others when I have difficulties using Massive Open Online Courses (MOOCs)	3.839	1.037	0.481	1.079
Hedonic Motivation (HM) (α = 0.910, CR = 0.943, AVE = 0.847)				
HM1 Using Online Courses (MOOCs) are enjoyable	3.712	0.968	0.915	2.832
HM2 Using Online Courses (MOOCs) are very entertaining	3.511	1.044	0.929	3.521
HM3 Using Online Courses (MOOCs) are fun	3.503	1.056	0.917	2.969
Price Value (PV) (α = 0.763, CR = 0.862, AVE = 0.676)				
PV1 Online Courses (MOOCs) are reasonably priced	3.712	1.119	0.816	1.509
PV2 Online Courses (MOOCs) are a good value for the money	3.511	1.127	0.791	1.561
PV3 At the current price, Online Courses (MOOCs) provides a good value	3.503	1.124	0.859	1.576
Habit (HT) (α = 0.725, CR = 0.841, AVE = 0.639)				
HT1 The use of Online Courses (MOOCs) has become a habit for me	3.124	1.032	0.752	1.408

Table 3 (continued)

Variable & Construct	Mean	SD	Factor Loading	VIF
HT2 I am addicted to using Online Courses (MOOCs)	2.934	1.071	0.790	1.517
HT3 I must use Massive Open Online Courses (MOOCs)	3.230	1.133	0.853	1.385
Behavioural Intention (BI) (α=0.888, CR=0.930, AVE=0.817)				
BI1 I will always try to use Online Courses (MOOCs) in my daily life	3.174	1.125	0.889	2.272
BI2 I plan to continue to use Online Courses (MOOCs) frequently	3.350	1.025	0.925	3.105
BI3 I intend to continue using Online Courses (MOOCs) in the future	3.617	1.050	0.897	2.672
Language Competency (LC) (α=0.771, CR=0.845, AVE=0.524)				
LC1 Students can actively participate in learning if the language of instruction is what they understand well	4.058	0.866	0.695	1.418
LC2 Language used in Online Courses (MOOCs) is important for me to adopt it	3.824	0.957	0.825	1.996
LC3 Language which the students may not be confident with may affect their approach to learning	3.853	0.962	0.775	1.872
LC4 I find it easy to develop rapport with the teacher delivering Online Courses (MOOCs) in my mother tongue	3.588	0.992	0.674	1.278
LC5 I believe that the Online Courses (MOOCs) if delivered in regional languages will have far wider acceptability	3.911	1.015	0.633	1.316
Teacher Influence (TI) (α=0.707, CR=0.810, AVE=0.472)				
TI1 I believe my teacher is an expert of his subject	4.106	0.870	0.500	1.244
TI2 My teacher is my role model	3.874	1.051	0.794	1.822
TI3 I follow my teacher's instructions on study related matter	3.998	1.004	0.815	1.971
TI4 My college encourages enrolment in online course (MOOCs) to gain additional knowledge and learn new skills	4.017	0.972	0.759	1.620
TI5 My teachers give additional weightage during evaluation on the successful completion of an online course (MOOCs)	3.739	1.125	0.491	1.235

Table 4 Fornell-Larcker Criterion

Constructs	EE	FC	HT	HM	LC	PE	PV	SI	TI
EE	**0.889**								
FC	0.544	**0.752**							
HT	0.324	0.460	**0.800**						
HM	0.318	0.420	0.507	**0.920**					
LC	0.329	0.600	0.399	0.417	**0.724**				
PE	0.396	0.470	0.440	0.608	0.553	**0.849**			
PV	0.260	0.400	0.700	0.536	0.350	0.414	**0.822**		
SI	0.350	0.442	0.448	0.488	0.449	0.601	0.414	**0.901**	
TI	0.154	0.404	0.301	0.325	0.527	0.345	0.279	0.294	**0.687**

Bold digits represent the square roots of AVEs

Table 5 HTMT Criterion

Construct	BI	EE	FC	HT	HM	LC	PE	PV	SI	TI
EE	0.501									
FC	0.784	0.686								
HT	0.843	0.402	0.636							
HM	0.683	0.353	0.542	0.613						
LC	0.623	0.397	0.810	0.516	0.492					
PE	0.669	0.450	0.621	0.537	0.682	0.677				
PV	0.836	0.312	0.541	0.815	0.643	0.432	0.494			
SI	0.579	0.395	0.573	0.553	0.544	0.546	0.683	0.495		
TI	0.486	0.215	0.569	0.424	0.417	0.720	0.474	0.373	0.400	

4.2 Structural model

With reliability and validity criteria of the model met, PLS results of structural model was analysed to investigate the association between the constructs. The results of bootstrap are shown in Table 6. In PLS path models, structural model and hypothesis testing is done by measuring path coefficients (β value) and the path models does not need the data to be normally distributed, it is computed with squared multiple correlations ($R2$) for each latent construct which reflects the fitment of model to the hypothesized relationships. For evaluating hypothesis relevance and importance, bootstrapping procedure was used (Chin, 1998). Table 6 reflects the hypothesized path coefficient values besides the T-statistics values. The results revealed that PV is a strong predictor of intention to adopt MOOCs. The association between PV and BI is significant with β = 0.316 and has positive influence on BI towards MOOC adoption which is in support of the extant study (Venkatesh, 2012; Raman & Don, 2013), however, contradicting the findings of El-Masri and Tarhini (2017). The BI changes in accordance to PV with a coefficient of 0.316.

Hypothesis	Path	β Values	P Values	Decision
H1	PE—> BI	0.127	0.005	Supported
H2	EE—> BI	0.066	0.039	Supported
H3	SI—> BI	0.026	0.547	Not Supported
H4	FC-> BI	0.238	0.000	Supported
H5	HM-> BI	0.145	0.001	Supported
H6	PV-> BI	0.316	0.000	Supported
H7	HT-> BI	0.121	0.084	Not Supported
H8	LC-> BI	0.035	0.355	Not Supported
H9	TI—> BI	0.044	0.181	Not Supported

Table 6 Path coefficient and T-Statistics value

Hence, H6 is proved. Other predictor variables having significant positive impact on intention to adopt MOOCs are PE ($\beta=0.127$) and EE ($\beta=0.066$) which is in support of previous studies (Al-Adwan, 2020; Fianu et al., 2018; Venkatesh et al., 2003). Hence, H1-H2 are proved. Consistent with prior research, FC ($\beta=0.238$) and HM ($\beta=0.145$) also have positive influence on BI of Gen Z towards MOOC adoption confirming the previous literature (Brown & Venkatesh, 2005; Raman & Don, 2013; Tseng et al., 2019). Hence, H4-H5 are proved. The relationship between SI & BI is not significant with $\beta=0.02$ and T-value$=0.60$ contradicting the previous studies (Khalid et al., 2021; Persada et al., 2019; Raman & Don, 2013) and supporting the studies of Jeng and Tzeng (2012) and Fianu et al. (2018). Hence, H3 is rejected. The independent variable of HT (($\beta=0.121$) has an insignificant influence on BI contradicting the findings of Gupta and Dogra, (2017) and in line with the findings of Raman and Don, (2013), hence, H7 is rejected. LC does not have a strong association with BI with $\beta=0.035$ contradicting previous studies (Aldahdouh & Osório, 2016; Anand Shankar Raja and Kallarakal, 2020) and supporting the findings of Barak et al. (2015) rejecting H8. TI does not have a significant impact on BI with $\beta=0.044$ thus contradicting the findings of extant studies (Huang et al., 2019; Hoi & Mu, 2021; Al-Adwan et al., 2021a). Hence, H9 is rejected.

Measuring the value of R2 In PLS path models, the squared correlation values of 0.75, 0.50 and 0.25 are viewed as substantial, moderate and weak respectively (Hair et al., 2014). R^2 statistics explains the change in the dependent variable explained by the independent variable(s). The R^2 value of latent dependent construct is of 0.69 as shown in Fig. 2 is greater than 0.50 and close to 0.75 therefore the R^2 value is considered to be moderate to high value.

Effect size f^2 The effect size is the measure of influence of each independent variable on the dependant variable. In PLS path model, when an independent variable is excluded from the model, it measures the variation in squared correlation values and ascertain whether the excluded independent variable has a strong effect on the value of dependent variable. The formula of effect size f^2 (Chin, 1998) is as under –
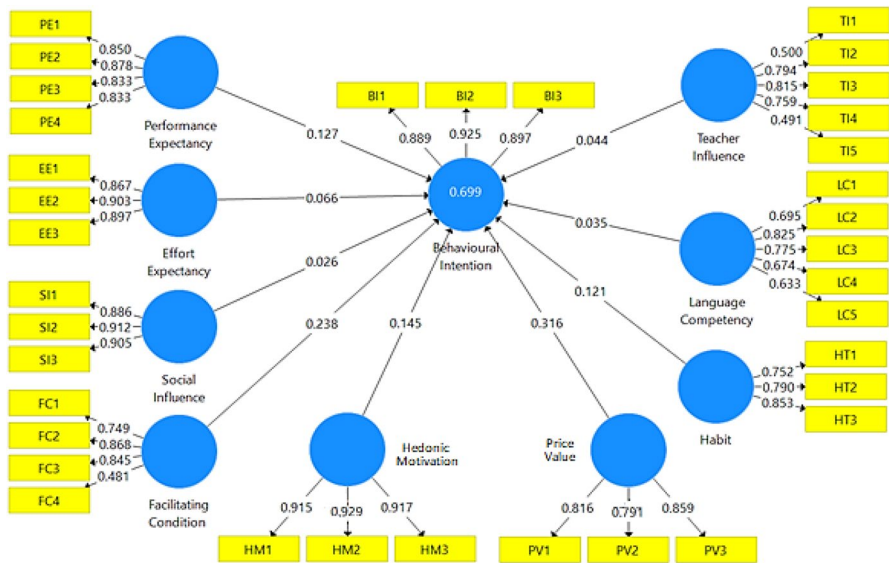
Fig. 2 Structural model

$$f^2 = R^2 included - R^2 excluded / 1 - R^2 included$$

The impact of predictor variable is high at the structural level if f^2 is 0.35 and it is medium if f^2 is 0.15 and small if f^2 is 0.02 (Cohen 1988). Inference of data analysed is as per Table 7.

Predictor independent constructs of FC (0.088), HM (0.036) and PV (0.059) have a medium effect on the dependent construct of BI to adopt MOOC whereas other constructs have a small effect.

Table 7 Effect size f^2

Independent Construct	Dependent Construct	Effect Size	Inference
Effort Expectancy	Behavioural Intention	0.010	Small Effect
Facilitating Condition		0.088	Medium Effect
Habit		0.008	Small Effect
Hedonic Motivation		0.036	Medium Effect
Language Competency		0.002	Small Effect
Performance Expectancy		0.024	Small Effect
Price Value		0.059	Medium Effect
Social Influence		0.001	Small Effect
Teacher Influence		0.005	Small Effect

5 Discussion and Implications

This study aims to validate and extend the UTAUT2 model in the context of MOOC and identify different factors influencing the intentions towards MOOC adoption. It is found that the predictor variables of PV, HM, FC, EE and PE have a significant influence on BI, which implies that they are important for BI of Gen Z MOOC learners to adopt MOOC. It is observed that PV has the strongest positive influence on BI towards MOOC adoption ($\beta = 0.316$) and is an important predictor of MOOC adoption among Gen Z learners attaching greater value to the trade-off between price of MOOC and the perceived benefit received in terms of their up-skilling and enhancing their employability. Now a day's majority of MOOC developers offer the course enrolment and content free of cost however charge for the certification, which troubles financially weak students hence MOOC developers need to keep in mind the variable of PV at the time of pricing their course. PV plays a vital role in influencing Gen Z intention to use new technology (Tseng et al., 2019). This indicates that developers and marketers of MOOCs must promote and position value and the perceived benefits of doing MOOC courses greater than the price paid for the course or the certification to attract Gen Z. HM also found to influence the BI of Gen Z learners towards MOOC adoption which is in line with the extant literature (Yang et al., 2012; El-Masri & Tarhini, 2017; Baptista & Oliveira, 2015). Gen Z, born in the digital world loves to live life online (Weinswig, 2016) finds learning through MOOCs exciting, and fun filled and an element of peer pressure makes Gen Z exhibit online behaviour. FC found to significantly influence learner's BI to adopt MOOC (Chang et al., 2019). The very thought of adding knowledge or a new skill to their existing skillset influences the BI of young under graduates and post graduates to adopt MOOC (Jambulingam, 2013). Ongoing pandemic and subsequent home confinement also influenced the intention to adopt online learning owning to their usefulness (Al-Adwan, 2020; Mittal et al, 2021) which in turn supported PE. Since MOOC courses doesn't require much of effort in enrolment and are easy to access and manage, EE too influence the intention of learners (Al-Adwan, 2020; Kala & Chaubey, 2022).

The study found the insignificant influence of the predictor variables of SI on BI which contradicts the existing studies (Rosaline & Reeves, 2017; Al-Adwan & Khdour, 2020; Persada et al., 2019) and supporting the previous studies (Fianu et al., 2018; Jeng & Tzeng, 2012). This indicates that the Gen Z ability and knowledge regarding MOOC is as a result of self-awareness which is gained by self-study therefore they need no external influence or social support to adopt MOOC. The variables of HT has insignificant impact on BI supporting the previous study of Raman and Don, (2013) and contradicting the findings of Gupta and Dogra, (2017). This could be because of students using MOOCs for educational purposes only and it is yet to become a part of their daily routine. Further research is required to identify the root cause.

Relationship between TI and BI is insignificant contradicting the existing research (Al-Adwan et al., 2021a; Chang et al., 2015; Hoi & Mu, 2021). Result

indicates that Gen Z does not get any encouragement or support from teacher fraternity to pursue MOOCs and it is not currently an integral part of their university curriculum or the evaluation criteria thus the influence of teacher who is considered a change agent found to be insignificant. This finding also substantiates the insignificance of habit construct on BI as MOOCs are yet to become an integral part of education system indicating its use is need based and not habitual. The association between LC and BI is not significant contradicting the existing research (Aldahdouh & Osório, 2016; Anand Shankar Raja and Kallarakal, 2020) and supporting the research findings of Barak et al. (2015). This indicates that the students enrolled in higher education programs of the universities sampled and studied are well versed in communication skills and language competencies and are comfortable with MOOCs content delivery and its understanding. They do not find language as a major determinant of MOOC adoption. This finding also underlines the fact that India is second largest English speaking nation in the world (mapsofworld.com, 2021). With the R^2 value of 0.699, this study confirms the moderate to high explanatory power of UTAUT2 model towards the intention to adopt MOOC in the Indian settings.

5.1 Theoretical implications

This research work adds to the existing pool of knowledge related to the literature on factors affecting technology adoption especially internet based technologies. It examines the factors influencing the intention towards MOOC adoption in India and contributes to the extant literature on MOOCs using UTAUT model (Mittal et al., 2021; Persada et al., 2019). The outcome of this study highlights the important role PV, HM, FC, PE and EE plays in influencing the intention of Gen Z towards MOOC adoption that validates UTAUT2 model. The study investigated the impact of extended constructs of LC and TI on MOOC adoption, however, found it to be insignificant which contradicts the existing literature (Aldahdouh & Osório, 2016; Anand Shankar Raja and Kallarakal, 2020).

5.2 Practical implications

The outcomes of this study provide newer insights on educational technology adoption by Gen Z. The study highlights that PV has strong influence on the BI (El-Masri & Tarhini, 2017; Tseng et al., 2019) of a learner to adopt MOOC which developers and marketers of MOOCs must keep in mind to increase its spread and usage which will not only complement studies in the physical classrooms but also help multitude of economically weaker section of the society to attain education (Meet & Kala, 2021). Developers and marketers should also look into integrating or enhancing the component of gaming and fun while developing MOOCs to attract Gen Z who pays much attention to HM (Baptista & Oliveira, 2015; Moorthy et al., 2019; Raman & Don, 2013) and this can be done by the gamification of courses, animations, simulations, enhanced peer to peer interaction, blended learning giving learners the feel of online and offline learning. FC is important for Gen Z before adopting MOOCs, therefore,

all the stakeholders engaged in the proliferation of MOOCs must ensure that a complete ecosystem of online learning ((Chang et al., 2019; Persada et al., 2019) is created at the HEIs level with students getting appropriate credits for MOOC certifications so that their efforts are justified and the outcomes valued. The study highlights positive influence of PE and EE on BI to adopt MOOC. Therefore, MOOC developers and marketers must design and market courses which are contemporary, industry relevant and can be accessed through mobile devices while on move, providing learners to re-skill and up-skill themselves, to enhance their competency and employability at workplace. The results reveal the insignificant impact of SI and TI on BI of Gen Z reflecting no impression of normative social influence on them and no encouragement from the teacher to pursue MOOCs alongside their regular studies. Teachers must encourage enrolments in MOOCs (Huang et al., 2019; Hoi & Mu, 2021; Al-Adwan et al., 2021a) and include them in their evaluation criteria to see the proliferation of MOOCs which offers contemporary courses which are not the part of many universities course curriculum helping students to up-skill themselves and enhance employability. MOOC can help governments in the massification of higher education, which is the need of hour as GER of many developing nations is much below the average GER of developed nations (AISHE, 2019–20). Governments should look at MOOCs as a tool that can bridge the digital divide and its integration with National Educational Policy shall contribute majorly in achieving SDG4 educational goals of country by 2030 as earmarked in United Nation's SDGs (Meet & Kala, 2021).

5.3 Limitations and future research directions

Future studies must be carried out to address the limitations and better generalizability of these results. First, the study carried out cross sectional research on Gen Z. A longitudinal research can suggest the change in the intention and behaviour of Gen Z over a period of time for better generalizability for the model. Second, the model explains 69% of the factors that affect the intention of MOOCs adoption, leaving 31% unanswered. The UTAUT2 model should be extended with additional constructs to enhance the explanatory power. Third, future research should consider K12 students as subject of their study to know their outlook towards MOOCs and how it can be integrated to their classroom education. Fourth, future research to study the impact of Gen Z demographic moderators and educational characteristics on BI and use of MOOCs. Fifth, a cross cultural research on MOOCs among countries would help in knowing the impact it creates on the society and nations at large in democratising education using MOOCs as a tool to improve literacy rates and employability of Gen Z in the developing nations.

6 Conclusion

MOOCs by virtue of ease of access and free education have been in limelight from last one decade and the outbreak of COVID 19 has re-emphasized its importance in complementing offline learning however, despite the merits, MOOCs adoption among students in higher education is low. Knowing the significance of MOOCs in

education and the gap in existing literature on student's BI to adopt MOOCs, this study sought to investigate factors affecting BI of Gen Z towards MOOC adoption by extending UTAUT2 theory with two additional constructs of language competency and teacher influence to examine enhancement in the explanatory power of theory. Results reveal that the extended UTAUT2 model explains 69.9% of BI to adopt MOOCs with the constructs of PE, EE, PV, HM and FC having direct positive influence on BI underlining its robustness to predict BI on MOOC adoption. Furthermore, the results deviated from the existing studies by indicating at the insignificant influence of constructs of SI, HT, LC and TI on BI towards MOOC adoption. The study confirms that the most critical factor affecting the future intention to adopt MOOCs is PV followed by FC, HM, PE and EE. This study adds to the extant literature on UTAUT2 model by testing it's applicability on BI to adopt MOOCs in Indian settings that has not been done before. It also provides crucial knowledge to advance online learning literature and executable insights significantly required by MOOCs creators and academicians to ramp up MOOC enrolments that is much desired in developing countries like India towards democratizing education.

Declarations

Conflict of Interest None.

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