# Exploring Factors Affecting the Adoption of MOOC in Generation Z using Extended UTAUT2 Model

A thesis submitted to the

University of Petroleum and Energy Studies

For the Award of

***Doctor in Philosophy***

In

Management

BY

**Rakesh Kumar Meet**

**August 2022**

Internal Supervisor

**Prof. (Dr.) Devkant Kala**

UPES

UNIVERSITY OF TOMORROW

School of Business

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**Prof. (Dr.) Devkant Kala**

Assistant Professor (Selection Grade),

Department of General Management, UPES



School of Business

University of Petroleum & Energy Studies

Dehradun 248007, Uttarakhand

# DECLARATION

I declare that the thesis entitled 'Exploring Factors Affecting the Adoption of MOOC in Generation Z using Extended UTAUT2 Model' has been prepared by me under the guidance of Dr. Devkant Kala, Assistant Professor (Selection Grade), School of Business, University of Petroleum & Energy Studies, Dehradun. No part of this thesis has formed the basis for the award of any degree or fellowship previously.

**Rakesh Kumar Meet**
**School of Business,**
**University of Petroleum & Energy Studies,**
**Dehradun-248007, Uttarakhand**
**DATE: 30.08.2022**

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# CERTIFICATE

I certify that Rakesh Kumar Meet has prepared his thesis entitled **"Exploring Factors Affecting the Adoption of MOOC in Generation Z using Extended UTAUT2 Model"**, for the award of PhD degree of the University of Petroleum and Energy Studies, under my guidance. He has carried out the work at School of Business, University of Petroleum and Energy Studies.

Supervisor

Dr. Devkant Kala

Assistant Professor (Selection Grade),

School of Business,

**University of Petroleum & Energy Studies,**

**Dehradun-248007, Uttarakhand**

DATE: 30.08.2022

# ABSTRACT

The advent of the Internet heralded the rise of scalable educational technology termed as massive open online courses (MOOC). It is easy to use, access, and be economical as well as flexible, providing students a 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 behavioral 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 Gen Z. The data of 483 students was collected from Indian HEIs using stratified random, purposive, and snowball sampling and analyzed using the partial least squares-structure equation modelling (PLS-SEM) technique. The results establish the general applicability of the UTAUT2 model in the context of MOOCs in Indian settings with an explanatory power of 69.9% and highlight the positive influence of price value, hedonic motivation, facilitating conditions, performance expectancy, and effort expectancy on MOOC adoption, besides the positive impact of educational characteristics (courses enrolled, nature of degree & type of institution) of the students on the factors influencing the behavioral intention towards MOOC adoption. However, the constructs of social influence, habit, language competency, and teacher influence unexpectedly do not have an impact on the behavioral intention of Gen Z towards MOOC adoption. Based on the research findings, study implications and future directions of the research have been suggested.

# DEDICATION

Praise be to God, for those who are righteous by His grace

To my parents for their encouragement and blessings to accomplish my life goals

To my wife for her rock solid support in all my endeavors to fulfill my dreams

# ACKNOWLEDGEMENT

I would like to thank my guide and mentor Prof. (Dr.) Devkant Kala, whose constant nurturing, unflinching support, and guidance through thick and thin in this academic pursuit steered this work. I would not have sailed this far in this journey without his guidance. I can foresee that the bonds we share now will strengthen in the times to come. A special reference to my wife Ms. Krishna R. Meet for always keeping my morale high and helping me in conceptualizing this work as she herself is the one who is learning through MOOCs since its inception and see in MOOCs huge potential to complement offline education. Special thanks to the management of Doon Business School for providing us conducive research environment to carry out this scholarly work. Heartfelt thanks to one and all associated with my work including all respondents and people who directly or indirectly became part of my work and helped me in carrying out my research work. A strong word of appreciation to the unconditional support and opportunity rendered by Dr. Sunil Barthwal, Dr. Prasoom Dwivedi, Dr. Joji Rao, Dr. Tarun Dhingra, Dr. Raaju Ganiesh Sunder, members of various research committees, and PhD program officials and the revered University officials. I express my deep reverence to the almighty who gave me courage and patience in trying times during this journey. I am fortunate enough to always have blessings of my affectionate parents Smt. Ramlesh and Sh. Bamdev Meet along with elders and relatives to finish this crucial task taken up by me. I always drive strength from my loving wife and kids Shivam and Veer who always encouraged me to be charged up and remain jovial during ups and down in my scholarly pursuit.

Thank you all for a new beginning!

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# ABBREVIATIONS

MOOCs: Massive Open Online Courses

GER: Gross enrolment ratio

Gen Z: Generation Z

HEIs: Higher education institutions

SDGs: Sustainable development goals

ICT: Information and communication technologies

IS: Information system

TAM: Technology acceptance model

UTAUT: Unified theory of acceptance and use of technology

PE: Performance expectancy

EE: Effort expectancy

SI: Social influence

FC: Facilitating conditions

PV: Price value

HM: Hedonic motivation

HT: Habit

LC: Language competency

TI: Teacher influence

BI: Behavioral intention

PU: Perceived usefulness

PEOU: Perceived ease of use

SEM: Structural equation modelling

PLS-SEM: Partial least squares- Structural equation modelling

ANOVA: Analysis of variance

## LIST OF APPENDICES

# 1 CHAPTER 1: INTRODUCTION

**विद्या ददाति विनयं विनयाद्याति पात्रताम् । पात्रत्वाद्धनमाप्नोति धनाद्धर्मं ततः सुखम् ॥**

**Knowledge makes one humble, humility leads to worthiness, worthiness creates wealth and enrichment, enrichment leads to right conduct, and right conduct brings joy and contentment.**

Education transforms lives and aids in enhancing growth, alleviating poverty and driving sustainable development and prosperity. It not just brings in harmony and abundance to an individual but to the entire society by upgrading our social life. It is a human right for everyone throughout life (United Nations Educational, Scientific, and Cultural Organization (UNESCO), 2022). A skilled and trained workforce is a must for innovation, growth and the success of a nation. Highly qualified people stand a better chance of getting good jobs, higher wages and are well equipped to handle any adverse situation be it a recession or any work related contingency better.

Institutions of higher education prepare individuals to not only secure better jobs and wages but also encourage them to be entrepreneurs and create jobs. It prepares individuals to actively contribute towards nation building and be a responsible member of society and a citizen of the country (The World Bank, 2017). Higher education can be termed as the propeller of performance, competitiveness, growth, and prosperity. Higher education enables an individual to thrive in today’s global economy. Contemporary universities provide their students with programmes and courses to prepare and up-skill them for different industries, and to keep pace with the global economy, which is constantly evolving at a faster pace influenced by technological innovations. One of the important missions of contemporary universities is to conduct research and find solutions to the challenges afflicting mankind, contributing to the welfare of society (qs-gen.com, 2018).

To any country, Higher education is of extreme importance to any country, and it is empowering as it helps and enables us to build an innovation and growth-oriented society. India has an ever-evolving higher education set up which extends the facility of knowledge dissemination in almost all spheres of education, be it arts and humanities; science, engineering, medicine, commerce, management, education, law, music and performing arts; etc. (Ministry of Human Resource Development (MHRD), All India Survey on Higher

Education (AISHE), 2019). India is gaining an important and prominent place in the education industry globally and stood 35th in the Worldwide Education for the Future Index 2019, advancing five places from 2018. Finland topped the index, followed by Sweden. (The Hindu Business Line, 2020).

India with one of the largest landmasses and being the second most populous country, has one of the largest tertiary education sectors across the world. It's enormity in size, below average literacy rate, and the developing nature of the country point towards humungous scope for development in the education system, which calls for sweeping reforms to tap this potential and improve literacy rates on par with the developed world (India Brand Equity Foundation (IBEF), 2020).

### 1.1 Demographic Advantage

India, to cater to the burgeoning education needs of its masses, has built one of the largest infrastructures of HEIs in the world and occupies an important place in the global education industry. However, there is huge scope to develop and ameliorate the education system. With the largest cohort of around 500 million people between the ages of 5 and 24, India has a tremendous opportunity at hand to grow the education industry multi-fold (India Brand Equity Foundation (IBEF), 2020). India's education industry is poised to grow from US $117 billion in FY20 to an expected US$ 225 billion by FY25 (IBEF, 2022). As per the EF English Proficiency Index 2021, India was ranked 48 among the 112 countries (ef.com, 2021), up by two places from 2020. Tremendous growth in the internet penetration would enable education delivery (IBEF, 2021). Overall, India has 1043 universities, 42343 colleges, and 11779 independent institutions registered on All India Survey on Higher Education (AISHE) website, with 38.5 million students enrolled in higher education in 2019-20 (AISHE, 2019-20). India is projected to have 900 million internet users by 2025 from 622 million in 2020, anticipating a robust increase by 45% in the coming years painting a rosy picture for online education business in India. While urban India registered a mild 4% growth in internet subscribers, taking the total to 323 million subscribers (67% of the urban population) in 2020, its rural counterparts grew by 13% to 299 million internet subscribers (31% of the total rural population) during the same period (IAMAI- Kantar ICUBE 2020 Report). This growth is pushed by the huge rise in smartphone users, at 750 million in 2021, which is projected to increase to 1 billion by 2026, with the rural masses pushing the sale of smartphones higher, as per the report of Deloitte's 2022 Global Technology, Media, and Telecommunications forecast. The outbreak of COVID-

19 expedited the creation of online programmes by higher educational institutions due to the rise in demand from consumers. Growth catalysed by the pandemic improving business models and the strengthening financials, India's Edtech industry is poised to attain a $30 billion mark in the next 10 years, according to RBSA Advisor, a transaction advisory firm (financialexpress.com, 2021). A report by market research firm Redseer highlighted that the lifelong learning and online tertiary education verticals within India's Edtech industry are projected to achieve $5 billion by 2025, and the entire scenario has been made conducive by the ease in government regulations (economictimes.indiatimes.com, 2022).

With online education around, the concept of continuous learning is growing and evolving. Three needs which have been driving the adoption of online education are –

1. Employability – Need to reskill and up-skill to stay ahead of curve in an organization
2. Social Learning – Learning together, developing social skills to be socially active
3. Entrepreneurship – Learn new technologies and skills to implement it in setting up a new business or using it in existing business to augment growth (KPMG, 2017).

The COVID-19 outbreak has wreaked havoc all across the world, impacting millions of lives. It has transformed the way education is imparted in 2020. It has accelerated the adoption trends, particularly the digitization of economy with more and more people adapting to technology to carry out their work from home confines. It has also acted as a testing ground for Education 4.0 by changing individuals' behaviour towards learning and integrating technology into reality. The pandemic impacted the entire world, making adoption of online learning a necessity rather than a choice for millions of students, not only in India but across the world (see Figure 1:1). As a contingency, many higher educational institutions (HEIs) have had to set up the remote learning infrastructure on war footing to adopt an online education model to ensure continuity in learning for their students (FICCI Higher Education Summit & Exhibition, 2021).

The spurt in MOOC adoption in the last few is as shown below –

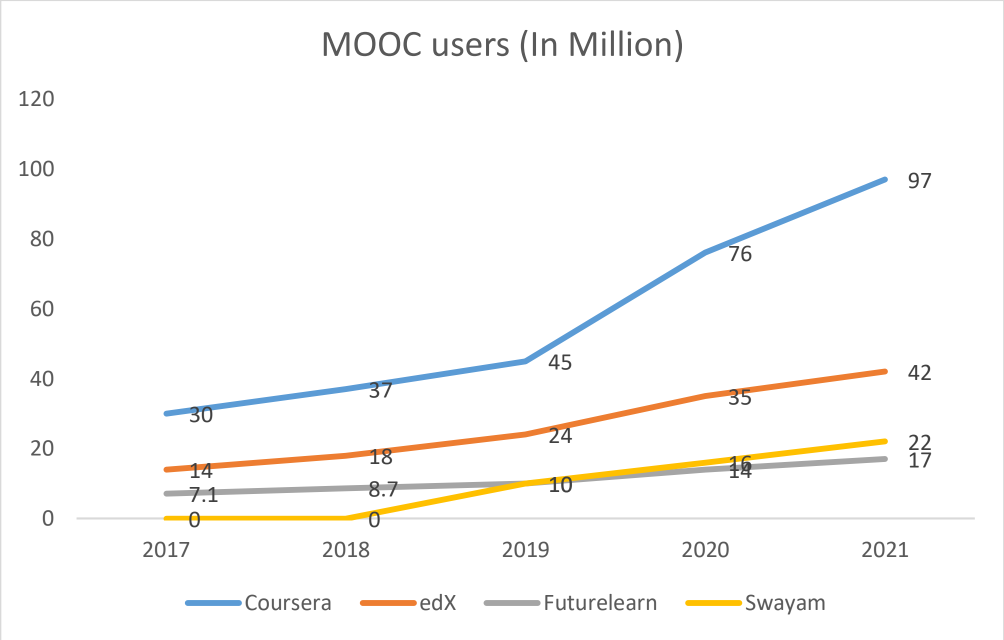



Figure 1:1: MOOC provider wise number of users

As per KPMG and Google (2017), key growth engines in India for online and blended learning are:

(a) Remarkable rise in smartphone and internet penetration;

(b) Affordability and accessibility of online learning;

(c) Reforms in education resulting in the improvement and spread of digital literacy; and

(d) Rise in demand of online courses by industry workforce and job-seekers for re-skilling and up-skilling themselves. However, still there host of challenges which needs to be taken off to improve GER of tertiary education in India.

## 1.2 Challenges

The current strength of educational institutions in India is insufficient to educate burgeoning population of Millennial and Generation Z.  The key statistics of higher education elicited in the Table 1-1 below suggest an of education gap between the haves and have-nots.

Table 1-1 India: Important performance indicators of higher education

| **Indicator** | **Total** | **Male** | **Female** |
|---|---|---|---|
| Total population (in crore)* | 121.1 | 62.3 | 58.7 |
| Literacy rate* | 74.0% | 82.1% | 65.5% |

| | | | |
|---|---|---|---|
| Population in the 18-23 age group (in crore) share in the total population (%)* | 14.1 (11.7%) | 7.3 (11.7%) | 6.8 (11.6%) |
| Gross Enrolment Ratio** | 27.1 | 26.9 | 27.3 |

Source: *Census 2011; **AISHE, Ministry of Education (MoE), 2019-20

### 1.2.2 Education Set Up

India is projected to have the largest population of people of college going age – a huge 140 million by 2030. To manage the burgeoning number of students' population and address their education needs and to become a 21st-century economic superpower, India needs to have at least another 1500 institutions by 2030 (UK-India Business Council, 2018). At present, 42,343 colleges and 1043 universities provide education to 34.25 million students (AISHE, 2019-20).

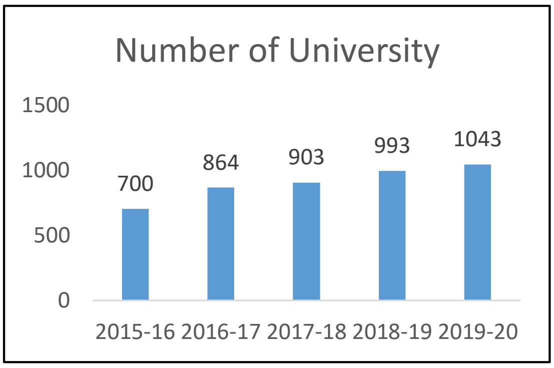



*Figure 1:2: Number of universities in India*

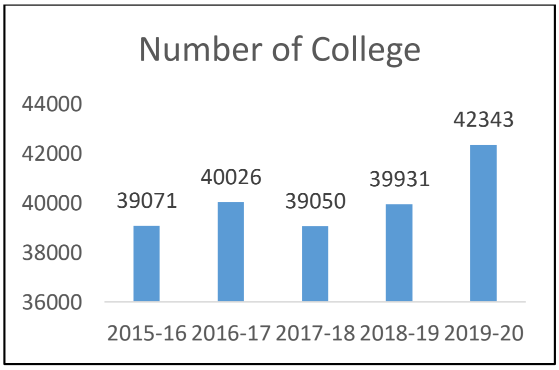



*Figure 1:3: Number of colleges in India*

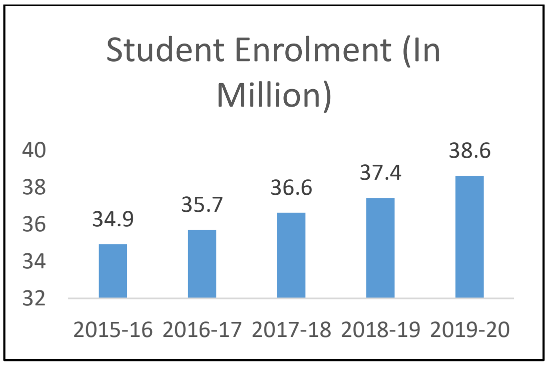



*Figure 1:4: Number of students pursuing higher education in India* *Source: AISHE, 2019-20*

Number of universities grew by 30.5% from 799 in 2015-16 to 1043 in 2019-20 (see Figure 1:2) whereas the number of colleges grew by 8.4% from 39,071 in 2015-16 to 42,343 in 2019-20 (see Figure 1:3). This increase in number of universities and colleges have also seen increase in the student enrolment from 34.9 million in 2015-16 to 38.6 million in 2019-20, a growth of 11.4% (see Figure 1:4).

### 1.2.3 Gross Enrolment Ratio (GER)

India's GER in tertiary education for the year 2019-20 was 27.1 per cent (see Figure 1:5) and it is calculated for students between the ages of 18 and 23. It is far from the GER of many rich and emerging nations, which have GER much above the 50% threshold (AISHE, 2019–20).

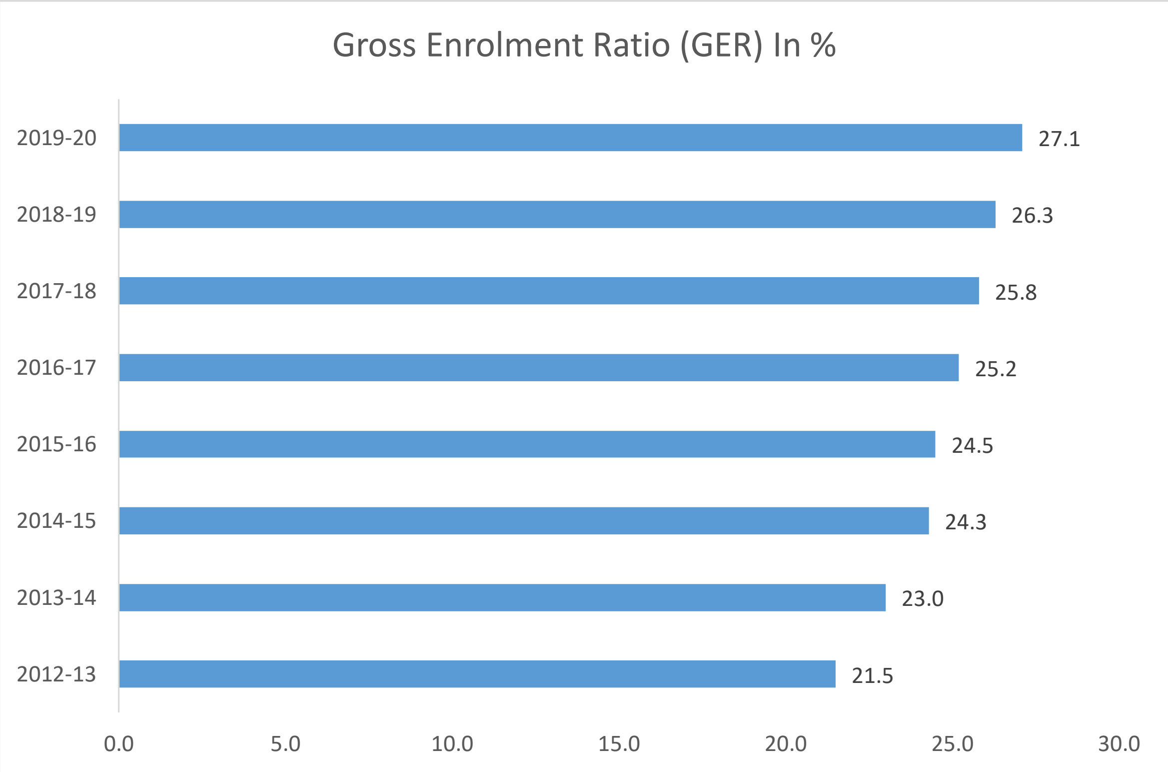



*Figure 1:5: GER progression in India* *Source: AISHE, 2019-20*

India's New Education Policy (NEP) 2020 has taken a target of almost doubling the Gross Enrolment Rate (GER) in higher education from 27.1% (2019-20) to 50% by 2030 (NEP,2020) which is not very ambitious when we compare our GER with China which is at 54.4% in 2020 (Xinhuanet, 2021).

A comparison of GER with other nations of the world suggests of huge gap in higher education between India and other major economies of the world (see Figure 1:6).

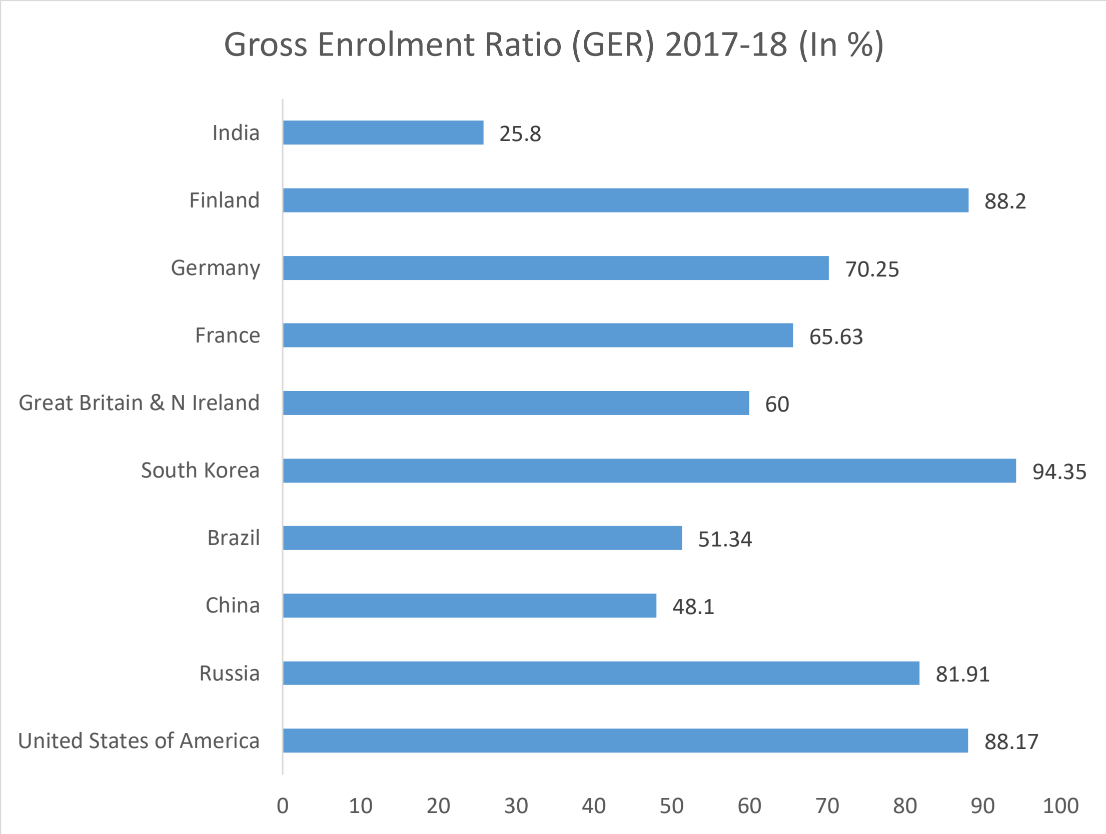



*Figure 1:6: GER country wise* *Source: UNESCO, 2018*

To improve student enrolment in institutions imparting higher education, Government of India has taken slew of measures (Palvia et al., 2018). Prominent among which and relevant to our study are:

i. Digital India and Skill India to improve digital literacy.
ii. UGC through its regulation has allowed the entry of reputed institutions in Open and Distance Learning to offer education on the distance mode.
iii. UGC encouraging the use of ICT technology- SWAYAM, India's own digital learning platform to reach out to people facilitating and enabling them to secure good quality education. (Source: information bureau, MHRD 2018)
iv. NandGhars (Tools as teaching aids)
v. India Skills Online (Portal for skill training)

With these measures in place, India has witnessed a major paradigm shift in the world of higher education in recent years. Advanced technological tools have been deployed in education to bridge the digital divide, e.g. multimedia tools for self-learning and the deployment of ICTs in the classrooms for better experiential learning.

Because of advancements in information technology and the advent of the internet, new forms of learning, namely, online learning and distance learning, have been introduced, and a plethora of educational institutions around the world have adopted these modes of education as one of the teaching modes to their participants who cannot attend the physical classroom due to personal or professional commitments. This kind of educational experience is much in demand as it enables learning from any part of the world. One of the recent educational technology innovations named as Massive Open Online Course (MOOC), is a kind of online education platform, flexible and omnipresent in nature.

In the subsequent section, I will explain online learning and the advent of MOOCs with one of the important objectives of democratizing education. Besides this, based on the extant literature, the definition, types, and characteristics of MOOCs are encapsulated. In the end, I will give the definition of Generation Z (Gen Z), which happens to be the subject of this study in relation to MOOCs.

### 1.3 Online Learning

In the past few years, there has been tremendous advancement happening on the technology front and technology is all pervasive as it has positively influenced all the sectors and education sector is no different and the impact of technological innovation has been felt in education too. Much has been written in the extant literature about the advantages technology can bring to education (Kirkwood and Price, 2014), including global connectivity with others; affordability and accessibility to learning resources from any part of the world; learning from the professors teaching in world's best universities and the democratisation of education. The concept of online learning was first used in 1995 when the first web-based Learning Management System (LMS) WebCT was developed, which later became Blackboard. Online learning is known by many connotations and similar sounding terms such as online education, blended learning, e-learning, online courses, etc. and it is now an integral part of education across the world. Online course delivery encompasses synchronous and asynchronous forms of interaction. In the synchronous form of learning, interaction between the instructor and the learners takes place in real time and the learners can receive feedback instantaneously whereas, in the asynchronous form of learning, learners can learn as per their own schedule and convenience but in a given timeframe.

Singh and Thurman (2019) defined online learning as "an experiential learning through the online computers latched onto the internet in a synchronous mode wherein the interaction between the learners and the instructors and among the learners does not mandatorily require their physical presence for participating in the online classroom" after collecting and reviewing the literature on online learning and education over the last 30 years.

Consequent to the popularity of the online courses, the government's push to democratise education and ever evolving educational technology, esp. in the areas of networking, cloud computing, and artificial intelligence, together as determinants (Songbin and Fanqi, 2015), gave rise to a learning platform having massive reach and which can cater to a large number of learners across the world at any given point in time, and this pedagogical method was named Massive Open Online Courses (MOOCs). White et al. (2014) mentioned about six distinct generations of distance learning or correspondence education associated with the advancement of technology and the same is utilised to comprehend the evolution of MOOCs.

1. **First generation**: Learning through mail.
2. **Second generation**: Use of video technology as a tool to enhance learning.
3. **Third generation**: Integration of various tools and telecommunications, referred as "telelearning" in learning, such as use of videoconferencing. It is at this time the concept of "open education" and "flexible learning" emerged.
4. **Fourth generation**: Emphasis on the use of technology and the internet in the 90's to generate eLearning experiences. Called "the flexible learning model".
5. **Fifth generation**: Use of Virtual Campus and educational technology resources led to the emergence of Virtual Learning Environments (VLE).
6. **Sixth generation**: Use of Web 2.0, created new learning opportunities. Increased use of social software tools, blogs, wikis and other social media platforms have changed the way people use the Internet and learn.

MOOCs can represent the advent of **seventh generation** in distance education as they it distinctly validate a model of distance education. COVID-19 has given MOOCs a major push to ensure continuity in education, signalling a big role MOOCs shall play in complementing traditional education, in the increasingly digitised world.

### 1.4 Advent of MOOC – Paradigm Shift

With technology evolving at a faster pace these days, access to education is available to the vast majority of the global population who are not able to attend higher education because of socio-economic, cultural, and other factors.

The Advent of the Internet gave rise to a new model termed as massive open online course (MOOC). David Cormier, a Canadian academician, termed the word “MOOC” in 2008 and George Siemens and Stephen Downes of University of Manitoba, Canada, were the first ones to make available their regular class of twenty-five students online to teach another 1500 students. MOOC is a scalable educational technology conceived and executed to provide best-in-class education to learners from the world’s best universities via web. MOOC is a way of learning in which various course programs are made available to the learners over the web. These learning programs are available 24/7 over the web, making it easy for the learners to access it from any part of the world with only requirement at the learners’ end is to have an internet connection and a digital device. Besides being economical and easy to use, MOOCs provide students an advantage of self-paced learning and the ease of accessing it from the confines of their homes or offices, in any part of the world. MOOC is bereft of age boundation and person of any age can access and learn from MOOCs. In the last few years, MOOC has gained much attention as technology enhanced learning (TEL) platform in tertiary education (Wosnitza & Yousef, 2014) and it has also enlivened the learners’ community across the globe by its ease of accessibility, quality and affordability. The New York Times also declared and celebrated the year 2012 as "The year of the MOOC" (nytimes.com, 2012).

A huge advantage that MOOCs have is that they are *scalable educational technologies* designed and developed by educators for the entire teacher and learner fraternity (UNESCO, 2016). It is regarded as a disruptive technology, which will transform the canvas of secondary and tertiary education. MOOC is regarded as a technology platform promoting and encouraging the concept of quality education and lifelong learning, which are the key components of Sustainable Development Goal (SDG4) announced by United Nations and to be accomplished by all the member countries by 2030 (www.unstats.un.org/sdgs). It will not be an exaggeration to call online learning truly ‘democratic’ as the people of economically weaker sections of society and those who were excluded from education before can access and attain knowledge through online education platforms (Rodrigues et al., 2020).

Digitalization of Education is a revolutionary development and MOOC has been featured in the “Innovation Pedagogy Report 2014” published by Open University. The report referred to MOOC as one of the top pedagogies that would change the education landscape to an unprecedented level. Technological advancement and its usage in education has turned the world into a global classroom, allowing millions of people access to world class education from the confines of their homes, from their offices (Innovation Pedagogy Report, 2014), while on the move or virtually from any place, with the only prerequisite being the availability of good quality internet bandwidth (Universities And Colleges Information Systems Association Report, 2014).

### 1.4.1 Types of MOOC

As mentioned in the extant literature, there are two types of MOOCs, viz. cMOOCs and xMOOCs. Kennedy (2014) posits that both types have different segments of learners utilising different approaches to learning and teaching methods.

The start of MOOCs was with a connectivist model targeting a segment of online learners; later, the concept evolved to a model named xMOOCs, which has an automated course outline and delivery while retaining the “sage on the stage” characteristics of a physical classroom (Kennedy, 2014).

Stephen Downes coined the terms ‘cMOOCs’ and ‘xMOOCs’ to differentiate between the MOOCs. The "c" in "cMOOC" stands for "connectivism," while "x" in "xMOOC" comes from HarvardX and MITX, which provided open access online courses (Schulmeister, 2014). cMOOCs are grounded on the connectivism learning theory, harping on the advantages of connecting with various learners, understanding their diverse opinions, and keeping end-objectives as their basis of learning, whereas xMOOCs are grounded in conventional classrooms, having a combination of pre-recorded video lecture with quizzes, tests, assignments, and projects. xMOOCs are professor centric whereas cMOOCs are learner centric (Yuan and Powell, 2013; Ross et al., 2014).

As George Siemens categorically put it: “cMOOCs is all to do with knowledge creation and generation, whereas xMOOCs is all to do with knowledge replication.”

### 1.4.2 Differences in MOOCs

Kennedy (2014) posits the differences between cMOOCs and xMOOCs, in the following areas: the degree of learner autonomy vis-a-vis the course structure; nature of the platform (cMOOCs are distributed while xMOOCs follow a centralised approach); and the teaching method. Following these distinguishing parameters, the subsequent paragraphs suggest the differentiation between the types of MOOCs. With regards to learner freedom, Siemens (2012) posits that cMOOC utilises community learning with a stress on autonomy, creation, and creativity. Errey and McPherson (2015) elucidated that cMOOC benefits from Web 2.0, which provides the learners a chance to cull study material suiting their requirement and for better experience and learning outcomes without any need to depend on instructor developed study material.

Yeager et al. (2013) in their study explained four important cMOOC principles: aggregation (wherein the content available on the portal is collated and shared with the community of learners through a daily newsletter); remixing (here the connection is made and developed and shared by means of blogging, content writing, tweeting, social bookmarking etc.); repurposing (learners create internal connections); and feeding forward (exchanging new connections with other learners). On the other hand, xMOOC provides self-learning courses with restricted opportunities for interaction between the learners and instructor (Kalz and Specht, 2013). In addition to this, learners in xMOOCs have access to content uploaded on the platform by the instructors teaching in the HEIs, whereas in cMOOCs, the role of instructor is that of a discussion facilitator who has developed a course structure and invited the learners to enrol in the courses and disseminate knowledge and experiences with other learners. Some scholars differentiated between two types of MOOCs with regard to their focus on learning.

Petkovska et al. (2014) highlighted that the major distinction (see Figure 1:7) between the two types of MOOCs is that in the case of cMOOCs, entire community of learners support in creating the content or reading material and accessing the course content using digital platforms such as social networks, blogs, etc. where as in the case of xMOOCs, instructor is the pivot of program as he is “Sage on the stage” responsible for conducting the program and directing learners to follow course related guidelines. Yuan and Powell (2013) describe xMOOCs as being for profit or for non-profit. Some examples of xMOOCs are Udemy, Coursera, EdX, Swayam, FutureLearn, Xuetang, etc. On the contrary, cMOOCs use social networking sites instead of a platform, which enables all learners to support each other by contributing and sharing content. In cMOOCs, assessment of a learner happens through peer review, i.e. learners get feedback from their fellow learners (Bates, 2014). As regards the pedagogy adopted, the structure of xMOOCs resembles that of traditional university courses resonating with Siemens (2012) views on xMOOCs.

Kalz and Specht (2013) drew a comparison between cMOOCs and xMOOCs based on interaction type. As per them “cMOOCs are restricted to interaction among the learners”, whereas in “xMOOCs the interaction of the learners happens with the study material or the course content”. Relatively, cMOOCs are less structured and depend solely on a learner’s motivation (Kalz and Specht, 2013); furthermore, the content is developed by learners spread across the world who support each other by contributing to the knowledge pool to study from, learn from and collaborate with fellow learners (Petkovska et al., 2014).

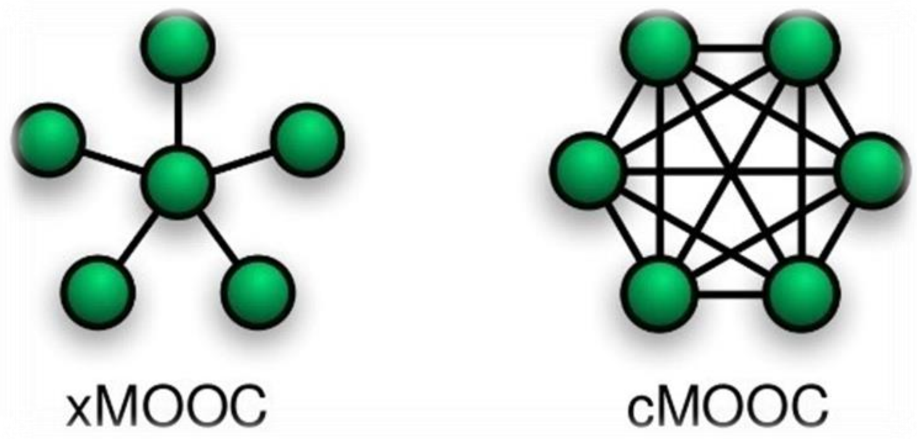



Figure 1:7: MOOC Taxonomy

### 1.4.3 MOOCs on Rise

Year 2012, is celebrated as “The Year of MOOC,” since massive open online courses have brought to the world, best of the education at our door steps trembling the tertiary education industry with the potentiality to disrupt the traditional university model. Though higher education institutions have been delivering online content to students through virtual learning environments, the rapid strides made by MOOCs, especially in the world of higher education, are regarded by many educators as an education revolution *(UNESCO, 2016).* Worldwide, MOOCs have been regarded and accepted as an effective and complementary learning tool to traditional modes of learning (Nayar & Koul, 2020). In recent years, MOOCs has attracted the attention of hordes of learners across countries. MOOCs developed independently by academicians are often promoted and hosted by people with expertise in managing online platforms. In 2011, professors from Stanford University developed a few more videos and uploaded them on the web through open online platforms. Subsequently, they made Coursera as an independent for-profit scalable educational technology in early 2012. Few more non-profit initiatives, viz. Udacity established by Sebastian Thrum and Udemy by Eren Bali also came into existence in 2012. Subsequently, MIT and Harvard also launched edX. MOOC initiatives from Americans led Europeans also to follow them and launch their own MOOC platforms, viz. Futurelearn and Iversity. Ownership of Futurelearn and Iversity is with the UK's Open University and a berlin based online education group, respectively.

Since its launch in 2008, MOOC has gained lot of popularity and it got a great fillip with the onset of pandemic COVID-19 in the beginning of year 2020. In 2020, MOOCs registered approximately 180 million global enrolments, which is a whopping 44% year-on-year growth in student numbers. (classcentral.com, 2020). By the end of 2021, 19400 MOOC courses (see Figure 1:8) have announced or introduced by over 950 universities across the globe. In 2021 alone, approximately 3100 new courses were introduced by universities (classcentral.com, 2021).

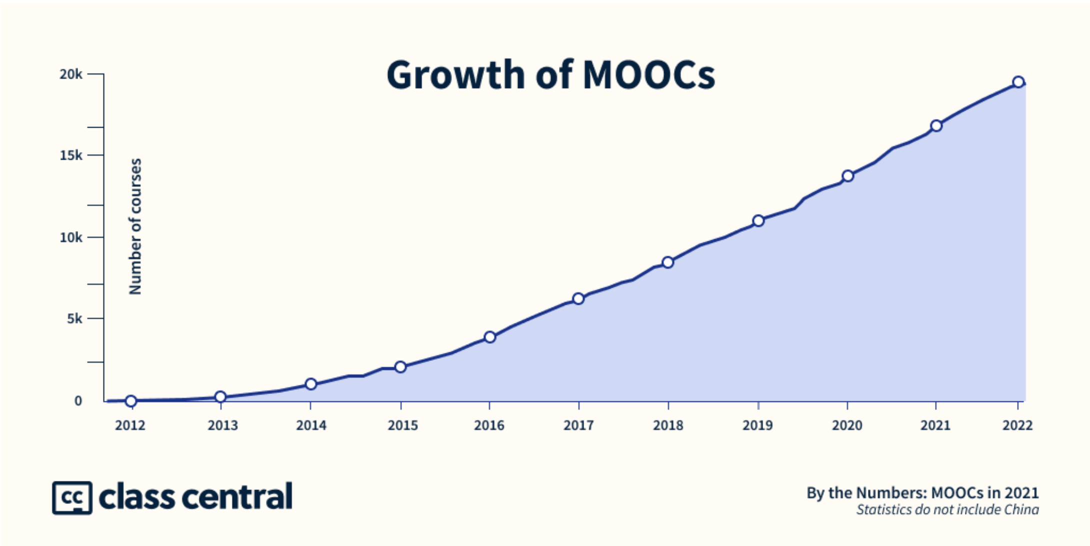



Figure 1:8: By the Numbers MOOCs in 2021

Table 1-2: Leading MOOC providers in terms of user base

| **MOOC Platform** | **Country** | **Inception Date** | **Users (Exit 2021)** | **Courses** |
|---|---|---|---|---|
| Coursera | USA | Apr-12 | 97 million | 6,000 |
| edX | USA | May-12 | 42 million | 3,550 |
| FutureLearn | UK | Dec-12 | 17 million | 1,400 |
| Swayam | India | Jul-17 | 22 million | 1,465 |

Source: (classcentral, 2021)

MOOC enrolment got a major boost during the pandemic times, with all the MOOC platforms recording good growth in user enrolments. Coursera, which attained a dollar valuation of over $5.8 billion in April 2021 during its IPO debut, saw an increase in enrolments from 76 million to 97 million in 2021 (see Table 1-2, Figure 1:9). edX saw enrolments move from 35 million to 42 million; UK-based Future-learn enrolments moved to 17 million users whereas India's Swayam user base moved to 22 million users (classcentral.com, 2020) and Coursera user base moved to 13.6 million (businesstoday.in, 2021).

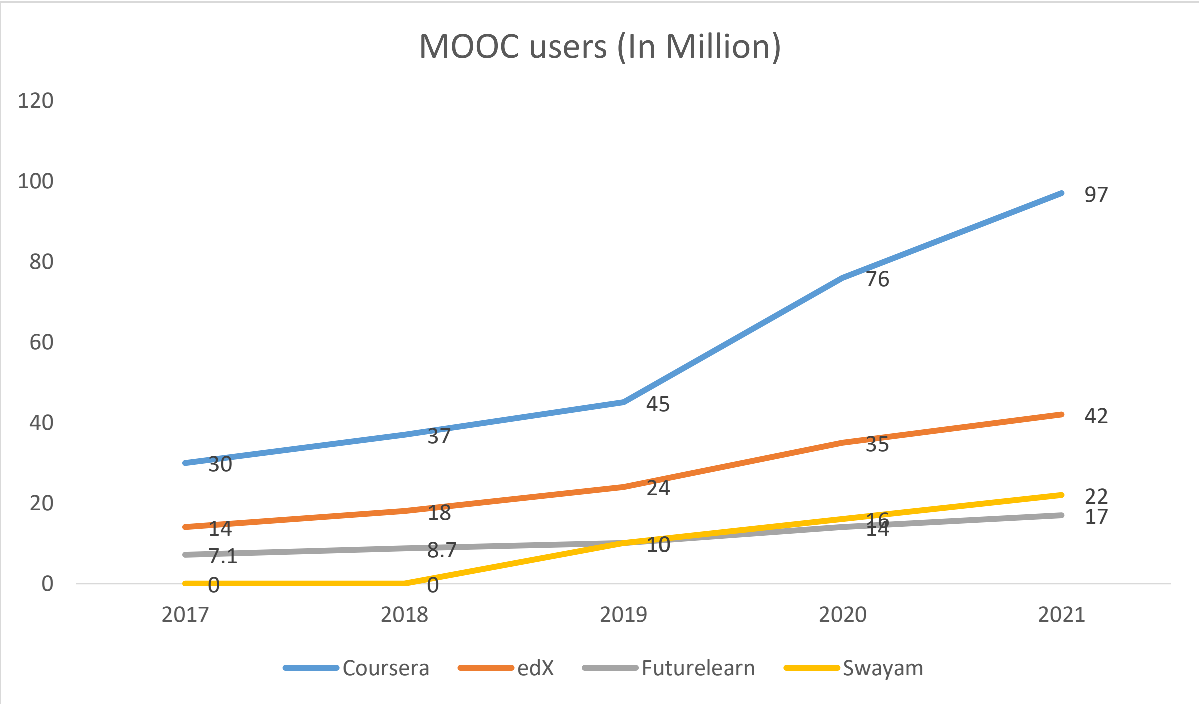



Figure 1:9: MOOC users

Exit 2018, China's XuetangX reported 14 million users. However, they didn't disclose the figures for the years of 2019, 2020, 2021 terming it as classified information (Classcentral, 2020).

### 1.4.4 MOOC in India

MOOCs provide a tremendous opportunity to every Indian who wants to learn, earn, teach, or innovate and, in this process, contributing their bit towards nation building and helping the country transform into a developed nation. In India, a developing nation, rural areas are home to 65% of the population, while cities are home to the remaining 35% (https://statisticstimes.com/demographics/country/india-population.php) and where people can't afford to get basic education, let alone quality education, MOOCs can definitely be a game changer and a big facilitator in improving literacy rates in rural India. A MOOC is a cost efficient and effective way of acquiring skill-based knowledge, and it doesn't need any brick-and-mortar structure in place, unlike traditional universities. What it requires is a good quality internet bandwidth and a desktop or a laptop, and you are all set to go. An improved literacy rate in rural India would eventually enhance the overall literacy rate of the country and economic conditions. According to Blackmon and Major (2017), MOOCs can be equated to an educational revolution in developing countries. Developing countries have a challenge of inadequate infrastructure, technological barriers and low literacy rates. Therefore, MOOCs in developing nations, or to say, the emerging economies, present a huge opportunity for tapping into the potential MOOC carries towards the democratisation of education, thereby improving social inclusion.

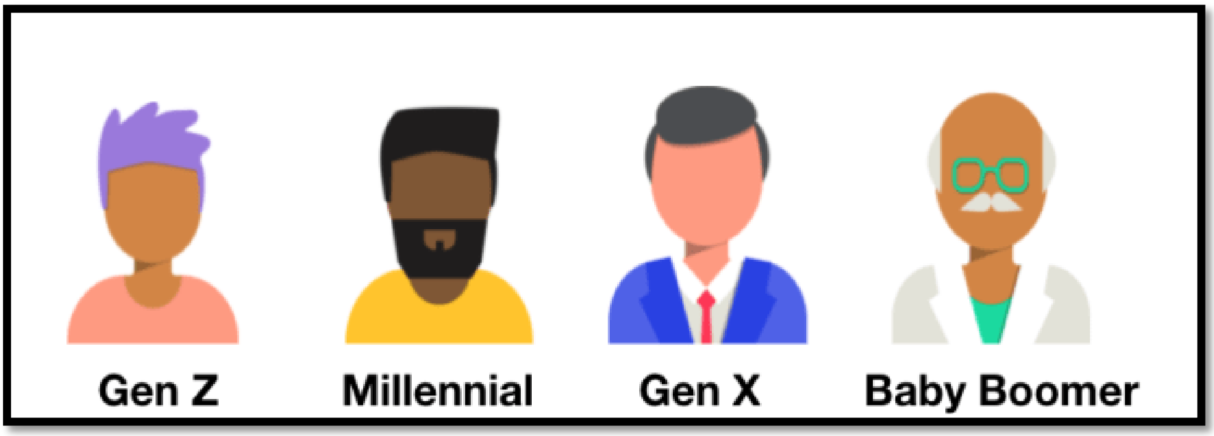
In India, research driven and technologically advanced educational institutions with better organizational capabilities are trying their best to cater to the ever-growing educational requirements of students, by offering MOOCs. Educational institutions of eminence like IITs, IIMs, and IISC and education-governing bodies' viz. UGC, AICTE, and MHRD have jointly taken various initiatives to reach out to learners in the remotest part of the country through online education. Some of the existing projects providing online education are mooKIT offered by IIT Kanpur, IITBX of IIT Bombay, and NPTEL (Chauhan, 2017). According to the 'Digital India' Initiative, the government of India is placing a lot of emphasise on the utilization of information and communications technology (ICT) tools in the classrooms. To meet the burgeoning requirements of education in the present and future, the Ministry of HRD, has launched and introduced an online education initiative known as SWAYAM (Study Webs of Active Learning for Young Aspiring Minds). SWAYAM being an Indian version of MOOC is all set to bring transformation in online education by extending reach and access to quality education at economical and affordable costs to all learners anytime, anywhere. SWAYAM has been instrumental and successful in bringing educational institutions of eminence and leading technology partners under one umbrella at a pan-India level (www.aicte-india.org/bureaus/swayam, 2016). Since its official launch in July 2017, SWAYAM has attracted over 16 million learners and is rapidly growing. The way it is growing, in a few years, SWAYAM could become the world's largest MOOC platform, providing courses in various disciplines developed and delivered by the professors of premier institutions of India such as IIMs, IITs, and Central Universities (classcentral.com, 2020). To ramp up adoption of online courses offered by SWAYAM, a credit transfer facility up to 20% is announced by

UGC/AICTE. It is an attempt by MHRD to encourage the use of online educational resources in universities (pib.nic.in, 2018).

### 1.5 Generation Z

The word "generation" is derived from a Greek word "genos", meaning "a group of many individuals of similar characteristics ". In research studies, it is generally contemplated as an aggregate of individuals who are born around the same time, sharing similar cultural background (Weingarten, 2009). As per "Generational Cohort Theory" (GCA), a generation is explained as "a homogeneous group of people sharing similar characteristics like similar birth years, cultural background, belief systems, habits, economic status, etc. (Kupperschmidt, 2000). All this homogeneity among people, results in, the creation of similar beliefs, likings, and behaviours among the cohort members, which they tend to exhibit in all they do, from socializing to purchasing related matters.

The start and end dates of the generational cohorts are not accurately prescribed. However, the generation periods normally have a range of 15-20 years (Özkan, A. P. P. M. (2017). Generational cohorts (see Figure 1:10) classified by research literatures based on year of birth **(**Brosdahl & Carpenter, 2011**).**




Born (1995 & After) Born (1981-1994) Born (1966-1980) Born (1946-1965)

Figure 1:10: Generational Cohorts Source: tourismtiger.com

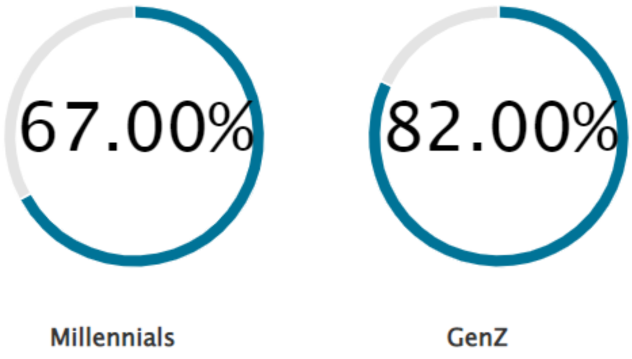
Each generation exhibits different characteristics, attitudes, and behaviors. Baby boomers are contributing to an ageing population in any country and they are characterized by higher average disposable income, thus catching the fancy of marketers **(**Kumar et al., 2018**).** Baby boomers, by virtue of belonging to an older generational cohort of post industrialization and pre-digital era have a least contribution or participation in the information society. Gen X, as per the research literature, consists of 'digital immigrants', who were born before the advent of the digital era thus they have to put in efforts to learn digital skills (Lissitsa & Kol, 2021). Gen Y, also called as Millennial, belonged to a period of globalization, rapid urbanization, tremendous rise of social media and technological advancement. Their friendships, hobbies, social interactions, and civic activities are highly influenced and mediated by digital tools and technologies. Generation Z (Gen Z) are highly educated and technologically sound and usually make well-informed purchase decisions (Rahulan et al., 2015). It is the demographic cohort born after the Millennials. There is no defined and accurate range of dates for when this cohort starts or ends, but researchers use 1995-2010 as their starting birth years (IBM, 2018; Rothman, 2016).

Some researchers contemplate them to be the individuals born after 1995 (Seemiller and Grace, 2017; Iorgulescu, 2016) others suggest that they are born from 1997 onward (Dimock, 2019), whereas some other asserts that Gen Z members are born after the year 2000 (Berkup, 2014). However what is common in all these assertions is that the Gen Z comprises of young people, majority of whom are engaged in studies at high school or university, while the oldest members of this generation have joined the professional world. In the extant literature, Gen Z is also known as (Poláková & Klímová, 2019): Google generation, D generation (for digital), V generation (for viral) or N generation (for Net). However, Prensky (2001) considered the name "Digital Natives" as more apt for Gen Z who is living a life engrossed in information and communication technology. All these sobriquets have one thing in common and is characterised by the availability of global information on a click of button (Cruz and Diaz, 2016).

Gen Z is quite distinct from the previous generations. What distinguishes Gen Z from others is that they are technology centric and prefers communicating with others through text messages using digital devices than in person (Poláková & Klímová, 2019). There is a change in generation with the change in technology. It is important to identify these changing generations to have knowledge of them so that every generational cohort needs and requirements are correctly identified and fulfilled. Categorizing people into generational cohorts provides a clear understanding of them and helps in identifying and interpreting different preferences among these generational cohorts in order to make better decisions about their development, technology, training, and their other requirements (Bresman & Rao, 2017; Szabo, 2020).While identifying them is not enough, it is also important to connect with them using the communication tool widely used by them and influencing their decision. (Kotler and Keller, 2012). Born in the digital era, it is clear and evident that technology is an integral part of Gen Z life. Higher education students studying in universities are good at understanding technology and its' use to accomplish their social and academic goals, exhibiting their multi-tasking abilities (Cruz and Diaz, 2016). The study by Pol´akov´a and Klímov´a reveals that Gen Z has a shorter span of attention as compared to the previous generations, which is a result of their incessant interaction with the internet environment, which offers them a flood of information, making the brain limit their attention span (Poláková & Klímová, 2019). Gen Z finds it difficult to sustain without digital resources in want of information need from various fields including education which is why they prefer learning online than offline in a brick and mortar set up (Rothman, 2016). As per the mentioned characteristics of Gen Z, the role of ICT and the internet is quite crucial and relevant for education.

Ease of online class access from home or office confines has made e-learning a development trend of education and learning (Cheng and Su, 2012). Besides this, evolution in mobile and computer technologies has given further impetus to online education on account of its ease. Technology, thus facilitates and enhances many areas of our lives, including digital self-education. Unlike a conventional teacher-centric classroom learning, digital learning, such as learning through mobiles, tablets, or laptops, offers a learner, "self-paced learning environment" (Xiao and Chen, 1998). As per Bloomberg report (2019), Gen Z makes up 32% of the world's population, with a staggering 472 million people in India and they remain online for an average of 8 hours per day (nokia.com, 2022). A large number of this generation are in high school and college, and the oldest members of this cohort have started their professional journey (Turner, 2015). Advancements in technology and access to theinternet have made this cohort well connected across the globe (Babin et al., 2016). Technology access for them is quite simple, as they are digital natives and have a strong experience with these devices since birth (Ramírez-Correa et al., 2019).

While this generation carries a positive attitude and is hopeful, they can also get stressed. Also called the 'iGeneration', they value comfort and convenience, which is reflected in their social media habits (see Figure 1:11) and high dependency on the internet (Research.com, 2020) besides their propensity towards personalisation. Gen Z buys mobile phones more than the older cohorts (gwi.com, 2020). To make them your customers, offer them comfort and convenience in terms of your products and service offerings, user friendly experience, ease of transactions, etc.




(fortuneindia.com, 2021).

*Figure 1:11: YouTube as preferred learning platform*

As this generation values comfort and convenience, which is ably supported with the availability of mobile devices and internet services 24x7 at their disposal, study in the area of educational technology adoption has gained traction in recent years. More so, with the onset of COVID-19 in 2020, which made everyone confined at home to safeguard their lives, online education has got major traction. Now when education is happening in a hybrid, online and offline mode, it is of paramount importance to study factors affecting users' behavioral intention towards adopting MOOC technology. The relevance of this study is even higher on account of the first ''digital natives'' entering university level education and being highly adapted and dependent on technology use with a lower span of attention.

While there are studies on MOOCs, the one focusing on Gen Z's behavioral intention towards MOOC adoption remains largely unexplored and demands for empirical exploration, especially in the Indian settings, are desired, as it is difficult to generalize the behavioral traits of a generation across the world as the same on account of their upbringing in different cultures and sub-cultures. Besides this, most of the research work on generation cohorts has happened in the developed economies, hence Gen Z has been chosen as a subject of study for four reasons. Firstly, MOOC as an educational technology resonates well with the quality, accessibility, affordability, and convenience (which Gen Z is inclined towards) as MOOCs can be accessed from anywhere in the world, be it from the confines of your home, office, or any other place. What you need is a digital device, viz. a mobile or laptop, and an internet connection. It is anticipated that higher internet penetration and adoption will spark a rise in the requirement for smartphones. This surge in requirements will be catalysed by the urge to adopt e-learning, e-health, fintech, OTT and other technology enabled services (Deloitte, 2022).

Secondly, in India the tertiary education GER exit 2019-2020 is barely 27.1 (AISHE 2019-2020) calculated in the age range of 18-23 years, including oldest members of Gen Z cohort and this cohort has a population of 141 Million (see Table 1-1). Thirdly, with the advancements in technology and a more connected world, generational shifts play a significant role in setting behaviour and trends (Dentsu, 2021), which inspired the scholar to determine the influences on the behavioural intention of Gen Z to MOOC adoption and, fourthly, to understand the impact of teacher influence, language competency, and the educational characteristics on MOOC adoption (Meet and Kala, 2021).

In a nutshell, a burgeoning population of Gen Z (Bloomberg, 2019) with high smartphone and internet penetration, spending 8 hours per day online (nokia.com, 2022) accessing internet to fulfil their health, education, entertainment, fashion, daily needs, etc. does not have their reported MOOC enrolments directly proportional to the tremendous growth witnessed in other emerging technology-based platforms.

## 1.6 Statement of the problem

### 1.6.1 Business Problem –

Against this backdrop, the business problem can be summarized as:
"Adoption of MOOC among Gen Z is not corresponding to the growth in internet and smartphones".

### 1.6.2 Research Problem –

"To examine factors impacting technology adoption and determine the influence of extending factors such as language competency, teacher's influence, and student educational course characteristics on technology adoption."

Despite having the excellent opportunity to learn from professors of renowned Indian and global institutions of higher education, the adoption rate of MOOCs is quite poor among students and not many quality empirical research papers on the adoption of MOOCs in the developing world, especially India, have been published yet (Virani et al, 2020). The prospects of MOOC transforming the education industry, and the paucity of empirical research in the field of MOOC adoption among Gen Z in the Indian context, has encouraged and motivated the scholar to undertake the present study to explore the causes of the problem as under –

What are the factors affecting MOOCs' adoption intention among Gen Z studying in the HEIs of India? In chapter three, the research gaps of this study have been explained in a more detailed manner to understand the significance and relevance of the study.

### 1.7 Research Significance

The educational technology innovation known as MOOCs was introduced in higher education a decade back, offering students certificates of course completion at no cost or nominal cost, and catching the fancy of millions of students. However, despite the explosive growth of internet and smartphone users in India, the pace of adoption is not in line with the potential to grow. Another challenge afflicting MOOCs is that the enrolment to completion ratio is abysmally low. The contribution of this study is significant for theoretical as well as practical reasons.

From the theoretical contribution perspective, this study, to my knowledge, is one of the first studies to explore factors affecting MOOC adoption among Gen Z studying in the HEIs of India. The following are specifics of the contributions made by this research to the body of knowledge regarding the adoption of emerging technologies:

1. The current study endeavours to build a model extending the theory of UTAUT2 with new constructs. The research aims to test the theory of UTAUT2 on MOOC adoption in Indian settings and also to increase the explanatory power of UTAUT2, taking into consideration two more constructs.

1.1. Examining the limitations and identifying the gaps in research in the extant studies. To address it and add knowledge to the existing literature in the field of technology adoption especially emerging technologies such as MOOCs.

1.2. Extending the theory of UTAUT2 with two new variables viz. Language competency and Teacher influence not examined before.

1.3. Empirically testing the applicability and adaptability of extended UTAUT2 theory. The new model developed can be tested by scholars doing research in emerging technology adoption in different contexts and cultural settings.

1.4. This empirical research was conducted and completed on relatively larger sample size (n=483) using multistage sampling method including sampling methods such as stratified random, purposive and snowball sampling to represent the population of study viz. Gen Z in a best possible way.

1.5. Preparing and validating a scale to measure various items by means of questionnaire, many of which have been contextualised for MOOCs.

1.6. This research measured the impact of UTAUT2 constructs on MOOC adoption intention and also tested it for the extended constructs of Teacher Influence and Language competency.

1.7. The study highlights interesting insights of Gen Z outlook towards MOOC adoption and the factors influencing their behavioral intention towards the same. Thus, it is anticipated that this research will act as guiding light for the scholars keen to know more about the Gen Z and the factors influencing them to adopt a new technology especially in the developing nations as the country of study India is a developing country.

1.8. The study utilises the widely used multivariate statistical analysis technique of structure equation modelling using PLS model utilising Smart PLS 3.0 software.

The practical contribution of this research offers valuable recommendations to MOOC designers, marketers, policy makers, and educators on the factors influencing Gen Z's behavioral intention towards MOOC adoption. While MOOC adoption across the world especially in the developing countries like India is growing however it is not growing at the pace at which it should grow contemplating the explosive growth of internet and smartphone users in India. Growth in MOOC user base looks pale when compared to the growth registered in other internet enabled technology platforms viz. food delivery services, ride hailing services, video sharing apps, OTT platforms etc. This research shows that MOOCs have the potential to democratize education by complementing offline traditional education with ways and means to increase adoption rates.

### 1.8 Thesis Outline

This section explains the thesis outline, which is as under:

**1.8.1. Chapter one** sets the tone of the research topic by highlighting the role and significance of higher education in any country, followed by the demographic advantages and challenges

India is facing on the higher education front, the definition of online learning and the evolution of MOOCs, types and differences between types of MOOCs, business trends and performance of MOOCs, definition and characteristics of Gen Z, the subject of this research and finally this chapter concludes by highlighting problem statement, business and research problem, significance of this research, and the layout of the thesis.

**1.8.2. Chapter two** provides the theoretical framework of the thesis and explains various theories related to the adoption of technology, including the definitions of the construct and studies done. It also describes in detail the theory of UTAUT, which is the theoretical framework of this study and its use in explaining the acceptance of new technologies worldwide.

**1.8.3. Chapter three** provides the details of literature review done on adoption of technological innovations and MOOCs in relation to UTAUT theory, chosen for this research followed by the explanation of research problem, gap areas, and the research objectives leading to hypothesis development with subsequent creation of the conceptual model.

**1.8.4. Chapter four** describes the research methodology deployed in the study to assess, evaluate, and validate the conceptual model.

**1.8.5. Chapter five** explains the data analysis done, findings and results followed by its interpretation.

**1.8.6. Chapter six** discusses research findings, theoretical and practical contributions and implications, limitations of study, future research avenues, and conclusion.

### 1.9 Summary

This chapter dwelled upon the introduction of research topics on education, followed by the challenges in education and the current infrastructure in education in India supported by key statistics. Subsequently, the chapter discussed online education and the transformation it has brought in the world of education with the introduction of MOOCs. Also discussed were the types of MOOCs, differences in types of MOOCs, and an introduction to Gen Z, followed by the description of problem statements and the structure of thesis abstract.

# 2 CHAPTER 2: THEORETICAL FRAMEWORK

## 2.1 Introduction: Technology Adoption

What makes an individual adopt a particular technology and in what time frame has always been an area of interest among scholars representing various disciplines (Straub, 2009). Technology adoption can be defined as an intent to acquire a new invention or innovation for availing the benefits it is claiming to provide. Consumer adoption of technology is the process consumers goes through in assessing the usefulness of technology and whether it will be beneficial to adopt it or not. According to Bagozzi & Dholakia (1999), consumer behaviour is often goal-oriented as consumers most of the time buys the products or services that enables the accomplishment of their goals (Howarth et al, 2016). This entire process is influenced by several factors, ranging from external to internal factors. Internal factors refer to the consumer's perception, attitude, self-concept, and personality traits, and external factors refer to socioeconomic, demographic, cultural, and environmental. All these factors play a vital role in a consumer's product or service adoption. Adoption of a product by a consumer differs on the basis of a product category, and when it comes to the adoption of innovative technology products, then the adoption process is also influenced by the feature/s incorporated in the new product. New technologies come with better functionality and ease of use. A Functionality means features a product is endowed with, and ease of use indicates the comfort in handling the product.

Technology nowadays is all pervasive and it has positively affected every possible domain of life, and its rapid evolution and adoption has its own share of challenges, which has gained the attention of policymakers, practitioners, and researchers. Organizations have made substantial investments to build the technology infrastructure. However, these investments may not reap dividends unless the innovative technology is being used by its intended users. There are several adoption and diffusion theories which suggest that: (a) technology adoption is a tedious, complex, society bound, progressive process; (b) people form an opinion of technology that defines their adoption process; and (c) ease in technology adoption needs to address cognitive, affective, and utilitarian concerns of an individual (Straub, 2009). Before we study how innovation diffuses in a society, it is crucial to comprehend the meaning of the term innovation. An innovation is something new that is added to society for the purpose of making daily activities easier for a person or society as a whole. Rogers (1995) described it as "a thought, an imagination, product or service seen as something new or contemporary by a person or other measures of adoption." Straub (2009) termed innovation as a concept of novelty. Adoption of technology can be defined as the desire to obtain a new invention or innovation in order to reap the benefits it claims to provide.

## 2.2 Adoption and Diffusion Theories and Models

Adoption and diffusion theories investigate individuals and the processes they undergo while accepting or rejecting a particular innovation. Some model point to adoption of not only the acceptance of innovation, but a step further of accepting it and making that innovation an integral part of their mundane affairs. Thus, adoption theory doesn't speak alone about the whole but the parts that make the whole (Straub, 2009). However, diffusion theory explains the proliferation of innovation in society. It talks about the factors, such as time and societal pressures, influencing the spread of innovation and whether it's been adopted and adapted by the population or society or whether it's rejected it. In contrast to adoption theories, diffusion theories take a broader perspective on the spread of an innovation in a time span. Figure 2:1 is a graphical depiction of individual adoptions. It explains the spread of innovation diffusion over a period of time amongst individuals making adoption decisions.

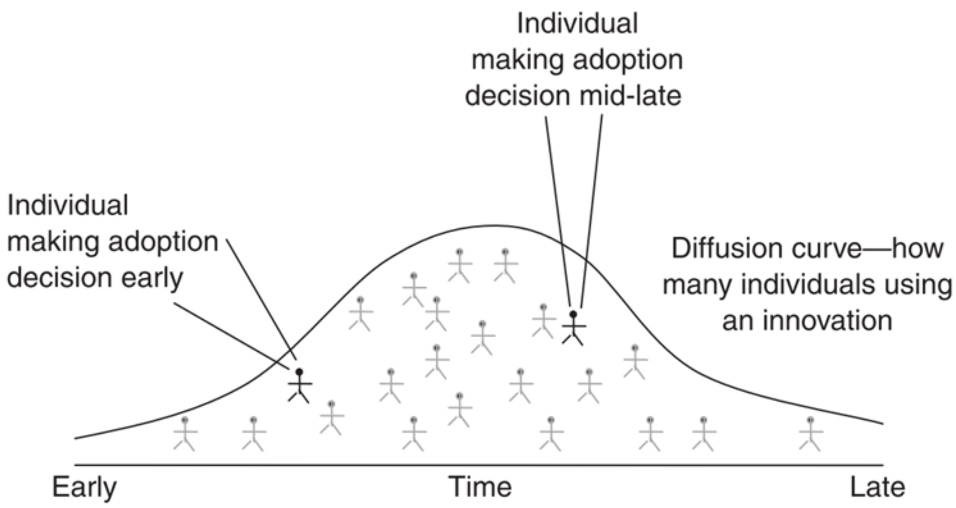



*Figure 2:1: How individual adoptions compose diffusion*

Many research studies are conducted across the nation to ascertain users' acceptance of technological innovations and their usage (Kim et al., 2019; Venkatesh et al., 2007).

Many studies have been conducted in the area of technology adoption, leading to various theories and models that explain organisational and user intentions to use new and emerging technologies that have their origins in the fields of information and communication, technology, psychology, sociology, and anthropology (e.g., Venkatesh et al. 2003; Taylor and Todd 1995b; Davis et al. 1989; Venkatesh and Davis 2000).

These theoretical frameworks identify certain independent variables that influence the dependent variables and explain a companys' or users' behavioral intention to adopt a technological innovation. Eight widely referred to and used theories in the field of technology adoption are as under:

1. Theory of Reasoned Action (TRA), Fishbein & Ajzen, 1975

2. Technology Acceptance Model (TAM), Fred D Davis, 1989

3. Motivational Model (MM), Davis and his research team, 1992

4. Theory of Planned Behaviour (TPB), Schifter & Ajzen, 1985

5. Social Cognitive Theory (SCT), Albert Bandura, 1986

6. Model combining the Technology Acceptance Model and the Theory of Planned Behaviour (C- TAM-TPB), Taylor and Todd, 1995

7. Model of PC Utilization (MPCU), Thompson and his research team, 1991

8. Innovation Diffusion Theory (IDT), Everett Rogers, 1995

Before we dwell on UTAUT, it is important to be introduced to these theories.

### 2.2.1. Theory of Reasoned Action (TRA)

It was Fishbein & Ajzen who first proposed the TRA as the first hypothesis to explain how technologies are adopted. It is a widely applied theory that describes the predictors of behavioral intentions (Fishbein and Ajzen, 1975; Ajzen and Fishbein, 1980). TRA posited that an "individual's act of a particular behaviour is affected by their behavioral intention (BI) which in turn is impacted by an individual's attitude and subjective norm (SN)" (Davis et al., 1989). BI indicates a person's intention to exhibit a particular behaviour (Fishbein and Ajzen, 1975). Attitude is described as a person's inclination or feelings (positive or negative) towards performing a task (Fishbein and Ajzen, 1975). SN pertains to a person's perception of whether or not their close and significant acquaintances believe they should display a particular behaviour (Fishbein and Ajzen, 1975). TRA explains that "an individual's attitude with regard to a behaviour is considerably influenced by their strong beliefs towards the results of that behaviour and its consequences" (Davis et al., 1989). Belief refers to "an idea that a person considers it to be true based on his knowledge, experiences, experiments, etc. (Davis et al., 1989). TRA is a widely accepted theory that explains people behavioral intentions for adopting new technologies. Attitude and SN were among the important variables studied to explain an individual's BI to adopt technology (Yuen and Ma, 2008). Figure 2:2 depicts the TRA model. Despite its ability to predict social behavior, TRA has the limitation of not fully explaining when an individual is not in control of his behaviour (Chan and Lu, 2004).

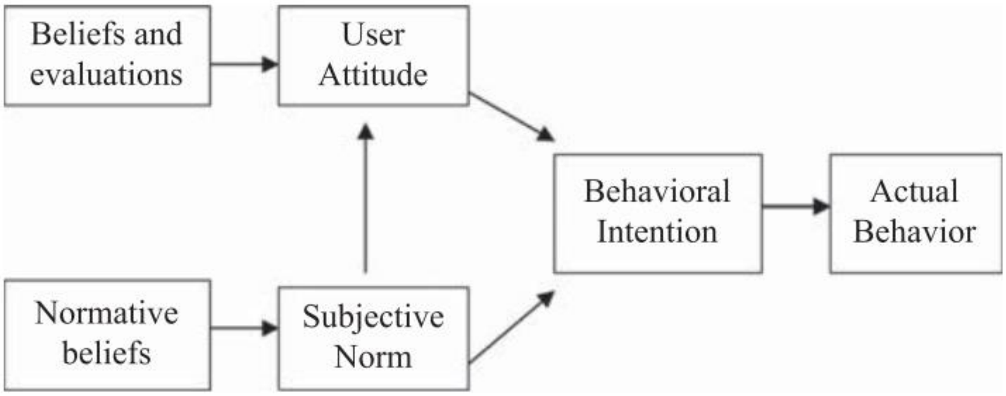



*Figure 2:2: Theory of reasoned action* *Source: Davis et al., 1989*

Behavioral intention refers to the chances of performance of any voluntary act. A person's feelings (whether favourable or negative) about engaging in a certain conduct are referred to as their attitude toward behaviour.

### 2.2.2. Technology Acceptance Model (TAM)

TAM, postulated by Fred D. Davis in 1989, is among the most extensively applied models to explain technology adoption (Lee, Kozar, & Larsen, 2003). It originated from TRA and elucidates factors influencing technology adoption by an individual. TAM comprises of two psychological variables, namely, perceived usefulness (PU) and perceived ease of use (PEOU), which influences people's behavioral intention towards technology adoption. Perceived usefulness is "extent a person considers using a technological innovation improves efficiency thus performance at work" (Davis, 1989) whereas perceived ease of use is "the extent a person considers using a technological innovation is without much effort and facilitates ease in doing a task" (Davis, 1989). In all probability, an individual may perceive an innovation or a technology to be useful and simultaneously consider it difficult to engage with, and it can be interpreted as the task accomplishment benefits of the technological innovation exceeding the efforts made in using it (Davis, 1989). According to studies, PEOU significantly affects PU, and both are thought to be influenced by external variables (Davis et al., 1989). TAM has been studied in several contexts and various geographical settings, including educator's acceptance of e-learning environments (Virani et al, 2020; Pynoo et al., 2011), MOOC adoption (Al-Adwan, 2020), usage of information and communication technology (Kaba and Osei-Bryson, 2013), mobile learning for sustainability in higher education (Al-Rahmi, 2021), and the effect of self-efficacy and perceived usability on technology acceptance by teachers (Holden and Rada, 2011). Figure 2:3 depicts TAM. This model, despite being used in explaining technology acceptance, has many limitations. It was tagged as over simplified (Bagozzi, 2007). Dishaw and Strong (1999) suggested of conducting more research to enhance the validity of the model. One more shortcoming of TAM is that it does not emphasize on the system characteristics as an influencer in technology acceptance, among the users during the performance evaluations (Holden and Rada, 2011). TAM has two key independent variables, namely, perceived ease of use (PEOU) and perceived usefulness (PU) and a dependent variable of BI, TRA, hypothesized as closely linked to actual behaviour (see Table 2-1). TAM was later extended as TAM2, with an additional independent variable of Subjective Norm (present in TRA), added as a predictor of behavioral intention (Venkatesh & Davis, 2000).

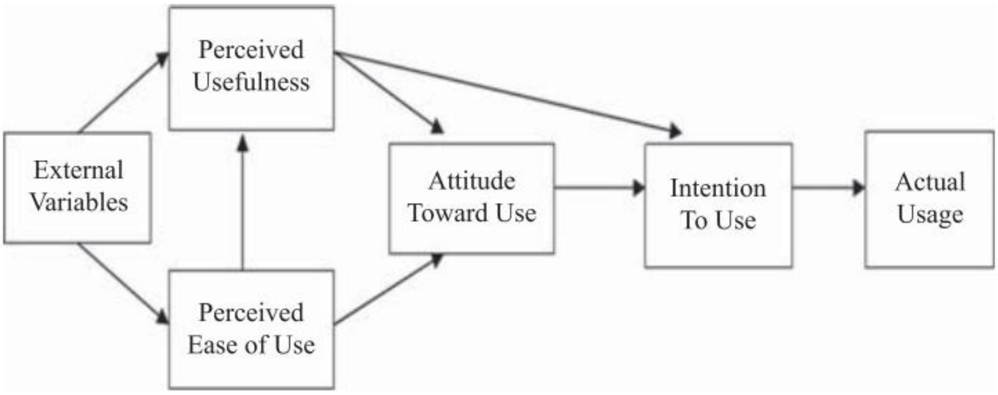



*Figure 2:3: Technology acceptance model* *Source: Davis et al., 1989*

### 2.2.3. Motivational Model (MM)

Many important theories examining individual's intentions and use behavior have emerged from research on motivation. The Motivation Model is a theory that Davis et al. (1992) proposed in relation to the function of motivation in technology adoption. Motivation theory helps explain behaviour in research done in the social sciences. Motivational theory has two important components of motivation, namely, extrinsic and intrinsic motivation. Extrinsic motivation is the belief that users will perform a task in order to achieve valued outcomes such as a pay raise or a job promotion, whereas intrinsic motivation is the belief that an individual will perform a task in order to satisfy his inner self or his inner quest for achievement and success. Many researchers have used this theory to comprehend the adoption of technological innovations (Koo et al., 2015; Venkatesh and Speier, 1999).

### 2.2.4. The Theory of Planned Behaviour (TPB)

TPB (Schifter & Ajzen, 1985) is an extension of TRA (Fishbein & Ajzen, 1975). This theory explains users' behaviour and establishes associations among the variables of belief, attitude, intention and behaviour. TPB refers to three variables describing behavioral intention: attitude towards behaviour, subjective norm, and perceived behavioral control (see Fig. 2:4). Attitude towards behaviour indicates an inclination, for or against, carrying out such behaviour. Attitude is a result of individual beliefs regarding conduct and the consequences, whereas subjective norm indicates belief that a person's acquaintances, namely, friends, siblings, relatives, colleagues, classmates, etc. approve or support a particular behavior (Fishbein & Ajzen, 1973). Subjective norm is the result of two important factors: normative beliefs that an individual attributes to important acquaintances, which shape his behavior, and motivation to act in accordance with their wishes. Last variable of perceived behavioral (PBC) control indicates individuals' perception of their ability or absence of it to perform a particular action (Ajzen & Madden, 1986). Many researchers have used TPB in explaining the technological innovation adoption. In examining learner behaviour and MOOC acceptance (Zhou, 2015; Yang & Su, 2017). Djafarova and Foots (2022), in their study applied the TPB model to comprehend Gen Z virtuous consumerism.

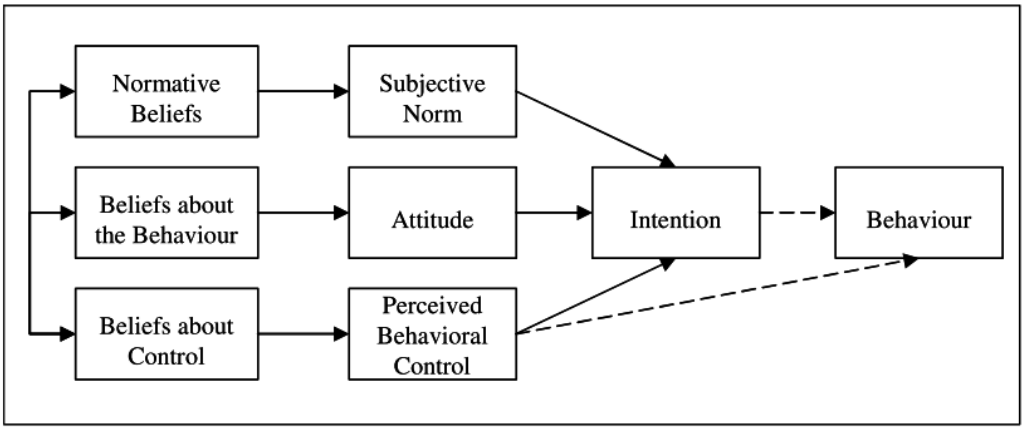



Figure 2:4: Theory of planned behaviour Source: Schifer and Ajzen, 1985

### 2.2.5. Social Cognitive Theory (SCT)

In 1986, Albert Bandura postulated his famous and widely accepted Social Cognitive Theory (SCT), which is used to investigate reasons why a person behaves in a certain manner in a particular situation. He combines the ideas of behaviourism and social learning in his model and postulates that an individual's learning occurs within a group of people and in society by means of constant interaction and exchange of knowledge. It happens on account of continuous interplay of a person, environment, and their behavior. SCT explains that behavior is managed by an individual through cognitive processes, and by environmental factors influenced by external social conditions (Cooper and Lu, 2016). Belief, perception, past experiences and requirements shape an individual's behaviour. Thus, a person's thought process and feelings are connected with his behavioral intention (Bandura, 1986). Bandura (1986) also revealed that environmental factors external to an individual also influence him and predict his behavior. The environment is both a physical and social environment. The physical environment refers to manmade objects and natural things around an individual, whereas the social environment refers to the social and cultural aspects an individual is surrounded by (Barnett & Casper, 2001). It also encompasses social norms, community membership, value system etc. (Bandura, 1991). Behavior is a key component of SCT (Bandura, 1991) and refers to how a person acts and reacts in a particular scenario (see Figure 2:5) and the behaviour also guides them during the technology acceptance (Ratten & Ratten, 2007).

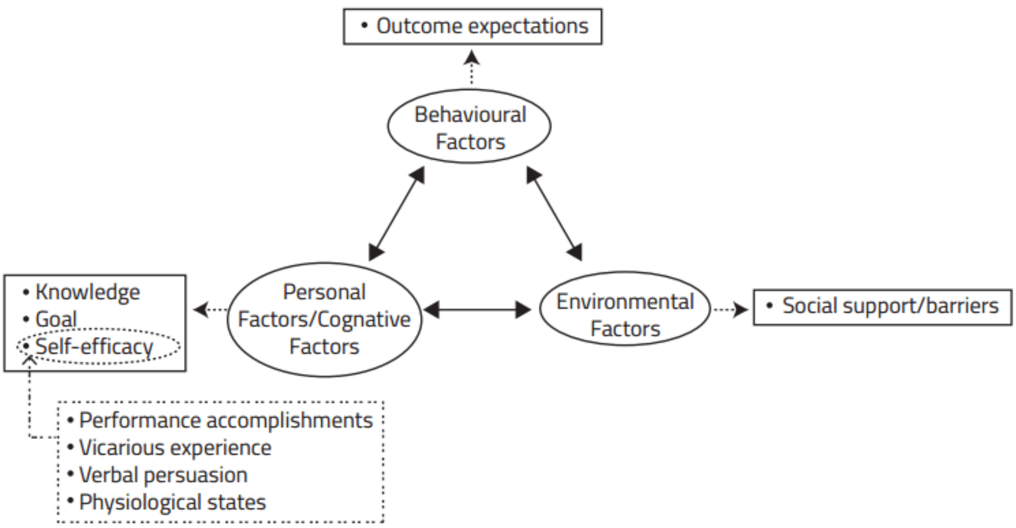



Figure 2:5: Social Cognitive Theory

### 2.2.6. Combined TAM and TPB (C-TAM-TPB)

In 1995, Taylor and Todd postulated a theory integrating the theories of TPB and TAM to achieve better predictive power for a newly conceptualised model of technology acceptance. The model integrated the variables of TPB with PU from TAM (Taylor and Todd, 1995b). This combined theory assumes that a behavior is explained by the intention to exhibit distinct behavior. Intention is predicted by the attitude towards behavior. Taylor and Todd assumed that the variable PEOU has a significant influence on PU (see Figure 2:6). Both PU and PEOU influence the attitude. As a result, attitude, SN, and PBC all have a significant and direct impact on behavioral intention.

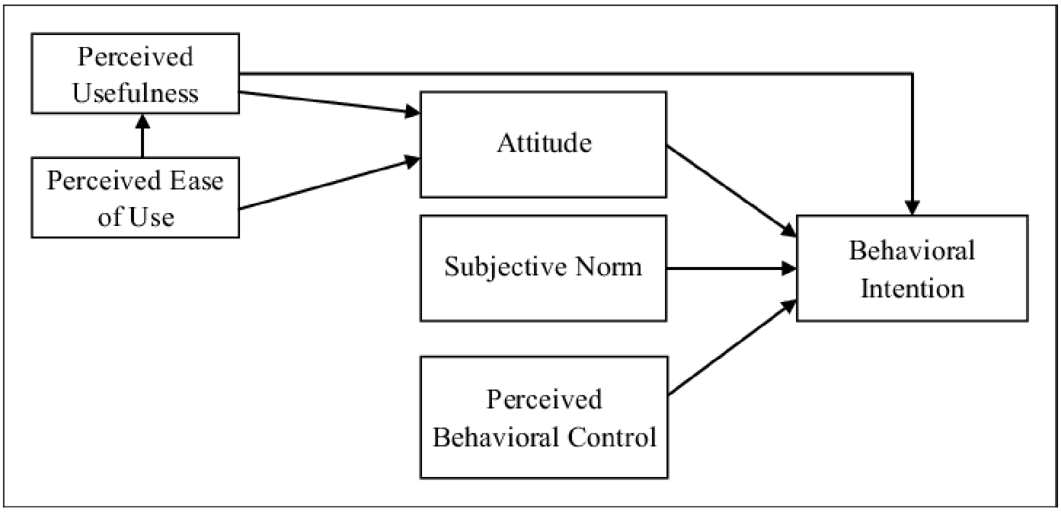



Figure 2:6: Combined TAM and TPB

### 2.2.7. Model of PC Utilization

The Model of PC Utilization (see Figure 2:7) postulated by Thompson and his research team in 1991 highlights that the variables of complexity, social factors, long-term consequences, and job fit have a major influence on personal computer (PC) use. Through his study, Thompson et al. (1991) explained the predictors of use behavior rather than behavioral intention. The variables of this model, namely, Job fit is "the extent to which an individual believes that implementing a technological breakthrough can facilitate and enhance performance at work" (Thompson et al., 1991), Complexity is explained as "the extent an emerging technology is considered hard to learn and adopt (Thompson et al., 1991), Long term consequences are "Results having a redemption in the time ahead" (Thompson et al.,1991), Affect towards use is "different reactions or feelings of happiness, sadness, joy, calmness, solitude, or gloom a person associates with an act" (Thompson et al.,1991). Social factors, taken from Triandis (1977), include norms, roles, and self-concept. Norms are the rules set by society about what is good or bad act to do or not do. Roles can be defined as expected behaviours from people holding positions in a group, while self-concept is an idea that an individual has of him/herself, the goals that an individual must chase or avoid, and the behaviours or the acts that an individual must or must not engage in (Triandis, 1977). Facilitating conditions are described as "tangible variables present in the surrounding environment that make the task easy for the user to perform and achieve" (Thompson et al., 1991).

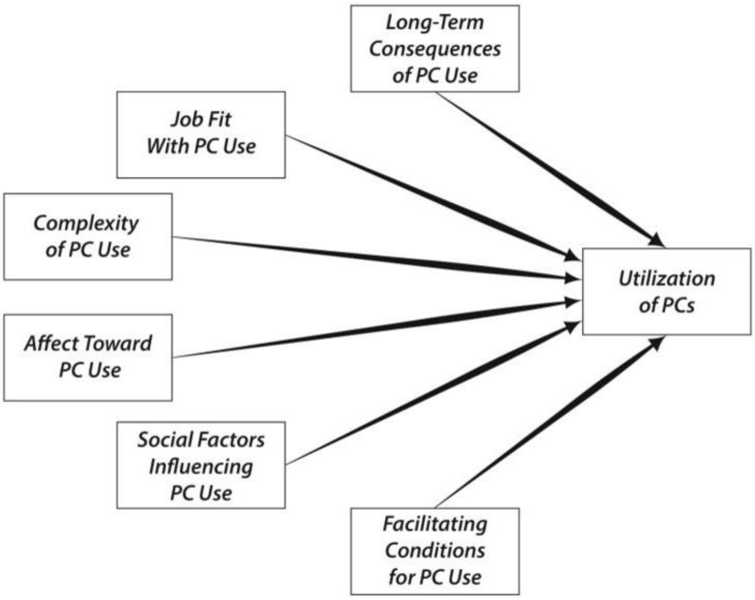



*Figure 2:7: Model of PC Utilization constructs and definition*

### 2.2.8. Innovation Diffusion Theory (IDT)

Innovation Diffusion Theory (IDT) by Rogers (1995) is among the most widely taught and often used theories to predict and explain the reasons for technology adoption among users. IDT explains the attributes of innovation affecting individuals' namely, complexity, compatibility, relative advantages, trialability, and observability (see Figure 2:8). Innovations that are regarded to be compatible with current practises and beliefs, offer less complexity, greater prospects, and are more noticeable, diffuse more quickly (Dillon and Morris, 1996). Compatibility can be defined as a perception of a person towards an innovation being in consonance with the prospective user's previous experiences, existing values, and needs. Likewise, Moore and Benbasat (1991) define compatibility as a degree by which a system or innovation observed is in line or expected to be in line with an individual's current standards, needs, requirements, etc. In the extant literature, compatibility has been frequently referred to and used as an important predictor of attitude towards adopting an innovation and BI to use (Venkatesh, Morris, Davis, & Davis, 2003). Trialability is a degree to which a person has the certainty of trying an innovation before making up their mind to accept it or not. An innovation that is testable signifies the positive intent of a consumer towards buying it. As regards complexity, it is described as users' perceived level of effort in comprehending the new technology and its adoption. Observability is explained as the "level of degree by which the outcome of innovation is clearly noticeable to those who are likely to adopt it". The extent to which a technological innovation is perceived as more advanced to an already-in-use system or technology is known as its relative advantage.

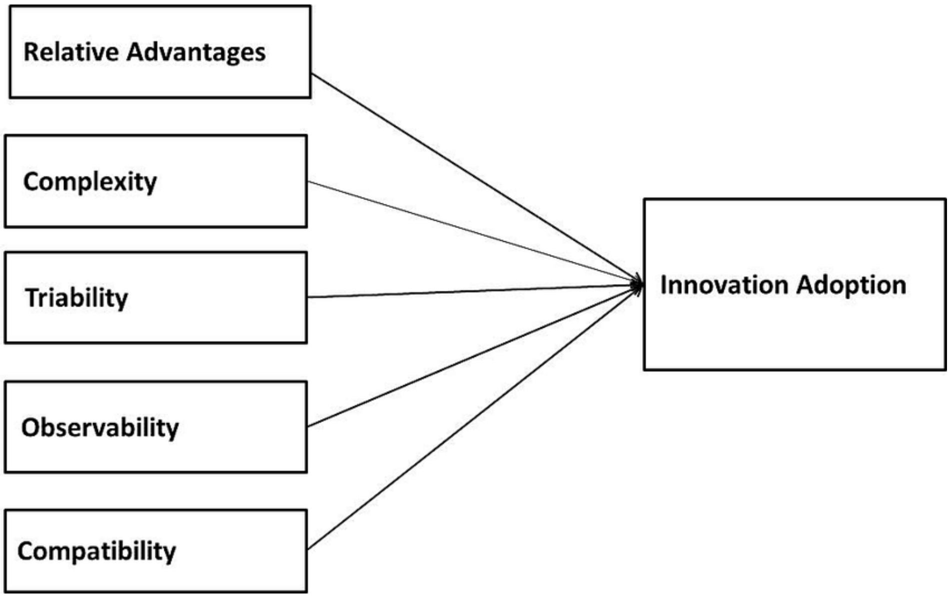



*Figure 2:8: Innovation Diffusion Theory constructs*

All the existing adoption theories and models are based on different knowledge streams, such as, IDT is grounded in sociology, TRA in social psychology (Taherdoost, 2018), SCT and TPB are psycho-social theories (Taherdoost, 2018). All these models and theories, to a great extent, have been effective in explaining diverse reflections of human behaviors in different settings and contexts.

### 2.2.9. Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) advanced a well-researched Unified Theory of Acceptance and Use of Technology (UTAUT) by synthesizing eight extensively used technology adoption theories and models, namely, TRA, TPB, TAM, MM, C-TAM-TPB, SCT, MPCU, and IDT. In organisational settings, UTAUT was proposed to explain users' behavioral intentions to adopt a technological innovation introduced in the organization. In their research work, they shared the findings of six-months of research conducted in a few organizations, suggesting that the eight contributing theories and models on technology adoption indicated a percent of variance in the range of 17 and 53 percent in users' intention to use technology. However, UTAUT has delivered the best result among all the eight individual theories, showing an adjusted $R^2$ of 69% (Venkatesh et al., 2003). The Theory of UTAUT comprises of four variables and four moderators affecting behavioral intention and use behavior. The theory (see Figure 2:9) explains the effect of constructs of performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) on behavioral intention (BI), which in turn predicts use behaviour. Gender, experience, voluntariness of change, and age were the moderating factors of BI (Venkatesh, 2000).

The graphical representation of UTAUT model:

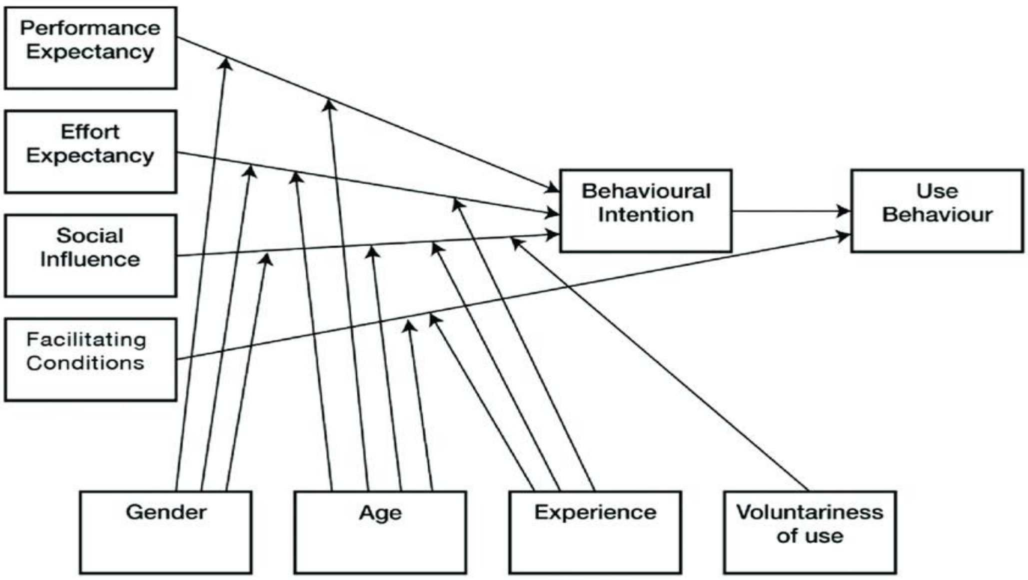



*Figure 2:9: UTAUT Model*

The explanation of UTAUT constructs by Venkatesh et al. (2003) is as follows –

**Performance Expectancy (PE):** Performance Expectancy is the extent to which a person feels that implementing a technology innovation would help him increase productivity and efficiency (Venkatesh et al., 2003).

Root constructs of PE and its definitions is as per the Table 2-2.

**Table 2-1: UTAUT root constructs and explanation – Performance Expectancy**

| **Performance Expectancy** | |
|---|---|
| Construct | Definition |
| Perceived Usefulness (Davis et al. 1989; Davis 1989) | Extent by which an individual think that using a technology would improve and strengthened performance at work. |
| Extrinsic Motivation (Davis et al. 1992) | Belief an individual carry out a task thinking of achieving the valued outcomes, such as salary hike or a job promotion. |
| Job-fit (Thompson et al. 1991) | Characteristics of technological innovation improving a persons' performance at work. |
| Relative Advantage (Moore and Benbasat,1991) | Extent an emerging technology is considered advanced than its antecedent. |
| Outcome Expectations (Compeau and Higgins,1995) | Outcome expectations is segregated into performance expectations which is work related and personal expectations which is individual related. |

**Effort Expectancy (EE):** Effort Expectancy measures how much a person or organization believes implementing a technology innovation will be simple and easy. Root constructs of EE construct and its definitions are as per the table (see Table 2-3) below –

**Table 2-2: UTAUT root constructs and definition – Effort Expectancy**

| **Effort Expectancy** | |
|---|---|
| Construct | Definition |
| Perceived Ease of Use (Davis et al. 1989; Davis 1989) | Extent an individual thinks that use of a technology is easy. |
| Complexity (Thompson et al. 1991) | Extent a technology is considered tough to comprehend and put in use. |

| | |
|---|---|
| Ease of Use (Moore and Benbasat,1991) | Extent adopting a technology or system is considered easy to use. |

**Social Influence (SI):** An individual belief that his important acquaintances (family, friends, classmates, colleagues etc.) feels he should adopt a technology. The root constructs of social influence construct and its definitions are as per the table (see Table 2-4) below –

**Table 2-3: UTAUT root constructs and definition – Social Influence**

| **Social Influence** | |
|---|---|
| Construct | Definition |
| Subjective Norm (Fishbein and Azjen 1975; Davis et al. 1989; Ajzen 1991; Mathieson 1991; Taylor and Todd 1995a, 1995b) | Belief that important others (acquaintances) think that we should adopt a technology or not. |
| Social Factors (Thompson et al. 1991) | Effects of societal influence on individuals. |
| Image (Moore and Benbasat,1991) | A belief on how utilization of a technology is considered to strengthened an individuals' status in the society. |

**Facilitating Conditions (FC):** An individual belief that there exists a support in the organization, be it technical or non-technical towards the adoption of an information system or technology. Root constructs (Table 2-5) of facilitating construct and its definitions are as per the table below –

**Table 2-4: UTAUT root constructs and definition – Facilitating Conditions**

| **Facilitating Conditions** | |
|---|---|
| Construct | Definition |

| | |
|---|---|
| Perceived Behavioral Control<br>(Taylor and Todd 1995a, 1995b; Ajzen 1991) | Individuals' perception of their ability or absence of it to perform a particular action |
| Facilitating Conditions (Thompson et al. 1991) | Support present in organizational system making the task easy for the user to accomplish. |
| Compatibility (Moore and Benbasat,1991) | Perception of a person towards an innovation being in harmony with the potential user's prior experiences,<br>existing, values, and needs. |

Based on literature review it is affirmed that UTAUT is one among the extensively used theory to explain technology adoption on account of its better explanatory power than any other theory or model on technology adoption. Williams et al. (2015) posited that UTAUT was postulated by diligently studying and synthesizing eight dominant theories on technology adoption. Many researchers have successfully utilized these theories in explaining technology adoption and the diffusion of these theories in multiple disciplines namely, psychology, information and communication technology, management, information systems, marketing etc. UTAUT gives a strong foundation to future research on technology acceptance (Abushanab & Pearson, 2007). In a study on how viable UTAUT Model is in a Non-Western Context, Al-Qeisi et al. (2015) posited that the UTAUT is useful in explaining online behaviour in non-western cultures too. McGrath et al. (2014) admired UTAUT model's ability to explain factors effecting the intention to use any technological innovation.

A study by Persada et al., (2019) posited UTAUT explaining 33% of respondents' behavioral intention in using Digital-Learning. Fianu & Blewett (2020) extended UTAUT model with additional constructs of instructional quality, system quality, and computer self-efficacy to explain MOOC adoption in Ghana. Raza et al., (2021) posited that social isolation, PE, SI, and

EE are important factors influencing students' use of LMS in the HEIs of Pakistan during the pandemic COVID-19. Ejiaku (2014) reported of several challenges encountered during ICT adoption in developing nations and posited that the required IT infrastructure, training of the employees, policies, and the culture of the country were the major challenges. Various research work have suggested that technology adoption does not have to do with only added features and extended benefits of technology alone but has also to do with the several other factors be it innovation, communication channels, time and social system (Roger, 1971); BI, attitude, and SN (Ajzen & Fishbein, 1975); affect, anxiety, observation (Bandura, 1986); factors of PU and PEOU (Davis, 1989); factors of PE, EE, SI and FC (Venkatesh et al, 2003).

### 2.2.10. UTAUT Model and Extended UTAUT2

***Background of UTAUT2 Model***

The advent of the internet and advancement in technology are touching every facet of an individual's life, and the emergence of new technology has increased the adoption of technological innovations among users in non-organizational contexts, which has necessitated user-focused research, e.g. extended UTAUT (Tamilmani et al., 2019). As postulated by UTAUT, the variables of PE, EE, SI, and FC significantly affect the BI of a user to adopt a technology, whereas BI and FC elucidate technology usage (Venkatesh et al. 2003). The seminal work on UTAUT revealed the benefits and utilitarian value of technology and it was developed for an organizational setting considering employee adoption of technology. Therefore, to have the broader acceptability of the model from an individual user perspective, the UTAUT model was extended with three new independent variables of hedonic motivation, price value, and habit to explain technology adoption among individuals in non-organizational settings, and the extended model is popularly referred to as UTAUT2 (Venkatesh et al., 2012). In UTAUT2, voluntariness of use is not taken as a moderator since user behaviour is voluntary and doesn't have any organizational command (Venkatesh et al., 2012).

Added variables explained are as below:

**Hedonic Motivation (HM):** It refers to an element of enjoyment, pleasure, and fun obtained by using technology (Brown and Venkatesh, 2005). Any new technology adopted by a user with the goal of providing self-fulfillment rather than utilitarian value to the home, and which only caters to an individual's fun and pleasure needs (Heijden, 2004). In information system research, HM (also used interchangeably with term perceived enjoyment in some studies) reportedly has a significant influence on acceptance of and application of technology (Heijden, 2004). In the consumer settings, HM is a key measure of technology adoption and use (Brown and Venkatesh 2005; Childers et al. 2001). Therefore, the UTAUT model was extended with HM to spell out consumers' BI to use technology. Yang (2010) revealed that HM, PE, SI, and FC significantly impact United States consumers' BI to use mobile shopping services.

**Price Value (PV):** UTAUT was developed and validated in the organizational settings and not in consumer settings. The main difference between these two settings is that in organizational settings, employees do not have to pay for accessing office technology set up or any other infrastructure. However, in case of an individual, it is not the case. He has to pay the price for adopting new technology, which makes him think about the cost of the product, which influence his buying behaviour. It is usually perceived that anything costly has good quality (Zeithaml, 1988). In light of these claims and patterns of behaviour, price is defined as an individual's mental evaluation of the perceived advantages of a technical innovation and the cost associated while adopting it (Dodds et al. 1991). Price as a construct has been added in the extended UTAUT on account of the difference between an individual's use and the organizational use setting, as in a user setting an individual buys the technological innovations however in case of the organizational settings, it's the organization. An individual's use of technology is significantly influenced by the cost of any goods or services.

**Habit (HT):** It can be defined as "an individual exhibiting a behavior in an automatic manner on account of learning" (Limayem et al. 2007), whereas Kim et al. 2005 defined it as "an automatic behaviour that occurs without any evaluations or intention; thus, repetitive past usage of any product results in automaticity, which is known as habit (HT). It has two features. First, it is regarded as a behavior (Kim and Malhotra 2005); second, it is assessed to what extent a person regards a behavior or action as automatic as a result of learning. EE, SI, FC HM, PV and HT, significantly influence BI, whereas BI, FC, PV and HT influence use behavior. Gender, age, and experience all play moderating roles. The extended model of UTAUT2 with new constructs of HM, PV, and HT has an explanatory power considerably higher as compared to UTAUT (see Figure 2:10) explaining 52 percent of the variance in users' technology use and 74 percent of the variance in users' intention (Venkatesh et al., 2016).

Graphical representation of UTAUT2 –

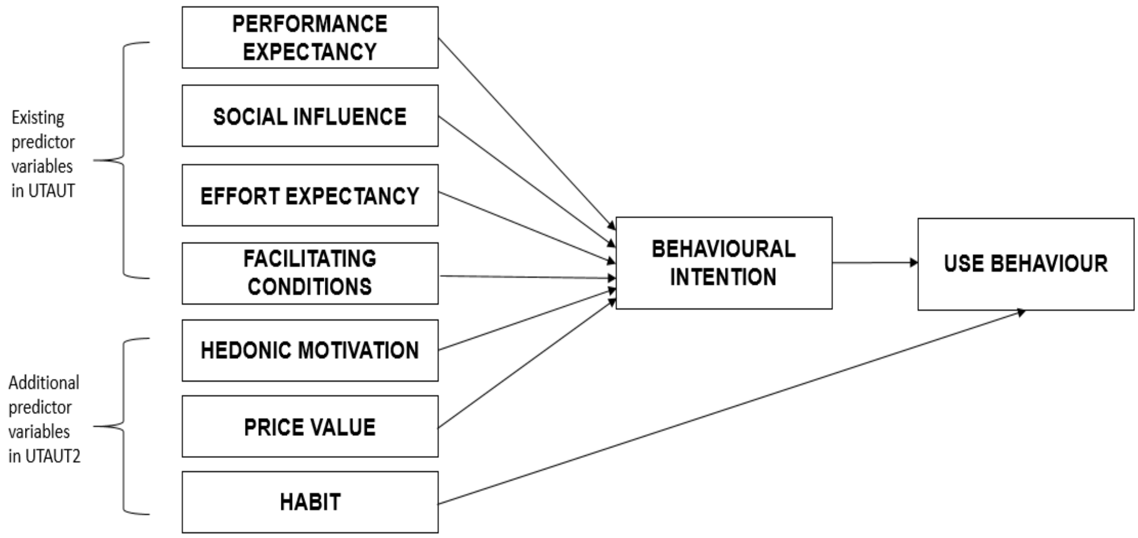



Figure 2:10: UTAUT 2 Model

### 2.3 Summary

This chapter gives a basic background on the eight widely used technology adoption models and theories used to explain technology adoption among organizations and individuals and the subsequent evolution of UTAUT by synthesizing these theories. Finally, this chapter explains the extended theory of UTAUT known as UTAUT2, setting the tone for the next chapter on literature review.

# 3 CHAPTER 3: LITERATURE REVIEW

## 3.1 Introduction

Despite significant growth in India's internet and smartphone user bases, adoption of MOOCs among Indian students has not kept pace with this growth. This chapter sheds light on the factors affecting the adoption of emerging technologies and also explores the factors that on adding to the existing theories and models, may enhance the explanatory power of those model by comprehensively reviewing the previous studies. The extant literature claims TAM to be one of the most used models in explaining technology adoption. However, in recent years, use of UTAUT in explaining technology adoption has grown on account of its better explanatory power (Tamilmani et al., 2021). Future studies should contemplate applying UTAUT2, which is an extended version of UTAUT with additional variables namely, HT, PV and HT added to it, to explain technology adoption (Chaiyasoonthorn et al., 2021). This chapter explains how emerging technologies are being adopted (including MOOCs) using the UTAUT theory postulated by Venkatesh et al. (2003), by citing relevant extant literature on the subject matter. Furthermore, this chapter also elaborates on gap identification, research gaps, and research objectives followed by hypothesis development.

## 3.2 UTAUT and Technology Adoption

The theory of UTAUT2 was propounded in the year 2012. It has received more than 6000 citations (Tamilmani et al., 2021) in IS and other fields, underlining its strong explanatory power and giving researchers enough reasons to use UTAUT2 as a theoretical framework in studying technological innovation adoption in consumer settings (Tamilmani et al., 2021). UTAUT2 studies are widely used in the user settings however it is not restricted to studying a phenomenon in the user context alone. Researchers have used the UTAUT2 theory to comprehend various user categories, such as "Citizens" adoption of m-health (Dwivedi et al., 2016). Furthermore, UTAUT2 has been used extensively in research to better understand the phenomenon of technology adoption across multiple domains (Herrero, San Martn, & Garca de los Salmones, 2017). Hu et al., 2020 applied UTAUT2 to explain mobile technology adoption among faculty members in HEIs. The adoption of learning management systems (LMS) among pre-service instructors was proven by Raman et al (2013). El-Masri and Tarhini (2017) used it to explain why e-learning systems were adopted in the United States and Qatar. Nikolopoulou et al. (2020) used it to explain the use of mobile handsets for studies by university students. Dhiman et al. (2020) used it to explain consumer adoption of smartphone fitness apps.

Eneizan et al. (2019) utilised it to explain customer acceptance of mobile marketing in Jordan. Tseng (2019) used it to explain teachers' adoption of MOOCs in Taiwan, while Mittal et al. (2021) explained the phenomenon of online teaching adoption in the HEIs of India during the COVID-19 pandemic.

### 3.2.1 UTAUT and MOOC: Global Experience

Online learning and ICT are transforming the educational environment around the world. The acceptance of such technologies has been tested using different theories and models that use different variables and constructs. UTAUT is one of the most widely applied theories to understand users' intentions and use behaviour towards varied technologies. As per research scholars' understanding and knowledge, the theory of UTAUT has not been studied and used to explain the phenomenon of MOOC adoption intention among Gen Z in the educational settings of India during COVID-19. UTAUT has been appreciated for its power to explain factors that influence and determine the adoption of a new technology. UTAUT has been tested in several technology adoption surveys in many industries, and its validity and reliability have been empirically confirmed. McGrath et al. (2014) revealed that UTAUT has been admired for its ability to suggest the factors of influence that regulate the approval and adoption of technological innovations. A study by Abushanab & Pearson (2007), used UTAUT in explaining internet banking adoption in Jordan, while Bhatiasevi (2016) used it to explain mobile banking adoption in Thailand. Im et al. (2011) applied UTAUT in a cross-cultural study to investigate the influence of culture on the adoption of two technologies: the MP3 player and Internet banking. Rodrigues et al. (2016) used UTAUT to elucidate the intention to use government services, while Gruzd et al. (2012) used it to explain the BI to use social media. Hoque & Sorwar (2017) tested and validated the UTAUT model in the context of adoption of health information technology and mHealth services. In the context of explaining the adoption of educational technologies too, UTUAT has been used in some studies (Decman, 2015; Ngampornchai et al., 2016; Rosaline and Wesley, 2017; Lawson-Body et al., 2018; Chaiyasoonthorn et al., 2021; Fianu et al., 2018). Wang et al. (2009), tested and validated extended UTAUT to explain m-learning adoption in Taiwan. Dulle & Majanja (2011) applied UTAUT to explain the adoption and use of open educational resources by scholars in Tanzania. Zur and Friedl (2021) highlighted the use of MOOCs in the workplace, resulting in just in time upskilling of employees and also giving them access to the external knowledge pool and intercultural learning. A study by Hone and Said (2016) posited that MOOC content, instructor interaction, and perceived effectiveness were found to play a significant role in learners' continuous use of MOOCs and recommended that MOOC providers incorporate a learner-instructor interaction component in MOOCs to enhance learner retention.

The extended theory of UTAUT, termed as UTAUT2, postulated in 2012, has garnered more than 10795 citations on Google scholar (as of July, 2022) in the last decade, mostly on account of its robustness to elucidate technology adoption in user settings. UTAUT2 has been assessed and evaluated in various settings. Researchers used it to elucidate the phenomenon of emerging technology adoption intentions and its use. Arenas-Gaitan et al. (2015) used it to elucidate the use of internet banking among elderly people in Spain. Mobile-payment and mobile-banking adoption (Slade et al., 2013). Mapping apps' adoption among travellers (Gupta & Dogra, 2017), Near-field communication (NFC) mobile payment adoption in hotels (Morosan, 2015). Online hotel reservations (Chang et al., 2019). m-shopping fashion app adoption (Khurana et al., 2019). Adoption intention and use of online games (Ramrez-Correa et al., 2019) and online shopping adoption intention and use (Tandon et al., 2020). Suo and colleagues, 2021), Intention to use social commerce (Shoheib and Abu-Shanab, 2022). Telemedicine adoption (Chen et al., 2021), intention to adopt personal cloud services (Schmitz et al., 2022). Users' intention to adopt m-commerce (Vinerean et al., 2022).

In the realms of explaining educational technology adoption intention and use, El-Masri et al. (2017) tested and validated the applicability of UTAUT2 in e-learning systems adoption. Altalhi's (2020) study reveals the positive and direct effects of BI, FC, and attitude on MOOC usage, as well as the indirect effect of PE on MOOC usage. Alowayr (2020), used it to explain learners' intention to adopt mobile learning in cross-cultural settings of Iraq and Saudi Arabia. Alvi (2021) used it to explain the intention of using social networking tools for learning among college students. Faqih and Jaradat (2021) utilised the theories of Task technology fit (TTF) and UTAUT2 to explain users' adoption intention of augmented reality in educational settings. Similarly, Buabeng-Andoh Charles's (2012) study highlighted that if a teacher has a positive attitude towards using technology and e-learning, then the same can be easily translated into students also adopting technology to facilitate their learning process and the role of an effective teacher elevates to that of a facilitator and an expert, once the lecture component of the course is outsourced to the MOOC instructor (Bruff, 2013). While UTAUT2 has been assessed and evaluated in different technological, environmental, geographical, and cultural settings to validate its appropriateness to explain adoption, there is a paucity of research on its applicability in the online learning context, especially in the emerging economies of the world (Mittal et al., 2020).

Only a few studies have used and tested UTAUT2 in the context of online learning. To analyse the phenomenon of MOOC adoption intention among Gen Z, Meet and Kala (2022) used UTUAT2, while Raman and Don (2013) examined teachers' acceptance of learning management software (LMS). Tseng et al. (2019), study on MOOC adoption by teachers; Hu et al. (2020), study on emerging mobile technologies adoption; Kala and Choubey (2022), study to figure out associations between variables of student technology acceptance, perceived learning, and student engagement on tourism-related MOOCs; Osei et al. (2022), study to understand the influence of personality traits on BI to adopt e-learning systems; a few studies have used UTAUT2 to explain the BI to use e-learning systems (Ibrahim et al., 2017; Salloum et al., 2019; Jameel et al., 2020; Raman and Thannimalai, 2021) and a study by Jung and Lee (2020), to understand the BI towards the use of open educational resources (OER) across different cultures.

Contemplating the scarcity of research using UTAUT2 to explain the phenomenon of MOOC adoption intention, researchers should use UTAUT2 as a theoretical framework to generalise its appropriateness and applicability.

### 3.2.2 UTAUT and MOOC Adoption: Indian Experience

MOOC adoption is growing, though not at the pace expected by experts. MOOCs have an immense potential to democratise education in a developing nation such as India, which has a tertiary education GER of just 27.1 (AISHE, 2019-20) and can complement offline education in skilling, reskilling, and upskilling the learners in a big and cost-efficient way. The world’s total MOOC user base has surpassed the 220 million-student mark across the world. By the end of 2021, more than 950 universities around the world had roughly 19,400 MOOCs on offer, with 70 degree-based courses (classcentral.com, 2021). In the last few years, MOOC enrolment has improved. India has emerged as Coursera's second-largest market after the United States, with 13.6 million users (businesstoday.in, 2021). The leading MOOC platforms in India are SWAYAM, NPTEL, mooKIT, and IITBX. The theory of UTAUT has been examined and identified as an acceptable model to study technology adoption in online digital learning. There is much research on technology adoption taking place in India in the context of new technological innovations. However, to the authors’ knowledge, there is a handful of research done on e-learning or MOOC adoption among Gen Z using UTAUT2 as a theoretical foundation in the Indian context. A review of the extant literature revealed some studies done in this regard. Using UTAUT, Mulik et al. (2018) discovered that PE, EE, SI, and FC, as well as the extended construct of perceived value, have a positive effect on MOOC adoption intention. Rosaline and Wesley (2017), in a study to explain the adoption of ICT tools among students, established a significant positive impact of factors PE, EE, and SI on BI to use ICT tools. In their study, Mittal et al. (2021) recognise PE, HM, and SI as major determinants influencing the intention to adopt online teaching. Alvi (2021) highlighted the role played by the variables of PE, EE, and SI in shaping the behavioral intention of students to use social networking tools in learning. Dhiman et al. (2020) study to investigate consumer adoption of smartphone fitness apps revealed EE, SI, HT, and the extended constructs of perceived value and personal innovativeness as the significant predictors of smartphone fitness app adoption intention, while a study by Mohan et al. (2020) highlighted PE, HT, and HM as significant predictors of MOOC adoption intention, whereas the influence of other factors such as EE, SI, and FC were found to be statistically insignificant.

Gupta (2020) posited that learners' BI to use MOOCs is positively impacted by perceived value, intrinsic motivation, social recognition, and perceived usefulness, whereas the factors of personal readiness, peer influence, and self-regulation didn't impact BI to use MOOCs. Another study found that academic recognition, openness, autonomy, and cost effectiveness of MOOCs are the significant determinants of MOOC adoption intention among students (Gupta, 2019). Trehan and Joshi (2018) attributed online communicative efficacy and self-directed learning as a significant predictor of MOOC adoption intention. Singh and Sharma's (2021) study revealed SI and FC to be the significant predictors of MOOC adoption intention among the students, besides the role of the factor of self-regulation in positively influencing self-efficacy among students while pursuing MOOCs. Meet et al.'s (2022) study on MOOC adoption among Gen Z reveals that HM, PV, PE, EE, and FC have a positive effect on the intention to use MOOC. However, the constructs of SI, and HT have a statistically insignificant impact.

MOOCs are in their nascent stage in India. There is an urgent need not only to create a clear understanding of MOOCs and their acceptance among teachers, but also to provide them with adequate training and infrastructure to create and use MOOCs in their routine classroom settings for better learning outcomes (Nath, 2019, Virani et al., 2020, Nayar and Koul, 2020).

The Theory of UTAUT2 has explained the impact of eight factors viz. PE, EE, FC, SI, HM, PV, and HT on BI and use behavior. However, several researchers have opined that language competency, teacher influence, and educational characteristics of students play a role in MOOC adoption. Hence, the need to evaluate the same has been felt by the scholar. Another problem staring at MOOC adoption and its sustainability is the completion of MOOC courses with majority of students leaving it in the middle. The leading MOOC platforms have a poor completion rate to the tune of 15 per cent for those who have enrolled for the course before its start (Hollands & Kazi, 2018). Many MOOCs have poor completion rates as low as 4 per cent or 5 per cent (classcentral.com, 2018). While MOOC have gained popularity among the urban people who have begun to explore various courses for their self-development and progression in career, rural people still have poor awareness and acceptance of MOOC despite the required infrastructure in many geographical areas which is a concerning area to study and understand (Raja & Kallarakal, 2020).

Review of the extant studies has led to the identification of following research gaps –

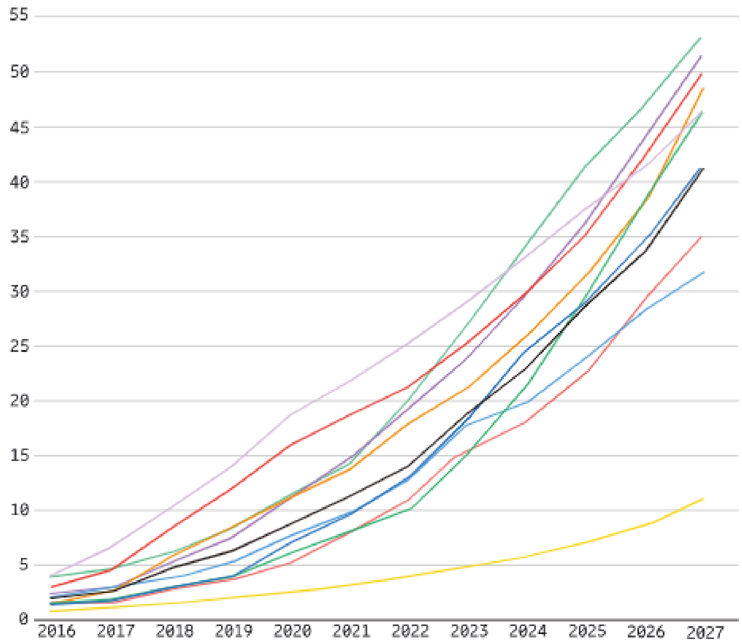
### 3.3 Research Gap

**RG1: There is a need to study factors leading to the adoption of MOOC among Gen Z**

Despite tremendous rise in internet and smartphone penetration in India, adoption of MOOC among Indian students is not corresponding to the growth in internet and smartphones. India would have 900 million Internet subscribers by 2025 as against 622 million in 2020, anticipating a robust rise in number by 45% in the coming five years painting a rosy picture for online education business in India. This growth is pushed by the huge rise in smartphone users at 750 million in 2021, which is forecasted to increase to 1 billion by 2026 catalysed majorly by the rural population, as per the report of Deloitte's 2022 Global TMT projections.

COVID-19 outbreak made every individual confined at home and dependent on the telecom infrastructure of the country, to fulfil home and office needs such as online education, zoom calls, office video conferencing, remote health consultations, online ordering, OTT content consumption, amongst others. As per the report, about 96% of internet subscribers use it for entertainment, 90% for communication and 82% for social media platforms. Around 45% of the internet users have made online transaction and 28% of them shop online regularly. Other key activities include gaming, learning and video streaming (economictimes.indiatimes.com, 2021).

This dependence on the mobile networks, to remain connected for work has seen data consumption per smartphone increasing from 16.1GB per month in 2020 to 18.4GB per month in 2021 (see Figure 3:1) and has made India second-highest globally in data consumption per smartphone and the trend is projected to grow to 50GB per month by 2027 (ericsson.com, 2021).




| Regions | 2021 | 2027 | CAGR 2021–2027 |
|---|---|---|---|
| North America | 14.6 | 52 | 24% |
| Western Europe | 15.2 | 51 | 23% |
| India | 18.4 | 50 | 18% |
| North East Asia | 13.9 | 48 | 23% |
| South East Asia and Oceania | 8.0 | 46 | 34% |
| GCC | 22 | 46 | 13% |
| Middle East and North Africa | 9.6 | 41 | 27% |
| Global average | 11.4 | 41 | 24% |
| Latin America | 7.9 | 35 | 28% |
| Central and Eastern Europe | 9.9 | 32 | 22% |
| Sub-Saharan Africa | 2.9 | 11 | 25% |

*Figure 3:1: Mobile data traffic per smartphone (GB per month)* *source: ericsson.com, 2021*

The share of 18.4 GB of this data consumption per user per month is more with any other technology platform than an online education platform and the same is evident from the growth being witnessed in other internet-based technology platforms. Besides the reasons listed in figure 3:2, India's online video market, ride hailing industry and online food delivery market have registered good growth. OTT market in India is growing at a faster pace and is considered an important market for not only India but entire world (ericsson.com, 2021).

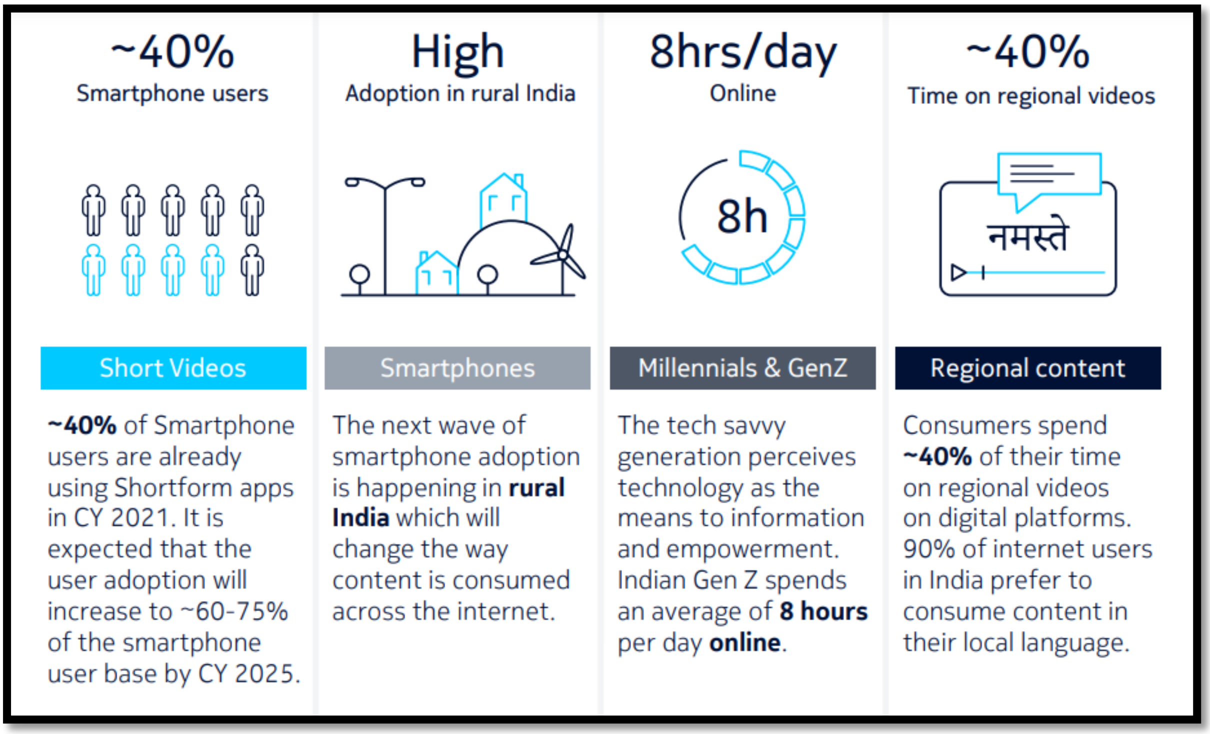



*Figure 3:2: The key drivers of data consumption* *Source: nokia.com, 2022*

It is projected that India will have 500 million plus video users by FY 2023, second only to China (KPMG, 2019)

- In India, monthly internet video traffic is anticipated to reach 13.5 Exabytes by 2022, an increase of 1.5 EB from 2017. By 2022, video traffic would account for 77% of all internet traffic (KPMG, 2019).
- India's total video market, which includes online platforms and television, will achieve $18 billion by 2026, from existing $11.6 billion. By 2026, 25% of the broadband users will pay for the sports content and online entertainment. (livemint.com, 2021).
- According to projections, India's ride-hailing market is projected to rise from $15.3 billion in 2017 to $43.3 billion by 2025, and the number of fleet vehicles would increase to 4.2 million from the current 1.4 million (Business Standard, 2019).
- The online meal delivery industry in India is anticipated to increase at a compound yearly growth rate of 30.55% (based on revenue) and 10.19% (based on number of users) between 2020 and 2024, generating $ 19.5 Bn in revenue and 300.57 Mn users by that time. Swiggy, FreshMenu, Faasos, and Zomato are significant companies in India's online meal delivery sector (Businesswire, 2020).
- Against this backdrop, we have currently 22 million registered users in SWAYAM and 13.6 million registered users of Coursera in India (businesstoday.in, 2021) suggesting

of a big chasm between availability of resources and its adoption (classcentral.com, 2021).

Another problem staring at MOOC adoption and its sustainability is the completion of MOOC courses with majority of students leaving it in the middle. The leading MOOC platforms have a poor completion rate to the tune of 15 per cent for those who have enrolled for the course before its start (Hollands & Kazi, 2018). Many MOOCs have a dismal completion rate as low as 4 per cent to 5 per cent (classcentral.com, 2018). While MOOC have gained popularity among the urban people who have begun to explore various courses for their self-development and progression in career, rural people still have poor awareness and acceptance of MOOC despite the required infrastructure in many geographical areas which is a concerning area to study and understand (Raja & Kallarakal, 2020).

**RG2: There is a need to study the influence of language competency on MOOC adoption among Gen Z**

Researchers emphasised the importance of conducting research to know the influence of language competency on BI to use technology and learning outcomes (Alcorn, 2013; Kornhaber et al., 2015; Jung & Lee, 2020). Language competency can be defined as students' knowledge of a language in which online education content is created and delivered. In IS research, it is posited that language impacts technology adoption (e.g. Gaskell & Mills, 2014; Zhang et al., 2017; Palange, 2019; Deng et al., 2019). Language used in creating and delivering MOOCs has a strong influence on learners in developing countries (Raja & Kallarakal, 2020), and this should be considered when designing and developing a MOOC (Shah & Khanna, 2021). Alcorn (2013) from the University of Pennsylvania pointed out that HEIs in India must take cognizance of the huge gap in demand and supply of quality education, its accessibility and affordability and HEIs must participate in designing and developing MOOCs of courses in demand in Indian vernacular language. Aldahdouh & Osório, (2016) posited the importance of language competency in MOOC enrolments and highlighted that students do MOOCs that are developed and delivered in language they are familiar with, and the same was echoed by Connolly (2016) in his study explaining barriers in online education. Education is all about connecting and engaging with the learners, and to do so communication plays a key part in the entire learning process, be it an online education or offline; learning outcome of an individual is posited to be superior if the course is taught in native language (UNESCO, 2008). In this context, if we see the linguistic diversity of India in terms of number of languages spoken (see

Table 3-1) and the number of speakers. According to reports, 528 million people in India speak Hindi as their first language, making it the most often used first and second language overall. In contrast, English ranks 44th as a first language and is the second-most widely used second language (www.livemint.com, 2020).

Table 3-1: Language by number of speakers in India (2011 Census)

| First language speakers | | Second language | Third language | Total speakers | | |
|---|---|---|---|---|---|---|
| Language | Figure | speakers | speakers | % of total population | Figure | % of total population |
| Hindi | 52,83,47,193 | 43.63% | 13,92,07,180 | 2,41,60,696 | 69,13,47,193 | 57.09% |
| English | 2,59,678 | 0.02% | 8,31,25,221 | 4,59,93,066 | 12,92,59,678 | 10.67% |
| Bengali | 9,72,37,669 | 8.03% | 90,37,222 | 10,08,088 | 10,72,37,669 | 8.85% |
| Marathi | 8,30,26,680 | 6.86% | 1,29,23,626 | 29,66,019 | 9,90,26,680 | 8.18% |
| Telugu | 8,11,27,740 | 6.70% | 1,19,46,414 | 10,01,498 | 9,41,27,740 | 7.77% |
| Tamil | 6,90,26,881 | 5.70% | 69,92,253 | 9,56,335 | 7,70,26,881 | 6.36% |
| Urdu | 5,07,72,631 | 4.19% | 1,10,55,287 | 10,96,428 | 6,27,72,631 | 5.18% |
| Gujarati | 5,54,92,554 | 4.58% | 40,35,489 | 10,07,912 | 6,04,92,554 | 4.99% |
| Kannada | 4,37,06,512 | 3.61% | 1,40,76,355 | 9,93,989 | 5,87,06,512 | 4.84% |
| Odia | 3,75,21,324 | 3.10% | 49,72,151 | 31,525 | 4,25,51,324 | 3.51% |
| Punjabi | 3,31,24,726 | 2.74% | 23,00,000 | 7,20,000 | 3,60,74,726 | 2.97% |
| Malayalam | 3,48,38,819 | 2.88% | 4,99,188 | 1,95,885 | 3,55,38,819 | 2.93% |
| Assamese | 1,53,11,351 | 1.26% | 74,88,153 | 7,40,402 | 2,35,39,906 | 1.94% |

Source: https://en.wikipedia.org/

In India, with internet penetration on the rise and its ease of accessibility across geographies, people are comfortable accessing content in the language of their choice. A report by Google suggested that in India, 90% of people search for content online in their local language (services.google.com, 2020). With an increasing number of users adopting the internet, the "3Vs", voice, video, and vernacular, have become important to the way Indians interact with the internet (financialexpress.com, 2021). Many Indian startups these days are "Going Local" by making their content available in local languages, which in turn is helping them to expand their user base. NextBigBrand unicorns, namely, Policybazar, InMobi, Byju’s, Zomato, etc., now have their content available in two to twelve regional languages (nextbigbrand.in, 2022). A report by Flipkart suggested that 15 million daily users connect to their application through a vernacular interface in the Hindi language with a retention rate of 95%

(thehindubusinessline.com, 2021). To provide ease of access to customers, Amazon also launched its services in various vernacular languages in India. As per industry reports, by the end of 2021, 75% of internet users will access content in their vernacular language. This burgeoning base of internet users, mainly from smaller towns, makes it mandatory for the e-commerce service providers to introduce access to their online marketplace in regional languages to provide a personalised and better experience (business-standard.com, 2021). A report by Ernst and Young (2022) highlighted that around 95% of the news consumption in India is happening in vernacular languages, and with the proposed launch of low-cost smartphones in the country, local news portals will further get a boost. According to projections, 60% of television viewing in 2025 would come from vernacular languages, up from 55% in 2020, and 50% of streaming video viewing will come from vernacular languages, up from 30% in 2019. (assets.ey.com, 2022). Researchers must look into how language proficiency affects BI acceptance of MOOCs given the variety of languages spoken in India and the proportion of non-native English speakers. Less research on learner factors such as English language ability, employment status, and previous MOOC experience in recent MOOC studies makes drawing meaningful conclusions difficult; thus, studies exploring MOOC delivery in vernacular language and its impact on MOOC adoption intention should be investigated (Deng et al., 2019 and Jung & Lee, 2020).

**RG3: There is a need to study the influence of teachers on MOOC adoption among Gen Z**

In ICT acceptance research, it is posited that senior leadership of an organisation plays a big part in determining the successful execution of ICT (Lee et al., 2005; Neufeld, 2007; Pynoo et al., 2011). Similarly, a need has been observed to assess and evaluate teachers' propensity and influence in encouraging online education to complement learning and the outcomes among MOOC learners (Bruff, 2013; Milligan et al., 2016). The term "teacher's influence" points to the role performed by a teacher in motivating students to supplement their in-person instruction with online courses in order to hear from a renowned professor who has a unique viewpoint on the subject matter. The teacher has a significant impact on how students behave both online and offline, and the teacher's prior exposure to and experience using online tools for teaching as well as their level of comfort using and managing MOOCs as either a developer or a student can influence students to pursue online learning (Garrison et al., 2000; Tseng, 2019; Jung and Lee, 2020). Chang et al. (2015) posited teachers' advice as one of the main reasons students enrol in MOOCs. Pynoo et al. (2011) suggest that principals or the school leadership team who nurture the policy of transparency, open communication, foster team spirit and trust, and communicate school vision, mission, and goals clearly to one and all in their team have a far greater influence on their colleagues and subordinates, which in turn reflects on the on-ground implementation of directives and policies. Milligan et al. (2016) study revealed that instructors could positively impact the learning processes of MOOC participants and suggested a great scope to evaluate instructors' qualities to influence MOOC learners. Wang et al. (2019) posited the relationship between teachers' technical and educational qualifications matters when it comes to technology adoption and a positive relationship between the two only results in teachers adopting certain technology. They proposed future studies to be undertaken on how teachers generate and organize the educational orientation of MOOC and how the college environment and culture affect the formation of teachers' teaching and technical concepts. et al. (2020) revealed the significant positive influence of instructor characteristics on BI towards e-learning platforms meant for medical education, followed by PE and learning value. Gharrah and Aljaafreh's (2021) study posited that the constructs of PE, SI, EE, HT and lecturer support have a significant and direct effect on the use of social networking sites for learning purposes in Jordanian universities.

**RG4: There is a need to study the influence of educational characteristics of students (courses enrolled, nature of degree & type of institution) in MOOC adoption**

In technology acceptance research, the need has been felt to conceive a model that encompasses factors that relate to education (Radovan & Kristl, 2017) and negligible research has happened on this matter, especially in online learning and MOOC contexts. The educational characteristics of students refer to the course, degree, and institution they are enrolled in. The Abu-Shanab (2011) study acknowledged the role of education as a moderator in relationships between adoption intention and other factors. Al-Ashban and Burney's (2001) study to explain telebanking adoption revealed that users' level of education plays a significant part in adoption intention and use of telebanking, while a study by Laukkanen and Pasanen (2008) suggested an insignificant influence of educational level in differentiating users' BI. Porter and Donthu (2006) study posited that education is related distinctively to beliefs about the Internet, and these beliefs impact the attitude of a user towards internet use. People with higher qualifications have better computer and information processing skills, which may make it easier for them to use the internet (Nasri, 2011). Highly educated people utilise online banking more frequently than the lesser educated people (Izogo et al., 2012). The study of students' educational characteristics (courses enrolled, nature of degree & type of institution) would provide researchers and practitioners with insights that would aid in the design and marketing of MOOCs.

Several researchers have given future research directions on extending present technology acceptance theories on account of research gaps, to enhance their explanatory power and generalizability. Venkatesh et al. (2012) used Weber’s (2012) framework of assessing, evaluating, and developing theories in the IS area to analyse UTAUT and its extensions, and identified limitations of this literature. In total, sixty-two UTAUT-based research papers, journals, and conferences suggested future studies to undertake the refinement of theory.

The potential for UTAUT extensions as a field of study to theoretically advance IS research on the adoption of technology and its use is huge (Venkatesh et al., 2016). Williams et al. (2015) noted that while some scholarly work has happened on MOOC adoption by American, European, and Chinese scholars, miniscule scholarly work has happened on technology adoption, particularly in MOOCs in Indian settings, which gives academicians and research scholars a platform for collaboration and work on, the evaluation and application of some pertinent and important theories. UTAUT2 has explained the effect of eight factors, viz. PE, EE, SI, FC, HM, PV, and HT on BI and towards technology adoption with a predictive power of 69% with 31% variance unexplained. Several researchers have opined that language competency, teacher influence, and educational characteristics of students play a significant role in MOOC adoption. Therefore, there exists a need to extend UTAUT2 with these variables to study MOOC adoption among Gen Z using UTAUT2 with additional variables.

To summarize, the research gaps (see Table 3-2) are as follows –

Table 3-2: Research gaps

| | |
|---|---|
| **RG1** | There is a need to study factors leading to the adoption of MOOC among Gen Z |
| **RG2** | There is a need to study the influence of language competency on MOOC adoption among Gen Z |
| **RG3** | There is a need to study the influence of teachers on MOOC adoption among Gen Z |

| | |
|---|---|
| **RG4** | There is a need to study the influence of educational characteristics of students (courses enrolled, nature of degree & type of institution) in MOOC adoption |

### 3.3. Research Questions

Based on the gaps presented above the managerial challenges posed can be summarized (see Table 3-3) in following research questions.

Table 3-3: Research questions

| | |
|---|---|
| **RQ1** | What are the factors leading to the adoption of MOOC in Gen Z? |
| **RQ2** | What is the influence of language competency on MOOC adoption amongst Gen Z? |
| **RQ3** | What is the influence of teacher on MOOC adoption amongst Gen Z? |
| **RQ4** | What is the influence of educational characteristics of students (courses enrolled, nature of degree & type of institution) on MOOC adoption in Gen Z? |

### 3.4 Research Objectives

A review of extant literature posited that scarce scholarly work has happened in the field of MOOC adoption by Gen Z, especially in Indian educational settings. Research has shown that the factors of PE, EE, SI, and FC have a positive influence on the adoption intention of e-learning platforms. Further to the same, we concur to the research done by Baker, Al-Gahtani, & Hubona, G. S. (2007), Dokument, D., & Nutzung, D. (2010), Buabeng-Andoh Charles. (2012), Wang & Xu, (2015), Wang et al., (2019), Tseng (2019), suggesting that language competency, teachers' influence, and educational characteristics of the students (courses enrolled, nature of degree, and type of institution) may also have a major influence on the adoption intention of online learning and the same is to be explored. Many researchers have focused on the behaviors commonly demonstrated by Gen Z. However, the factors effecting the adoption of MOOCs by Gen Z have not been extensively researched in Indian educational settings. Developing this insight is critical for the educators and marketers of the MOOC platform to take adoption of the MOOC platform to a higher level, thereby benefiting the users in acquiring knowledge-based skills. This will enable Gen Z to be successful at college and, subsequently, at the workplace. Based on the review of extant literature and identified study gaps, the following objectives (see Table 3-4) are framed for the present research work:

**Table 3-4: Research Objectives**

| | |
|---|---|
| **RO1** | To identify factors which affect the adoption of MOOC in Gen Z. |
| **RO2** | To examine impact of language competency on the adoption of MOOC among Gen Z studying in the institutes of higher education in India. |
| **RO3** | To examine impact of teachers' influence on the adoption of MOOC among Gen Z studying in the institutes of higher education in India. |
| **RO4** | To examine influence of the educational characteristics of students (courses enrolled, nature of degree & type of institution) on the adoption of MOOC. |

Thus, the main objective of the research is to identify the factors impacting MOOC adoption among Gen Z studying in the HEIs of India. Future studies should contemplate the UTAUT2 model to study technology adoption, which is an essential aspect of our research work. Consequently, we have adapted extended UTAUT2 to assess and evaluate its appropriateness and applicability as a model in relation to MOOCs in the Indian context and also to research the influence of extended factors of language competency, teacher influence, and educational characteristics of students (courses enrolled, nature of degree & type of institution) on MOOC adoption, which once proved, will enhance the explanatory power of the extended UTAUT2 model.

### 3.5 Hypotheses Development

Last decade has seen the rise of MOOCs, and they are gradually becoming a part of the learning processes of millions of students across the globe (classcentral.com, 2020). MOOCs' emergence as a cost-efficient and scalable, and omnipresent educational technology can help the government in democratising education with social inclusion (UNESCO, 2016).

An extensive review of literature acknowledges that UTAUT is among the most extensively used theories to explain technology adoption, primarily on account of it being developed by the synthesis of eight different theories (Williams et al., 2015). Seminal work on UTAUT has four independent constructs namely, PE, EE, SI, and FC, successfully explaining BI of learners in an e-learning context (Chaiyasoonthorn et al., 2021; Persada *et al.*, 2019; Fianu *et al*., 2018;

Dečman, 2015; Rosaline & Wesley, 2017), whereas the extended framework UTAUT2 was created to clarify the adoption of technology in consumer contexts (Jewer, 2018). However, there hasn't been much research done on evaluating and assessing the application of UTAUT 2 in the educational settings. (Mittal *et al*, 2021). Few studies which has employed UTAUT2 to explain technological innovation adoption in educational context are authored by El-Masri and Tarhini, 2017; Tseng *et al*., 2019; Mittal *et al.*, 2021. Considering fewer studies and variability in the generality of the existing research, it has been recommended to employ UTAUT2 as a theoretical foundation in future studies (Chaiyasoonthorn et al., 2021).

Venkatesh *et al.* (2012), who postulated UTAUT2, demanded its extension so that its predictive power is enhanced. Therefore, an extended version of UTAUT2 was used in the present work to identify factors impacting the adoption intention of MOOCs among Gen Z, as statistical evidence explaining the phenomenon in the Indian context is not available. Based on the recommendation of the extant literature (Tseng *et al*., 2019, Milligan *et al*., 2020), the present research work employed UTAUT2 and extended it with two more constructs, namely, language competency (Jung & Lee, 2020; Deng *et al*., 2019) and teachers' influence (Tseng *et al.*, 2019; Pynoo *et al.*, 2011; Chang *et al*., 2015). This work was carried out also to validate the influence of existing UTAUT2 constructs of PE, EE, SI, FC, HM, PV, and HT (Venkatesh *et al*., 2012) on Gen Z BI to use MOOCs in the Indian context. A person indulges in using technology based on the understanding that the use of technology may upgrade, amplify, and strengthen performance. Existing research on technology adoption has shown that the variable performance expectancy (PE) has a significant positive impact on BI's decision to employ e-learning (Jambulingam, 2013; Deman, 2015; Fianu et al., 2018; Mulik et al., 2018; Persada et al., 2019). Because of its applicability, the PE concept has encouraged people to engage in online teaching and learning during COVID-19 (Mittal et al., 2021). The study hypothesised that the digitally savvy Gen Z in higher education institutions that are being kept at home to prevent pandemics from spreading may view MOOCs as a source of knowledge and skill enhancement, which would strengthen and improve their employment and employability in the workforce and workplace, respectively. Therefore, it is posited that:

***H1**. Performance expectancy influence Gen Z Behavioral Intention to adopt MOOC.*

Effort expectancy (EE), which is similar to ease of usage (TAM), is defined as a "degree of ease of use in handling any technical breakthrough with less efforts" (Davis et al., 1989, Thompson et al., 1991, Moore and Benbasat 1991). Previous research have suggested that EE has a favourable impact on BI's capacity to employ new technology (Venkatesh et al., 2003; Im et al., 2010). Al-Adwan (2020) claimed that perceived ease of use (effort expectancy) has a favourable influence on an individual's BI to embrace a MOOC. According to a 2016 study by Weinswig, Gen Z may find using MOOCs to be simple and convenient due to their natural aptitude for using digital devices and the internet. Therefore, it is posited that:

***H2.*** *Effort Expectancy influence Gen Z Behavioral Intention to adopt MOOC.*

Social influence plays a vital role in our buying behaviour and the same applies when it comes to buying any innovative product or service, be it a recently launched technology product. The social construct was not a part of TAM theory; however, it was included in UTAUT, which improved its explanatory power as social influence impacts a user's behavioral intention (Mulik et al., 2018, Gupta et al., 2008). The influence of society on a person when it comes to adopting a new product is defined as the influence of family, friends, acquaintances, institutions, and their beliefs (Venkatesh et al., 2003), and this point has been acknowledged in previous studies on technology adoption (Tseng et al., 2019; Al-Adwan et al., 2018; Radovan, 2017; El-Masri and Tarhini, 2017).

This construct of social influence shares a similar definition as that of subjective norm, an independent construct used in two prior models, namely, TAM2 (an extension of TAM) by Venkatesh & Davis (2000) and Theory of Planned Behavior (TPB) by Ajzen and Fishbein (1980). Studies report that the current generation falls back on the advice of family, friends, and peers to adopt technological innovations (Rosaline & Wesley, 2017; Persada *et al*., 2019). Similar behaviour can be observed among adolescents and college-going Gen Z on social media platforms where they are found seeking external validation of their presence by means of likes, comments, and shares from their kith and kin. Thus, it is posited that:

***H3***. *Social influence impact Gen Z Behavioral Intention to adopt MOOC.*

The Facilitating Conditions (FC) construct is a composition of variables picked up from various studies, such as Perceived Behavioral Control (Ajzen, 1991; Taylor and Todd 1995a, 1995b), Facilitating Conditions (Thompson et al. 1991), and Compatibility (Moore and Benbasat, 1991). FC is defined as users' cognition about the presence of resources in the environment, i.e. at home or work, to carry out a task efficiently (Venkatesh *et al*. 2003; Brown and Venkatesh 2005). Extant literature revealed FC positively impacts BI and use behaviour of online learners (Persada et al., 2019, Chang et al., 2019; El-Masri and Tarhini, 2017; Fianu et al., 2018) and the adopters of ICT (Šumak and Šorgo, 2016; Rosaline and Wesley, 2017). Taking cognizance of this, NEP (2020) of India envisages ramping up the online learning ecosystem for learners (IBEF.ORG, 2022) across the country to promote education. Thus, it is posited that:

***H4**. Facilitating conditions influence the Behavioral Intention of Gen Z to adopt MOOC.*

The definition of hedonic motivation (HM) is "the degree of pleasure, happiness, and fun obtained using a technology" (Brown and Venkatesh, 2005). The level of customer satisfaction determines whether technological improvements are adopted in the online world (Yang et al., 2012). HM has a big impact on BI's decision to use internet-based technologies such e-learning, mobile banking, learning management systems, digital social media, etc. (Venkatesh et al., 2012; Raman and Don, 2013; Moorthy et al., 2019; Baptista and Oliveira, 2015). Previous research has indicated that HM influence the BI towards technology use (El-Masri and Tarhini, 2017; Moghavvemi et al., 2017). Gen Z is being influenced by social media-fueled peer pressure to value experiences more highly and to live an intensely immersive lifestyle. Because Gen Z is naturally adept at using digital devices, they will be early adopters of all new consumer technologies (Weinswig, 2016). Thus, it is posited that:

***H5.** Hedonic motivation influence Gen Z Behavioral Intention to adopt MOOC.*

The pricing value (PV) is described as a user's "mental exchange between the perceived benefits of using a technology and the amount spent for using it" (Venkatesh et al., 2012). Existing literature has demonstrated the direct influence of PV and BI on online learning (Tseng et al., 2019; Raman and Don, 2013; El-Masri and Tarhini, 2017). Since the focus of the study is college-bound adolescents between the ages of 18 and 23 who depend on their parents for monthly subsistence. Therefore, it is posited that:

***H6.** Price Value influence Gen Z Behavioral Intention to adopt MOOC.*

The term "habit" (HT) refers to "an automatic behavior that occurs without any evaluations or intention" (Limayem et al., 2015). Prior studies revealed that HT has a significant effect on the BI and use behavior of a user (Venkatesh *et al*., 2012), e.g., the impact of HT on internet-based technologies' adoption intention (Gaitan et al., 2015; Gupta and Dogra, 2017; El-Masri and Tarhini, 2017). This study assumes that Gen Z has a learned behavior to use technology due to their innate ability to handle digital devices (Weinswig, 2016), which may positively affect their adoption intention to use MOOCs. Thus, it is posited that:

***H7.*** *Habit influence Gen Z Behavioral Intention to adopt MOOC.*

Language proficiency relates to a student's understanding and proficiency in the language used to generate and distribute online educational materials. Language has an impact on how new technologies are adopted in the field of IS and internet-based technologies (Gaskell and Mills, 2014; Zhang et al., 2017, Deng et al., 2019, Palange, 2019). According to the body of existing research, the factor of language in emerging nations has a significant impact on the students' decisions to enrol in MOOCs (Aldahdouh and Osório, 2016; Raja and Kallarakal, 2020). For local learners who are not fluent in a foreign language, taking a MOOC in a language other than their own could be challenging. In order to democratise education, all worldwide MOOC platforms should consider offering MOOCs in local languages (Jung and Lee, 2020). It is also to be noted here that the population of English-speaking individuals in India is second only to that in the United States (mapsofworld.com). Studies in the past have stressed the significance of examining how language affects online learning (Kornhaber et al., 2015; Lopez et al., 2020; Deng et al., 2019; Jung and Lee, 2020). Investigating the impact of language proficiency on MOOC adoption intention is crucial given the variety of languages spoken throughout Indian states. Given the ubiquity of non-native English speakers participating in MOOCs, it is hypothesised that their language proficiency affects Gen Z's BI with regard to MOOC uptake. Thus, it is posited that:

***H8****. Language competency influence Gen Z Behavioral Intention to use MOOC.*

The role a teacher plays in encouraging and motivating a learner to supplement offline learning with online education for the purpose of knowledge and skill development is referred to as the teacher's influence. Teachers, who are viewed as change agents, have a significant impact on students' cognition and use behaviour toward online learning (Pynoo et al., 2011; Lee et al., 2005; Neufeld, 2007; Pynoo et al., 2011; Rodrigues et al., 2020). Senior leaders in an organisation also play a significant role in determining the success or failure of the ICT implementation (Hone and Said, 2016; Huang et al., 2019; Hoi and Mu, 2021; Al-Adwan et al., 2021; Melovi et al., 2021). To the best of researcher's knowledge there's negligible research happened in understanding teachers' influence on MOOC adoption. However, few studies have insinuated towards teachers' acting as an influencer and a facilitator in MOOC adoption as they invariably engage the students during the learning process of a particular course (Gharrah and

Aljaafreh, 2021; Prasetyo et al., 2020; Chang et al., 2015; Tseng et al., 2019; Fianu et al., 2020; Jung and Lee, 2020). Students consider teachers to be more erudite than themselves and given the rising need to move towards blended learning, the role of teachers is changing in the online education space. Bruff (2013) considers him a person who can affect the learning process adopted by Gen Z MOOC participants and have a strong impact on the learning mechanism and the outcomes of MOOC learners (Bruff, 2013; Milligan *et al.,* 2020). Thus, it is posited that:

***H9****. Teacher influence influences Gen Z Behavioral Intention to use MOOC.*

Many top educational institutions have begun offering MOOCs as complementary to traditional education in enhancing specific knowledge or cultivating in-demand skills (Chang et al., 2015). In technology acceptance research, the need has been felt to conceive a model that encompasses factors that relate to education (Radovan and Kristl, 2017), and negligible research has happened on this matter and its impact on online learning and MOOCs. Some researchers have explored the role of education in influencing new technology adoption. A study by Abu-Shanab (2011) posited the significant influence of education as a moderator on the association between behavioral intention and other factors in internet banking adoption. According to Al-Ashban and Burney's (2001) study, education level significantly influences telebanking adoption intentions and use in Saudi Arabia. On the contrary, Laukkanen and Pasanen's (2008) findings revealed that level of education is not significant in differentiating among users. People with higher qualifications have better information processing skills and the competency to handle computers, which can facilitate Internet use (Nasri, 2011). The level of education has a positive correlation with internet usage (Porter and Donthu, 2006). According to Izogo et al. (2012), consumer education level influences e-banking adoption. For educational purposes characteristics of students refer to the course, degree, and institution they are enrolled in. It is opined that educational characteristics have a major influence on MOOC adoption. Therefore, based on future research directions and observations, we posit that:

***H10.*** *The impact of educational characteristics (Courses Enrolled, Nature of degree and Institution) of students on behavioral intention towards MOOC adoption differs significantly.*

Post developing the hypothesis the proposed conceptual model (see Figure 3:3) of the research created is as below -

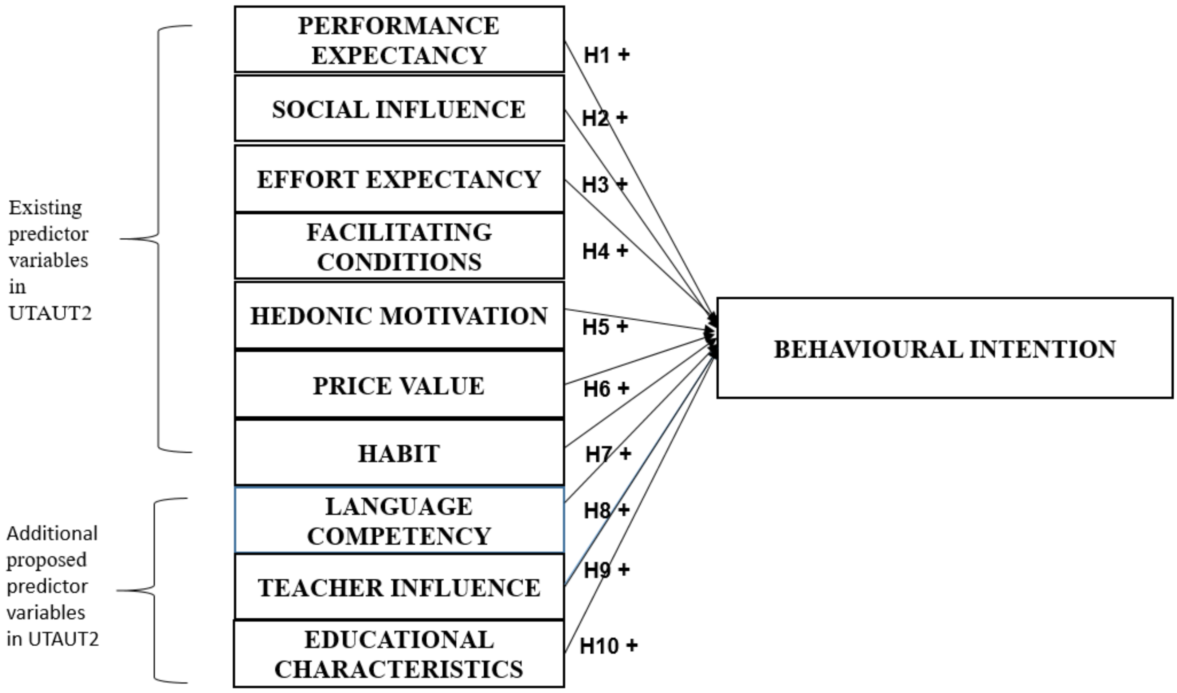



*Figure 3:3: Proposed conceptual model of the research*

### 3.6 Summary

This chapter dwelled in detail on the literature review done on adoption of new technologies and MOOCs in relation to the theory of UTAUT and UTAUT2 chosen for this research and the work done by the researchers so far in this domain, followed by the explanation of research problems, gap areas, and research objectives leading to the development of ten hypotheses, of which seven are reflective constructs and three formative constructs. A post-hoc development conceptual model is created.

# 4 CHAPTER 4: RESEARCH METHODOLOGY

## 4.1 Introduction

The research methodology appropriated in this study is explained in detail in this chapter. It describes various stages in research and the methods used. The first section of the chapter emphasises the selected research methodology. The second section dwells on the research approach and explains the procedure selected for the collection of data and its subsequent analysis. The methods used to conduct research are solely motivated by the fundamental goal of expanding existing knowledge on the adoption of emerging technologies. To be precise, the objective is to explore factors affecting Gen Z MOOC adoption intention. The research is investigative in nature, to find out prominent factors relevant to the research phenomenon. By adopting a quantitative research approach, it is possible to obtain rich information about the topic and subject of study.

## 4.2 Methodology

The research methodology used to conduct this work specifies data collection process, data analysis, and the interpretation proposed by the scholar (Creswell, 2009). Research to gain knowledge can be assessed and evaluated by using qualitative, quantitative, and mixed methods approaches (Creswell, 2009). Two approaches frequently applied in social science research are inductive and deductive (Bryman and Bell, 2007). Quantitative methods are deductive in nature, and the researchers employ statistical measures to conduct the research. A deductive approach is used for testing a theory. A researcher proposes a conceptual model or a theory and develops a hypothesis, followed by a research methodology to evaluate and validate it. Whereas, in the inductive approach, which has to do with building a theory, a researcher would collect and analyse the data and based on the results, develop a theory (Bryman and Bell, 2007; Saunders et al., 2009). The selection of a research strategy solely depends on the objectives of research. According to Creswell (2009), experiments and surveys are two main strategies of inquiry in quantitative studies, whereas ethnography, ground theory, narrative research, case studies, and phenomenology are the methods adopted in qualitative research; and in mixed methods research, both quantitative and qualitative methods are utilised.

## 4.3 Research Design

This section explains research paradigm adopted, research design, sampling process, data collection instruments, and data analysis techniques and tools adopted.

### 4.3.1. Paradigm Adopted in this Study

Positivism is aligned with a deductive approach of research design to examine and verify hypotheses by operationalizing constructs and measures; results derived from hypothesis testing are added to the existing knowledge pool to advance the field of study. Research work carried out using the positivism paradigm focuses on recognising associations or causal relationships between the variables through quantitative methods, where findings from a scientifically chosen sample size are favoured (Park et al., 2020). In the social sciences, research instruments and tools deployed, such as surveys, questionnaires, statistical models, hypothesis testing and theory confirmation, etc., indicate the impact of positivism (Hughes and Sharrock 1997). Many research methods can be utilised to examine the intriguing research queries. However, the current study uses exploratory quantitative research. Based on the recommendations of extant literature and the merit of research, a quantitative method is chosen to test and validate the proposed model (Rodrigues et al., 2021). Research by Meet and Kala (2021) and Alemayehu and Chen (2021) revealed the considerable use of quantitative research methods to study the MOOC phenomenon and to quantify results.

### 4.3.2. Population and Sampling

Population can be described as "the number or group of people staying in a particular geography and is of researchers' interest to examine" (Sekaran and Bougie, 2016). Sampling can be defined as selecting an adequate number of people or the object of study in a manner that represents the true nature of the population of study (Sekaran and Bougie, 2016). Sampling is regarded as a cost-effective and useful method of conducting a research survey because it is practically impossible for a researcher to survey an entire population due to resource constraints, whether financial or time-related, as occurs in the government-mandated Census (Saunders et al., 2009). In carrying out sampling, the probability method and the non-probability method are two sampling techniques used by the researchers. In the probability sampling method, every person in a given population has a chance to be selected for examination, and it is done randomly. Tansey (2007), whereas in the non-probability sampling method, respondents are chosen as per the research objective and the convenience of a researcher, non-randomly (Tansey, 2007).

For this quantitative research study, the probability sampling method was chosen for the following research (Tansey, 2007):

(a) Preventing biasness in sample selection,

(b) Ensuring generalization.

We began our research by choosing the probability sampling method of stratified random sampling for data collection from different strata of higher education institutions viz. private universities, state universities, central universities, deemed universities, college affiliated to central/state Universities, and the autonomous institutes. The choice of sampling method was based on the suggestions of many authors who have researched on technology adoption and have mentioned so in their research limitations (Alraimi et al., 2015; Šumak and Šorgo, 2016; Fianu et al., 2020; Altalhi, 2021). While stratified random sampling was chosen at the beginning of research, to arrive at maximum accuracy in research findings, the onset of pandemic COVID-19 in 2020 threw a spanner in the work in terms of random data collection from the strata chosen for sampling. Thus, we resorted to a multistage sampling method including stratified random, purposive and snowball sampling, requesting acquaintances in the respective strata (universities/colleges) to help collect the data from their respective acquaintances representing the Gen Z cohort.

#### 4.3.2.1 Sampling Frame

A sampling frame (see Table 4-1) is a list of target populations who can be sampled, which may include an institution, individual, or households (Saunders et al., 2009). The sampling frame consists of Gen Z studying in the higher education institutions of India viz., Central Universities, State Universities, Private Universities, Deemed Universities, Autonomous Institutes and Colleges Affiliated to Central/State Universities. Online courses in particular, MOOCs were initially introduced in India in the management streams, engineering/technology, and sciences, so the focus of this research has been kept limited to these streams (Kaushik and Agrawal, 2021).

Table 4-1: Sampling frame (Number of HEIs)

| Name of State | Private Univ.* | State Univ. | Central Univ. | Deemed Univ. | IOE * | IONR * | Total |
|---|---|---|---|---|---|---|---|
| Himachal Pradesh | 17 | 7 | 1 | 0 | 0 | 3 | 28 |
| Punjab | 16 | 12 | 1 | 2 | 0 | 3 | 34 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Delhi | 0 | 9 | 7 | 7 | 3 | 1 | 27 |
| Haryana | 24 | 20 | 1 | 6 | 1 | 2 | 54 |
| Rajasthan | 53 | 24 | 1 | 8 | 1 | 3 | 90 |
| Uttar Pradesh | 32 | 31 | 5 | 9 | 2 | 3 | 82 |
| Uttrakhand | 18 | 12 | 1 | 3 | 0 | 3 | 37 |
| Jammu and Kashmir | 0 | 8 | 2 | 1 | 0 | 3 | 14 |
| Chandigarh | 0 | 1 | 0 | 1 | 0 | 0 | 2 |
| Total | 160 | 124 | 19 | 37 | 7 | 21 | 368 |

*Univ. – University
*IOE - Institute of eminence
*IONR - Institute of national repute

#### 4.3.2.2 Sampling unit

Gen Z (18-23 years of age, born between1995-2010).

As per the Gen Z definition, the age bracket of study cohort falls between 10 years to 25 years age bracket however we have taken the age bracket of 18-23 years for study purpose considering the GER of Higher education in India is computed for the mentioned age bracket (MHRD, AISHE, 2019)

#### 4.3.2.3 Sample and data collection

Due to the spread of COVID-19 pandemic and subsequent to social distancing norms, online surveys (Google Forms) is conducted on Gen Z studying in the HEIs based out of Northern India. Sample size was calculated after considering the sample size determination formulas given by Yamane (1967), Cochran (1977) and Cohen (1988).

Cochran formula (Cochran, 1977) was found to be the most suitable, especially in situations with large or infinite populations (Israel, 1992; Bartlett et al., 2001). Cochran Formula is represented as -

$$n = \frac{Z^2pq}{E^2}$$

Here, "n" refers to the sample size, "$Z^2$" indicates z value located in the z table, "p" refers to the approximated proportion of a characteristics available in the population, q is (1-p) and E is precision level.

Since the population of our study is large, therefore the sample size determination on confidence level of 95%, 5% precision maximum variability of 0.5 comes to –

$n = (1.96)^2\ (0.5)(0.5)\ /\ (0.05)^2$ = 385 Students

### 4.3.3. Questionnaire Method

After identification of the research gaps, a research instrument, viz., a survey questionnaire, was developed. Online surveys are considered to be a faster data collection technique. This technique helps the researcher to reach out to a larger number of respondents quickly and in a cost-effective way (Kraut et al., 2004). In information systems research, survey design is recommended (Azawei and Alowayr, 2020). Many UTAUT-based studies used the survey method to explain educational technology adoption (Hu et al., 2020; Mohan et al., 2020; Jung and Lee (2020); Chen et al., 2021; Osei et al., 2022; Raman and Thannimalai, 2021). Also, many quantitative research on MOOCs based on UTAUT theoretical framework has also used the same method (Fianu et al., 2018; Tseng et al., 2019; Wan et al., 2020; Altalhi, 2020), thus the present research also has utilized survey questionnaire as a tool to collect data.

#### 4.3.3.1. Designing the Questionnaire

Steps followed in framing the questionnaire are as under –

1. Identifying the aim of collecting data to verify research assumptions.
2. Reviewing extant literature to figure out survey instrument designed to access and explain similar phenomenon.
3. To create and calibrate the construct measurement items to evaluate association or causal relationships between the variables.
4. Using sufficient number of items for every construct as -

a. Only one item cannot explain entire construct.
b. Either three or more than three items per construct reduces chances of biasness in parameter estimation (Gerbing and Anderson, 1985; Kline, 2011).

The aim of the questionnaire was to gather feedback of the learners towards factors influencing adoption intention to use MOOCs. Thus, close-ended questions with scaled-response format were used for questionnaire development. Since it is simple for participants to understand and respond, the study used a 5-point Likert scale, ranging from one (strongly disagree) to five (strongly agree) (Pearse, 2011).

While designing an online questionnaire, scholars examined various types of survey tools to choose the most appropriate. Options considered for the online survey were SmartSurvey, Google Forms, and SurveyMonkey. Among these tools, Google Forms was chosen for creating online questionnaires as Google Forms has the advantage of having many add-ons for integration with other tools of survey. The introductory page of the Google Form questionnaire explains the objective of research and instructions pertaining to filling out the form, along with qualifiers (questions), whether the respondents have ever enrolled in MOOCs or not. Those who hadn't qualified for the research criteria of MOOC enrolments were considered non-qualified respondents and were directed to a termination page thanking them for their attempt to be part of the survey. The Questionnaire had five key sections (see Appendix for the instrument). Section A, which is the first section, is designed to understand respondents' initiation into MOOCs and their views on usage frequency and experience with MOOCs. The ensuing Sections B, C, and D are primarily to obtain responses on the variables influencing learners' intention towards MOOC adoption using the Likert scales. Finally, Section E is meant to collect demographic details of the participants using nominal scales. Finally, respondents were urged to briefly write about challenges they faced while pursuing MOOCs and specify the reasons, as it will help in improving the design and structure of MOOCs. And lastly, they were appreciated for their collaboration in filling out the form.

### 4.4. Operationalization of the Variables

Review of extant literature, and feedback received from the interview with experts and FGD of students studying in three B-Schools of Northern India were also taken to operationalize theoretical constructs. Construct items of the questionnaire were adapted from prior studies to adjust into context of the present research. The items of constructs of PE, EE, SI, FC, and BI termed as UTAUT constructs were taken from prior work of Venkatesh et al. (2003) and adapted in relation of MOOCs while the items in the scale assessing HT, HM and PV were adapted from study of Venkatesh et al. (2012) and modified in with the present research on MOOCs. Likewise, for the constructs of language competency and teacher influence, items of the scale were taken from scholarly work of Barak et al. (2015) and Sebastianelli et al. (2015) respectively and revised in context of the present research. All the constructs were measured on a five-point Likert scale with 1= strongly disagree, 2=disagree, 3=neutral, 4=agree, and 5= strongly agree. All the items adopted in this study were framed in English language.

Items per construct are as follows: PE (4 items), EE (3 items), SI (3 items), FC (4 items), HT (3 items), HM (3 items), PV (3 items), BI (3 items) LC (5 items), and TI (5 items). Overall, the survey instrument has 52 items assessing their respective constructs.

Tables 4-2-1 to 4-2-10 represents the operationalization of variables in the conceptual model.

**Table 4-2: Operationalization of Constructs**

**Table 4-2-1: Operationalization of Performance Expectancy**

| Code | Item | Reference |
|---|---|---|
| PE1 | I find Online Courses (MOOCs) useful in my studies | Adapted from Venkatesh et al. (2003), Tarhini and Masri (2017), Persada et al. (2019), Jung and Lee (2020), and modified in context of MOOCs. |
| PE2 | Online Courses (MOOCs) increases my chances of achieving knowledge that is important to me | |
| PE3 | Online Courses (MOOCs) enables me to accomplish my task more quickly. | |
| PE4 | Online Courses (MOOCs) increases my productivity (It adds to my knowledge). | |

**Table 4-2-2: Operationalization of Effort Expectancy**

| Code | Item | Reference |
|---|---|---|
| EE1 | How to use Online Courses (MOOCs) is easy for me. | Adapted from the research of Venkatesh et al. (2003), Tarhini and Masri (2017) Persada et al. (2019), Jung and Lee (2020), and modified in context of MOOCs. |
| EE2 | My interaction with Online Courses (MOOCs) is clear and understandable. | |
| EE3 | I find Online Courses (MOOCs) easy to use. | |

**Table 4-2-3: Operationalization of Social Influence**

| Code | Item | Reference |
|---|---|---|
| SI1 | People who are important to me think that I should use Massive Open Online Courses (MOOCs). | Adapted from the research of Venkatesh et al. (2003), Tarhini and Masri (2017), Persada et |
| SI2 | People who influence my behavior think that I should use Massive Open Online Courses (MOOCs). | |

| | | |
|---|---|---|
| SI3 | People whose opinions that I value prefer that I use Massive Open Online Courses (MOOCs). | al. (2019), Jung and Lee (2020), and modified in context of MOOCs. |

| Table 4-2-4: Operationalization of Facilitating Condition | | |
|---|---|---|
| **Code** | **Item** | **Reference** |
| FC1 | I have the resources necessary to use Online Courses (MOOCs) | Adapted from the research of Venkatesh et al. (2003), Tarhini and Masri (2017), Persada et al. (2019), Jung and Lee (2020), Prasetyo et al.(2021), and modified in context of MOOCs. |
| FC2 | I have the knowledge necessary to use Massive Open Online Courses (MOOCs). | |
| FC3 | Online Courses (MOOCs) is compatible with other technologies (Mobile/Laptops/Tablets) I use. | |
| FC4 | I can get help from others when I have difficulties using Massive Open Online Courses (MOOCs). | |

| Table 4-2-5: Operationalization of Hedonic Motivation | | |
|---|---|---|
| **Code** | **Item** | **Reference** |
| HM1 | Using Online Courses (MOOCs) are enjoyable. | Adapted from Venkatesh et al. (2012), Tarhini and Masri (2017), Jung and Lee (2020), and modified in context of MOOCs. |
| HM2 | Using Online Courses (MOOCs) are very entertaining. | |
| HM3 | Using Online Courses (MOOCs) are fun. | |

| Table 4-2-6: Operationalization of Price Value | | |
|---|---|---|
| **Code** | **Item** | **Reference** |
| PV1 | Online Courses (MOOCs) are reasonably priced. | Adapted from Venkatesh et al. (2012), Tarhini and Masri (2017), Jung |
| PV2 | Online Courses (MOOCs) are a good value for the money. | |
| PV3 | At the current price, Online Courses (MOOCs) provides a good value. | |

| | | |
|---|---|---|
| | | and Lee (2020),and modified in context of MOOCs. |

| Table 4-2-7: Operationalization of Habit | | |
|---|---|---|
| **Code** | **Item** | **Reference** |
| HT1 | The use of Online Courses (MOOCs) has become a habit for me. | Adapted from Venkatesh et al. (2012), Tarhini and Masri (2017), Jung and Lee (2020),and modified in context of MOOCs. |
| HT2 | I am addicted to using Online Courses (MOOCs) | |
| HT3 | I must use Massive Open Online Courses (MOOCs). | |

| Table 4-2-8: Operationalization of Behavioral Intention | | |
|---|---|---|
| **Code** | **Item** | **Reference** |
| BI1 | I will always try to use Online Courses (MOOCs) in my daily life. | Adapted from the research of Venkatesh et al. (2003), Venkatesh and Zhang (2010), Tarhini and Masri (2017) Persada et al. (2019), Jung and Lee (2020), and modified in context of MOOCs. |
| BI2 | I plan to continue to use Online Courses (MOOCs) frequently. | |
| BI3 | I intend to continue using Online Courses (MOOCs) in the future. | |

| Table 4-2-9: Operationalization of Language Competency | | |
|---|---|---|
| **Code** | **Item** | **Reference** |
| LC1 | Students can actively participate in learning if the language of instruction is what they understand well | Items taken from Barak et al. (2015) and |

| | | |
|---|---|---|
| LC2 | Language used in Online Courses (MOOCs) is important for me to adopt it | modified in MOOC context. Inputs received during the FGDs were also considered. |
| LC3 | Language which the students may not be confident with may affect their approach to learning. | |
| LC4 | I find it easy to develop rapport with the teacher delivering Online Courses (MOOCs) in my mother tongue | |
| LC5 | I believe that the Online Courses (MOOCs) if delivered in regional languages will have far wider acceptability | |

**Table 4-2-10: Operationalization of Teacher Influence**

| Code | Item | Reference |
|---|---|---|
| TI1 | I believe my teacher is an expert of his subject | Items were adapted from the research work of Sebastianelli et al. (2015), Prasetyo et al. (2021), and modified into the MOOC context. Inputs received during the FGDs were also considered. |
| TI2 | My teacher is my role model | |
| TI3 | I follow my teacher’s instructions on study related matter | |
| TI4 | My college encourages enrolment in online course (MOOCs) to gain additional knowledge and learn new skills | |
| TI5 | My teachers give additional weightage during evaluation on the successful completion of an online course (MOOCs) | |

Before distributing questionnaire developed in English language, individuals were informed about the participation which was voluntary. Data gathered through this exercise was kept confidential.

### 4.5. Pretesting the Questionnaire

It is extremely important to pretest the survey instrument to detect and determine any mistake committed while designing the questionnaire such as questions framing, vagueness of words etc. and also to confirm the reliability (consistency) and validity (accuracy) of the survey instrument.

To pretest the questionnaire, present research adopted three methods namely, expert panel review, interviews, and a pilot study.

### 4.5.1. Interviews

Five professors from three different premier B-Schools of the country are approached for verifying the content and construct validity of the questionnaire. Similarly, views of students studying in three B-Schools of Northern India were also taken by conducting three focus group discussions (FGD) towards reinforcing and establishing construct validity.

### 4.5.2. Expert Panel Review

The objective of an expert review is to identify and remove out-of-context questions from the questionnaire, reword them as necessary, and identify any potential issues with participants' comprehension of the questionnaire so that they can be fixed for the questionnaire's administration. Two research scholars, three academics, and two business professionals made up the committee of experts charged with analysing and approving the 52-item questionnaire. The pre-defined theoretical constructs and associated items were included in the survey instrument. Three important questions were asked to assess each item: the applicability of the item statement in measuring the construct; the statement's legibility; and the modifications required, if any. Other questions concerning experts' advice were on the size of the questionnaire and the response format (five-Likert scale). All experts were satisfied with the measurement items with the minor suggestion of providing clarity on certain terms or phrases. Based on the expert's valuable feedback, minor changes were incorporated into the questionnaire.

### 4.5.3. Pilot Study

A pilot study was carried out to examine items' discrimination, internal consistency, response rate, and parameter estimation (Johanson and Brooks, 2010). A pilot study was necessary to determine the reliability and validity of the questionnaire items and it was conducted on a sample of 100 students (not a part of the main survey) studying in the HEIs of India who had finished MOOCs during the period April–May '2021. In total, 132 responses were received, out of which 32 responses were removed from research analysis because they had more than

50% of missing data. Thus, only 100 responses meeting research criteria were chosen for analysis. Data analysis was done using IBM SPSS Version 20.0.

### 4.5.4. Reliability and Validity of the Instrument

To check internal consistency of reflective measures, Cronbach's alpha was computed using SPSS Version 20.0. The internal consistency is "degree to which measures are positively correlated. The closer the value of Cronbach alpha reliability is to 1, more reliable are the measurements (Sekaran and Bougie, 2016). Table 4-3 shows the benchmarked values of Cronbach's alpha test of reliability as described by Sekaran and Bougie (2016).

Table 4-3: Values of Cronbach's alpha reliability

| Value of Chronbach alpha reliability | Evaluation |
|---|---|
| Less than 0.6 | Poor |
| In 0.7 range | Acceptable |
| Above than 0.8 | Good |

The Cronbach alpha value of 0.953 confirmed the reliability of the instrument used in the pilot study and the study suggested that the average time taken by the respondents to fill the form was of 10 minutes.

### 4.5.5. Sharing the Final Questionnaire

The hyperlink of the questionnaire was shared with the respondents through email and WhatsApp. The process of data collection took 14 weeks from June-September'2021. After receiving requisite count of responses, questionnaire hyperlink was closed. The response rate of survey conducted was 88.78%. Out of 876 respondents reached over email and WhatsApp for the survey, 544 respondents participated in the survey, out of which 483 responses were used for the final analysis. Cross-sectional research design was adopted in this study and the primary data of 483 students were gathered from Gen Z MOOC learners deploying online survey from various HEIs (see Table 4-4) located in the Northern cities of India using multistage sampling method namely, stratified random, purposive and snowball sampling.

Table 4-4: 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

### 4.5.6. Data Screening

Before moving on to analyse the data, we screened the data as it is a fundamental thing to do before testing the hypotheses (Kline, 2011). Data screening was done to confirm the usability, reliability, and validity of data before applying data tools and techniques for analysis.

### 4.5.7. Number of Responses

In total, we gathered 544 responses in the last and final round of data collection. Of total responses gathered, 61 were rejected, out of which 14 respondents denied using any online course before and rest of the 47 respondents were disqualified on account of 70% plus data missing in their response sheet (questionnaire). Thus, the balance 483 responses were utilized for analysis.

### 4.5.8. Non-Response Bias

On account of prevailing pandemic, online survey was conducted to collect primary data, therefore there's a challenge to calculate the response rate. To address this issue, we assessed difference between the demographic details of the first third and the last third of respondents (Sun et al., 2018). Results indicated no demographic contrast between two sub-groups except the frequency of login. To be sure, we compared the variable means for these two sub-groups to see any difference however didn't find any therefore response bias is not of any concern for this study.

### 4.5.9. Data analysis methods

This study employed descriptive statistics to study the demographic details of the sampled data. Statistical software platforms namely, SPSS 20.0 and Smart PLS 3.0 were used. Structural Equation Modelling (SEM) was used to analyse and assess the relationships between dependent and independent variables of the study. Analysis of variance (ANOVA) was used to measure major differences between the means of the educational characteristics of students.

### 4.5.10. Summary

Details of the research design used in carrying out the study are explained in this chapter. It encompasses the research paradigm and research design adopted in this study. Research design includes target population and sampling frame of study; sampling method used; calculation of sample size; designing of the research instrument by operationalization of factors followed by pretesting of the questionnaire by means of a pilot study; and establishing reliability and validity of the instrument, leading to a full-scale survey. In the end, statistical tools used for data analysis of the survey data were discussed.

# 5 CHAPTER 5: DATA ANALYSIS AND INTERPRETATION

## 5.1 Introduction

This chapter presents and explains the quantitative findings from the data analysis. The outcomes of data analysis related to each research objective and hypothesis are presented in this chapter. For this study, data analysis tools of SPSS and PLS-SEM were employed. The four steps of data analysis were: (a) data screening, including demographic information about the respondents; (b) testing and validating the measurement model; (c) testing and validating the structural model; and (d) analysing the study's findings to determine the influence of students' educational characteristics on their behavioural intentions toward enrolling in MOOCs.

## 5.2 Findings of the research

### 5.2.1. Respondents' Demographic Details

The term demographics indicates to specific data pertaining to the population of a given geography. Information about the demographic of an individual gives valuable inputs regarding the respondent and helps in determining whether the individuals or the respondents in a research study are a true representative of the sampled population for generalising research results. By definition, demographic variables are independent as they cannot be manipulated (Salkind, 2010).

#### 5.2.1.1 Respondent Age

Age is regarded as an important factor in comprehending the respondent profile as it has a notable effect on the behavioral intention of a person. It is well established that different generational cohorts behave differently from each other, and researchers have attributed this evolution of mankind and the environment around especially the technological innovations. Gen Z is quite distinct from the previous generations. What distinguishes Gen Z from others is that they are technology centric and prefers communicating with others through text messages using digital devices than in person (Poláková & Klímová, 2019). There is a change in generation with the change in technology. It is important to identify these changing generations to have knowledge of them so that every generational cohort needs, and requirements are correctly identified and fulfilled. Considering the stated facts, an attempt was made to classify the respondents based on their age.

**Table 5-1: Respondent age**

| Demographic | Characteristics | Frequency | Percentage |
|---|---|---|---|
| Age (In years) | 20 and less | 155 | 32.1 |
| | 21-25 | 328 | 67.9 |

**n=483**

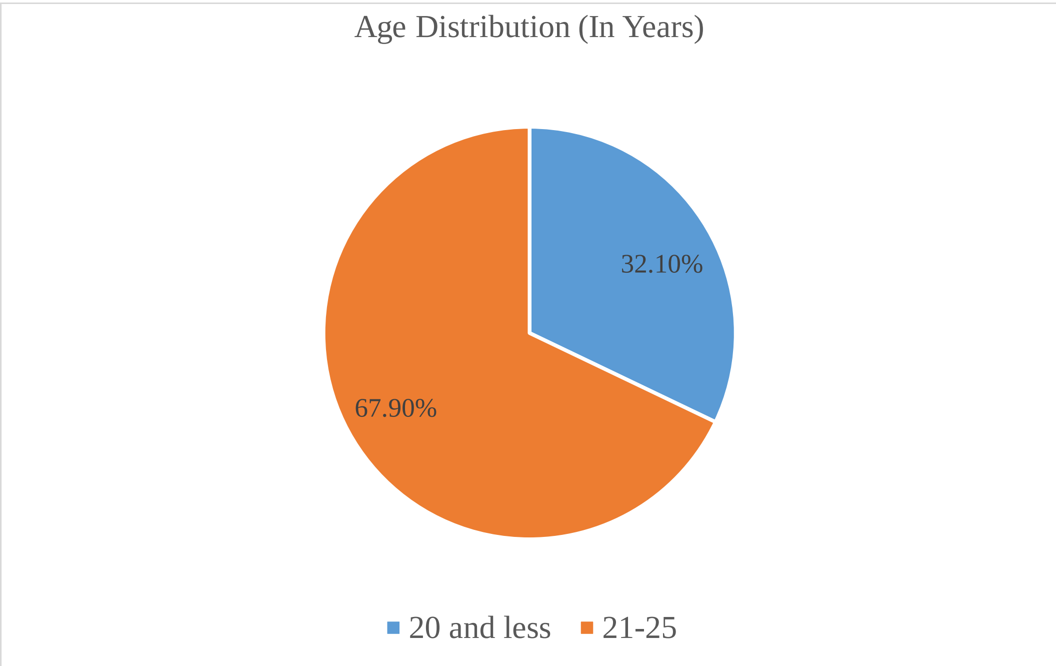



*Figure 5:1: Respondent Age*

The analysis of data presented in the table 5.1 and figure 5.1 indicates the age-wise distribution of respondents across the representative sample. 32.1% of the sampled data having age less than 20 years and 67.9% having age in the range of 21-25 years.

#### 5.2.1.2 Respondent Gender

Gender has consistently been a distinctive demographic factor. It has been investigated to comprehend respondents' attitudes on an issue and, in light of present study, their intention to use MOOCs. In this context, the classification of respondents was done based on their gender. The gender-wise classified categories included male and female respondents. Of all the respondents surveyed, 50.3% were female and 49.7% male (see Table 5-2, Figure 5:2)

Table 5-2: Respondent gender

| Gender | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Male | 240 | 49.7 | 49.7 | 49.7 |
| | Female | 243 | 50.3 | 50.3 | 100.0 |
| | Total | 483 | 100.0 | 100.0 | |

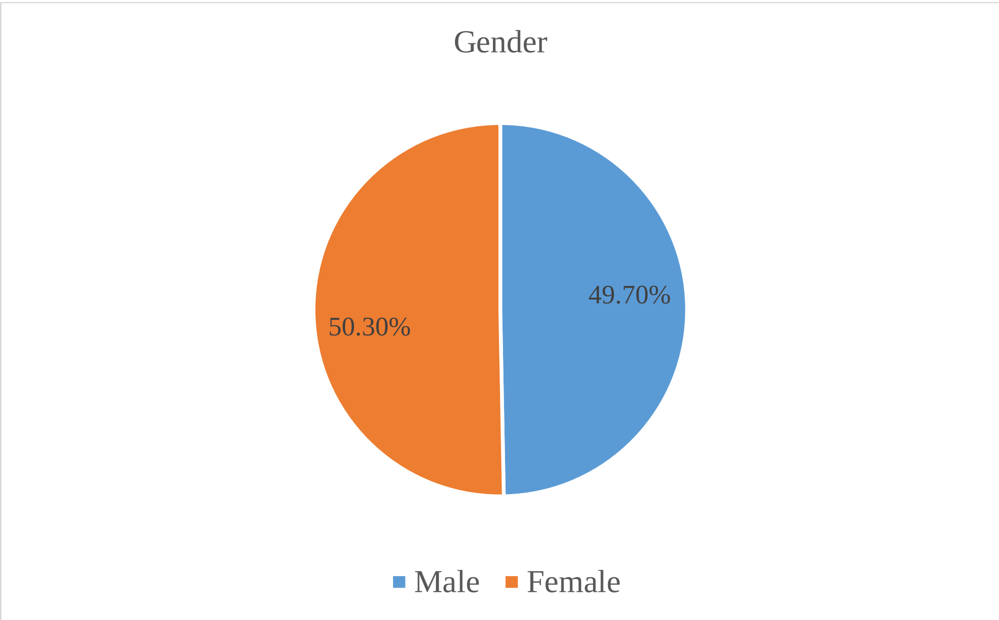



*Figure 5:2: Respondent Gender*

### 5.2.1.3 Respondent Education

It's posited in the extant literature that education plays an important role in determining use intention of a person. The higher a person is educated more is the likelihood of technology adoption (Nasri, 2011; Izogo et al., 2012), thus it is important to study the influence of level of education in context of this study as well.

Of all the respondents, 55.7% were doing their graduation and balance 44.3% post- graduation (see Table 5-3, Figure 5:3).

Table 5-3: Respondent Education

| Level of Education | | | | | |
|---|---|---|---|---|---|
| | | Frequency | Percent | Valid Percent | Cumulative Percent |
| Valid | Graduate (Bachelor Program) | 269 | 55.7 | 55.7 | 55.7 |
| | Postgraduate (Master Program) | 214 | 44.3 | 44.3 | 100.0 |
| | Total | 483 | 100.0 | 100.0 | |

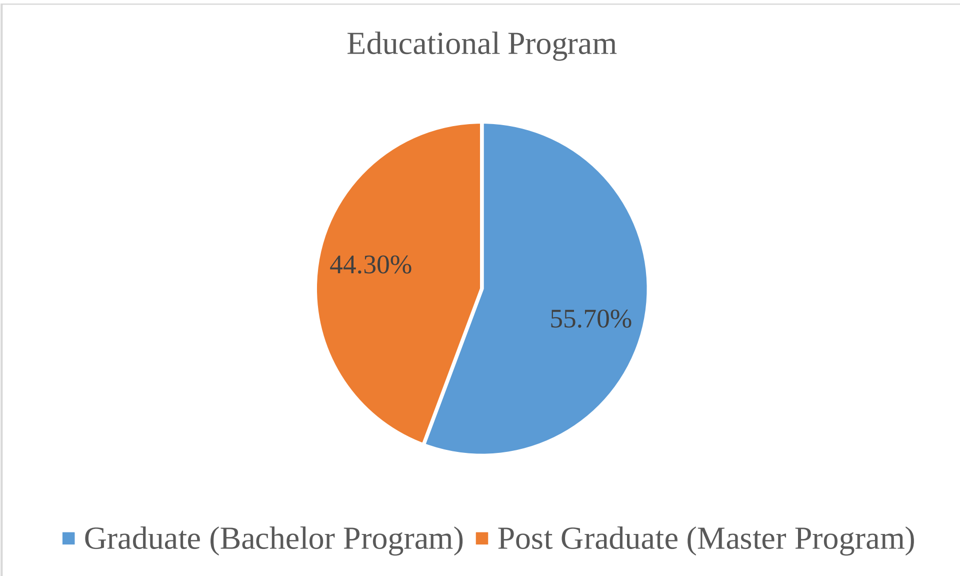



*Figure 5:3: Respondent Education*

### 5.2.1.4. Respondents' Education Stream

Online courses especially, MOOCs were initially introduced in India in the management, engineering/technology and sciences streams, thus the focus of this research has been kept majorly restricted to these streams (Kaushik and Agrawal, 2021) to know how these streams impact the factors of MOOC adoption intention.

Of all the respondents participated in the study, 49.28% are pursuing Management/Administration streams, 17.60% Engineering, 15.53% Commerce, 13.66% in other subject streams like Arts and Humanities, Designing, Music etc., followed by 3.93% in Science (see Table 5-4, Figure 5:4)

Table 5-4: Respondent education stream

| Course Stream | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Science | 19 | 3.9 | 3.9 | 3.9 |
| | Engineering | 85 | 17.6 | 17.6 | 21.5 |
| | Commerce | 75 | 15.5 | 15.5 | 37.1 |
| | Management/Administration | 238 | 49.3 | 49.3 | 86.3 |
| | Any Other | 66 | 13.7 | 13.7 | 100.0 |
| | Total | 483 | 100.0 | 100.0 | |

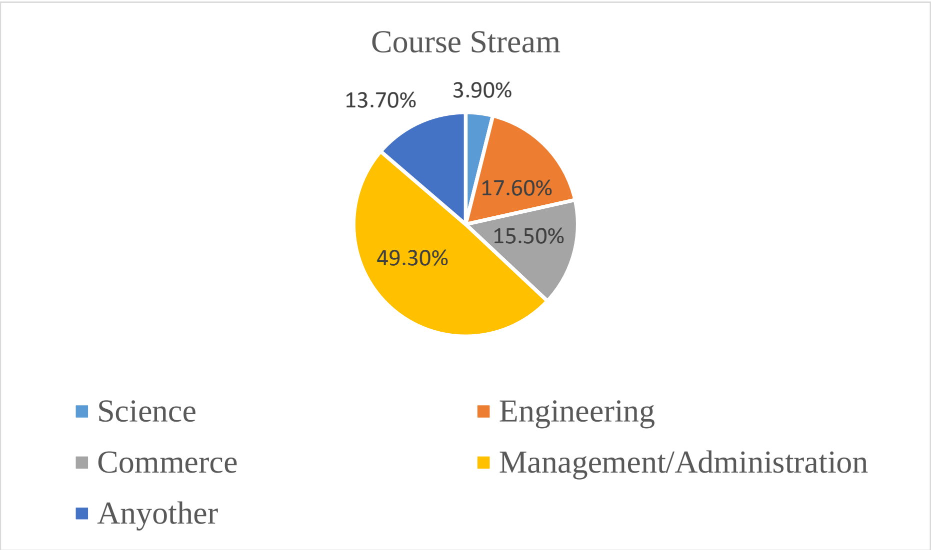



*Figure 5:4: Respondent Course Stream*

#### 5.2.1.5. Respondents' Institution Type

In India, there are different types of institutions in terms of its affiliations, ownership and prominence. Institutions owned by government (central/state), private players, and some partially funded by the government and the private player. Every institution by virtue of it prominence, ranking, governance, and affordability attracts different categories of students exhibiting varied behaviors. Given the difference in the institutions, students and the faculty teaching there, it is intuitively expected that there exists difference in the use intention of MOOCs among the students of various institutions.

Multistage sampling method namely, stratified random, purposive and snowball sampling is chosen. Thus, the respondents are selected from the strata of different types and category of HEIs in the Northern states of India (see Table 5-5, Figure 5:5). Therefore, in the same proportion as the count of these institutions, total number of respondents are chosen randomly. Of the total, 37.68% are from Private College/University, 32.09% are from State universities, 11.08% are from Central universities, 10.56% from Deemed universities, 5.18% from the Institution of national repute and 2.70% from the Institution of eminence.

Table 5-5: Respondent university type

| University Type | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Private College/University | 182 | 37.7 | 37.7 | 37.7 |
| | State University | 155 | 32.1 | 32.1 | 69.8 |
| | Deemed University | 51 | 10.6 | 10.6 | 80.3 |
| | Central University | 57 | 11.8 | 11.8 | 92.1 |
| | Institution of Eminence (IOE) | 13 | 2.7 | 2.7 | 94.8 |
| | Institution of National Repute | 25 | 5.2 | 5.2 | 100.0 |
| | Total | 483 | 100.0 | 100.0 | |

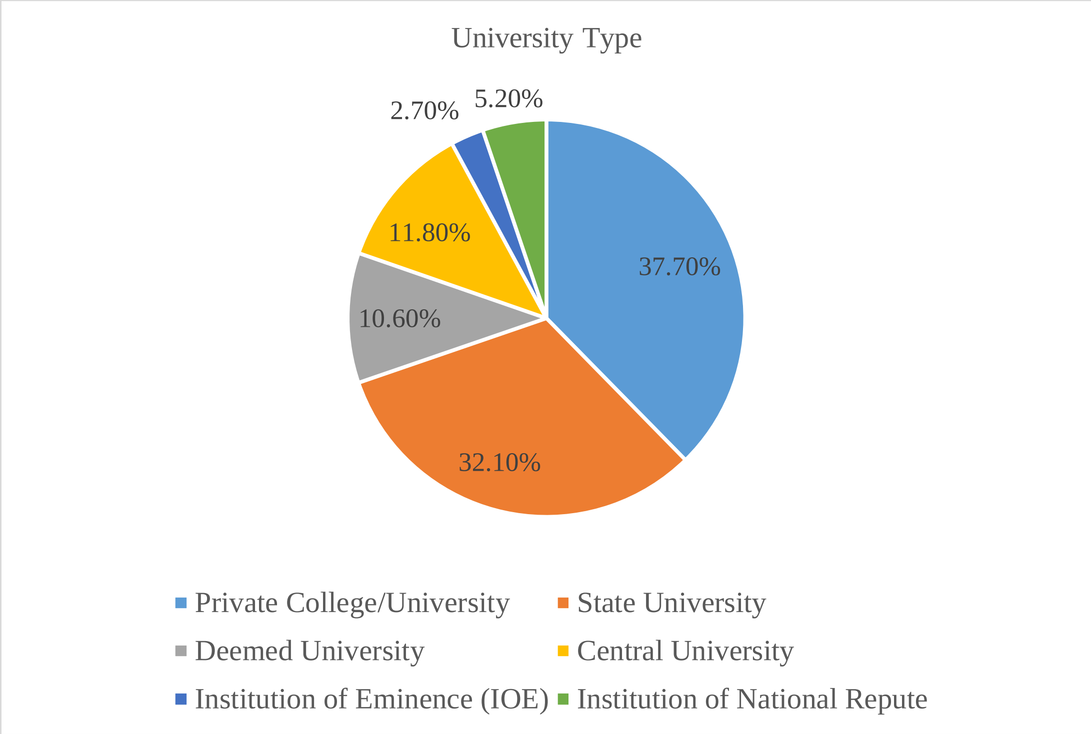



*Figure 5:5: Respondent University Type*

### 5.3. Respondent view about the Online Courses

Feedback from the respondents was taken to know their view on online courses pre and post COVID-19 to understand the influence of pandemic on online education adoption and how it is shaping their behavior towards online education especially MOOCs.

#### 5.3.1 Before COVID 19: Respondent view about the Online Courses

Out of the total respondents, majority of them (70.6%) who agree that before COVID-19, online courses were considered as just a source of complementary knowledge with only 10.2% disagreeing to it and remaining 19.3% chose to neither disagree nor agree. This result suggests that online courses were considered as just a source of complementary knowledge before the onset of pandemic (see Table 5-6).

Table 5-6: Respondent view on online courses before COVID-19

| Parameters | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Strongly Disagree | 11 | 2.3 | 2.3 | 2.3 |

| | | | | | |
|---|---|---|---|---|---|
| | Disagree | 38 | 7.9 | 7.9 | 10.1 |
| | Neither disagree nor agree | 93 | 19.3 | 19.3 | 29.4 |
| | Agree | 214 | 44.3 | 44.3 | 73.7 |
| | Strongly Agree | 127 | 26.3 | 26.3 | 100.0 |
| | Total | 483 | 100.0 | 100.0 | |

### 5.3.2 After the onset of COVID 19: Respondent view about the Online Courses

However, the onset of pandemic results in change in the view of respondents with majority (80.1%) considering online courses as an integral part of formal education with only 6.2% disagreeing to it and remaining 13.7% chose to neither disagree nor agree. This result suggests that the pandemic has made online courses an important part of their learning system (see Table 5-7, Figure 5:6).

Table 5-7: Respondent view on online courses after the onset of COVID-19

| Parameters | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Strongly Disagree | 10 | 2.1 | 2.1 | 2.1 |
| | Disagree | 20 | 4.1 | 4.1 | 6.2 |
| | Neither disagree nor agree | 66 | 13.7 | 13.7 | 19.9 |
| | Agree | 148 | 30.6 | 30.6 | 50.5 |
| | Strongly Agree | 239 | 49.5 | 49.5 | 100.0 |
| | Total | 483 | 100.0 | 100.0 | |

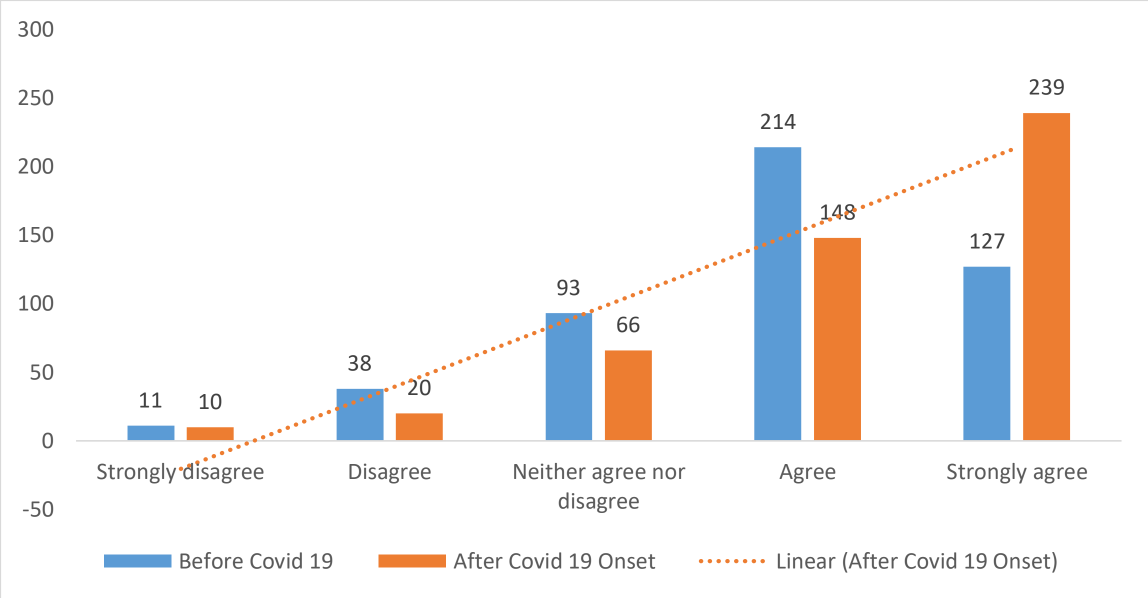



*Figure 5.6: Respondent view about the Online Courses, before and after COVID-19 onset*

It is evident from the respondents' feedback that online courses were considered as just a source of complementary knowledge before the on-set of COVID-19 however post pandemic break out and with most of the citizens home confined, online courses have become an important part of their learning system for 49.5% of the respondents as against 26.3% before pandemic highlighting change in intention and adoption behavior of the respondents.

## 5.4 Number of Online Courses (MOOCs) respondents have completed while pursuing UG/PG studies.

Non degree MOOCs are generally short duration courses for few hours or weeks and can be completed fast. To know the sampled data MOOCs usage pattern they were asked about number of courses they completed at the time of filling the questionnaire. Out of the total respondents, 45.8% have done less than 3 online courses while pursuing their UG and PG studies followed by 32.7% doing 3 to 5 online courses, 12.8% doing 6 to 8 online courses and 8.7% doing more than 8 online courses (see Table 5-8, Figure 5:7)

Table 5-8: MOOC course completed

| Parameters | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Less than 3 | 221 | 45.8 | 45.8 | 45.8 |
| | 3-5 | 158 | 32.7 | 32.7 | 78.5 |

| | | | | | |
|---|---|---|---|---|---|
| | 6-8 | 62 | 12.8 | 12.8 | 91.3 |
| | More than 8 | 42 | 8.7 | 8.7 | 100.0 |
| | Total | 483 | 100.0 | 100.0 | |

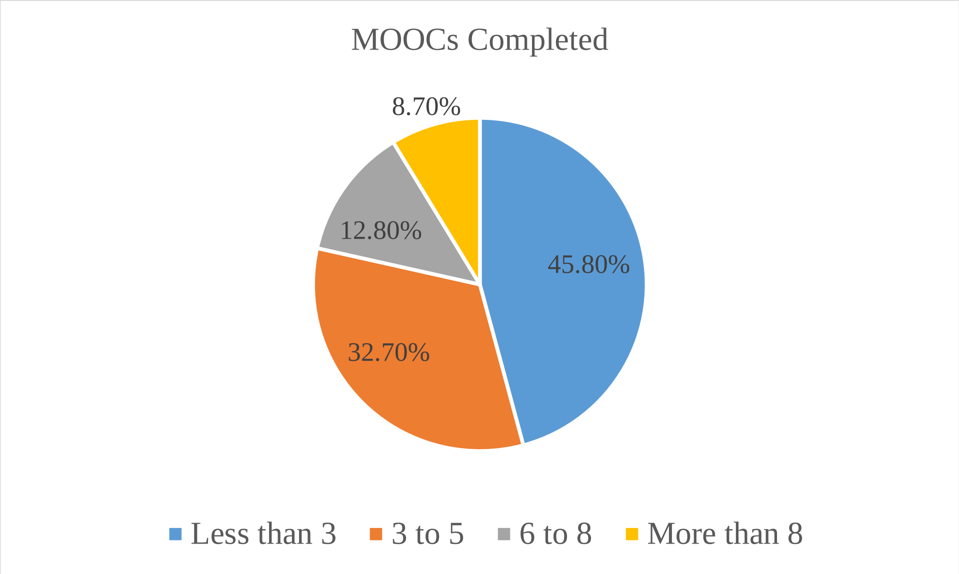



Figure 5.7: Online courses done

**5.5 Source of influence to do Online course**

It is important to comprehend motivation of a person to draw key insights about their cognitive process and nature. It defines what influences a person to strive for doing a particular job and achieving goals. Motivation suggests uniqueness about a person (positivepsychology.com, 2019). In case of MOOCs, it is extremely important for researchers and practitioners to understand learners' needs and to act on it to promote MOOC enrolments and completion.

All the 483 sampled respondents attended this multi response question, with 35.8% respondents attributing the reason to do an online course to their "self-motivation to learn more", 26.7% attributed it to their "teacher's instruction", 17.5% to the "Free/Economical pricing", 14.7% to the "Brand of Institute/university" and 5.2% attributed it to peer pressure, friend's advice, and digital marketing by the MOOC providers (see Table 5:9).

Table 5-9: Source of influence to do Online course

| | Cases | | | | | |
|---|---|---|---|---|---|---|
| | Valid | | Missing | | Total | |
| | N | Percent | N | Percent | N | Percent |
| Online Course | 483 | 100.0% | 0 | 0.0% | 483 | 100.0% |

| Online Course | | Responses | | Percent of Cases |
|---|---|---|---|---|
| | | N | Percent | |
| Variables | Self-motivation to learn more | 287 | 35.8% | 59.4% |
| | Your teacher's instruction | 214 | 26.7% | 44.3% |
| | Free/Economical pricing | 140 | 17.5% | 29.0% |
| | Brand of Institute/University | 118 | 14.7% | 24.4% |
| | Any other reason | 42 | 5.2% | 8.7% |
| Total | | 801 | 100.0% | 165.8% |

Unexpectedly, none of the respondent assigned any value to the option of "university/college influence to pursue an online course".

**5.6 Subject stream of online certification**

Respondents were asked about the subject streams in which they have done MOOCs certifications to know the courses in demand.

All the 483 respondents except for one responded to this multi response question, with 40.6% respondents cited doing online course/s in Management, 16.4% in Technology, 11.0% in Arts and Humanities, 8.3% in Science, 7.6% in Languages, 5.3% in Social sciences, 1.5% in Music, and 9.4% in other streams such as analytics, film making, designing, etc. (see Table 5-10).

Table 5-10: Online certification course stream

| | Cases | | | | | |
|---|---|---|---|---|---|---|
| | Valid | | Missing | | Total | |
| | N | Percent | N | Percent | N | Percent |
| Online Certification Stream | 482 | 99.8% | 1 | 0.2% | 483 | 100.0% |
| | | | | | | |

| Online Certification | | Responses | | Percent of Cases |
|---|---|---|---|---|
| | | N | Percent | |
| Stream | Arts and Humanities | 79 | 11.0% | 16.4% |
| | Science | 59 | 8.3% | 12.2% |
| | Technology | 117 | 16.4% | 24.3% |
| | Social Science | 38 | 5.3% | 7.9% |
| | Management | 290 | 40.6% | 60.2% |
| | Languages | 54 | 7.6% | 11.2% |
| | Music | 11 | 1.5% | 2.3% |
| | Any other | 67 | 9.4% | 13.9% |
| Total | | 715 | 100.0% | 148.3% |

Of 483 sampled respondents, all of them responded to this multi response question except one student, with 40.6.% respondents cited doing online course/s in Management, 16.4% in Technology, 11.0% in Arts and Humanities, 8.3% in Science, 7.6% in Languages, 5.3% in Social sciences, 1.5% in Music, and 9.4% in other streams such as analytics, film-making, designing, etc.

### 5.7 Online platform accessed for online course

Respondents were asked about the MOOC platforms they have accessed to do their respective courses and to know which platform has a major share of users. Out of 483 respondents, 479 responded to this multi response question barring four respondents. Majority, 44.3% of them have accessed Coursera platform for doing the online courses followed by Swayam/NPTEL at 11.8%, edX 8.7%, Future learn 3.8% and a whopping 31.4% respondents doing the online courses from multiple platforms such as Khan Academy, Upgrad, Unacademy, BYJUs, YouTube etc. (see Table 5-11).

Table 5-11: Major online platforms accessed by student

| | Cases | | | | | |
|---|---|---|---|---|---|---|
| | Valid | | Missing | | Total | |
| | N | Percent | N | Percent | N | Percent |
| Online Platform | 479 | 99.2% | 4 | 0.8% | 483 | 100.0% |

| | | Responses | | Percent of Cases |
|---|---|---|---|---|
| | | N | Percent | |
| Online Platform | Coursera | 305 | 44.3% | 63.7% |
| | Swayam/NPTEL | 81 | 11.8% | 16.9% |
| | EdX | 60 | 8.7% | 12.5% |
| | Futurelearn | 26 | 3.8% | 5.4% |
| | Any other | 216 | 31.4% | 45.1% |
| Total | | 688 | 100.0% | 143.6% |

MOOC platform Coursera emerged as the platform of choice among users followed by Swayam/NPTEL, EdX and Futurelearn. None of the respondent was found using Udemy, a United States based MOOC platform.

### 5.8 Hours spend on online course in a week

Respondents were asked about the amount of time they are spending in accessing online courses to figure out their usage frequency in a week, research posited 43.06% accessed the online course for less than three hours a week followed by 33.13% for 3-5 hours, 13.66% for 6-8 hours and 10.14% accessing online courses for more than 8 hours (see Table 5-12, Figure 5:8).

Table 5-12: Frequency of online course usage

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Less than 3 hours | 208 | 43.1 | 43.1 | 43.1 |
| | 3-5 Hours | 160 | 33.1 | 33.1 | 76.2 |
| | 6-8 Hours | 66 | 13.7 | 13.7 | 89.9 |
| | More than 8 Hours | 49 | 10.1 | 10.1 | 100.0 |
| | Total | 483 | 100.0 | 100.0 | |

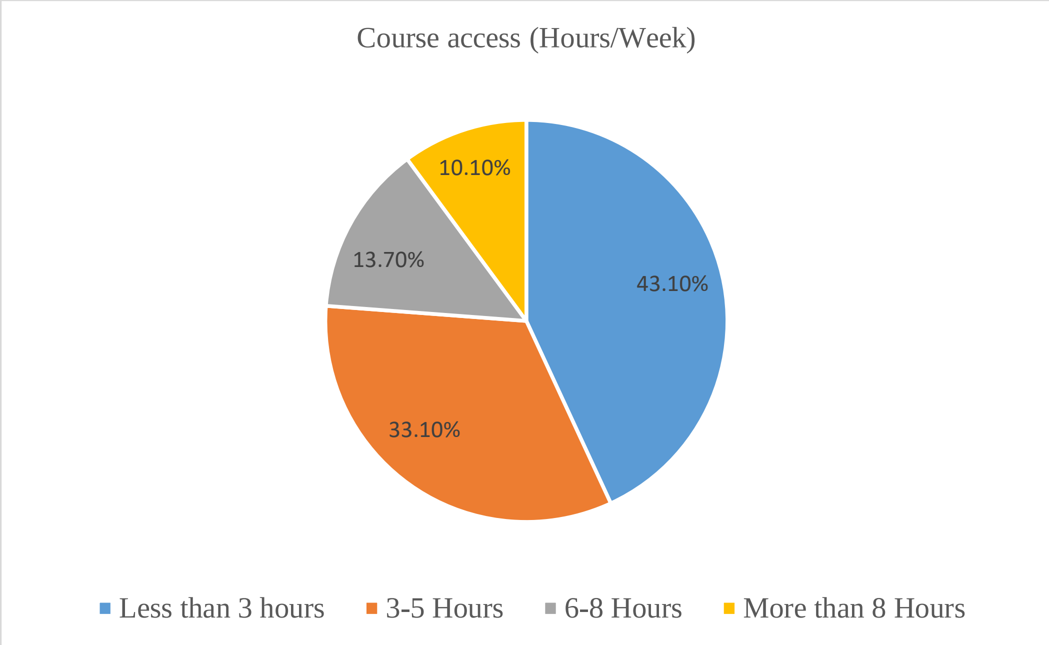


Figure 5.8: Hours spend per week on online courses

Majority of the respondents highlighted the use of MOOCs as less than 3 hours suggesting that most of their educational requirements are met through online teaching conducted by their college professors.

### 5.9 Descriptive Statistics

Descriptive statistics (see Table 5-13) of the constructs influencing the MOOC adoption intention highlights that for the construct of performance expectancy the mean scores ranged between 3.648 (± 0.978) and 3.986 (± 0.929), for the construct of effort expectancy the mean ranged from 3.600 (± 1.011) to 3.851 (± 1.004), for the construct of social influence the mean ranged from 3.602 (± 1.005) to 3.658 (± 1.000), for the construct of facilitating conditions the mean ranged from 3.536 (± 1.059) to 3.839 (± 1.037), for the construct of hedonic motivation the mean ranged from 3.503 (± 1.124) to 3.712 (± 1.119), for the construct of price value the mean ranged from 3.503 (± 1.124) to 3.712 (± 1.119), for the construct of habit the mean ranged from 2.934 (± 1.071) to 3.230 (± 1.122), for the construct of behavioral intention the mean ranged from 3.174 (± 1.125) to 3.617 (± 1.050), for the construct of language competency the mean ranged from 3.588 (± 0.992) to 4.058 (± 0.866), and for the construct of teacher influence the mean ranged from 3.739 (± 1.125) to 4.106 (± 0.87).

Table 5-13: Construct and Variable Descriptive Statistics

| Construct and Variable* | Mean | SD |
|---|---|---|
| **Performance Expectancy (PE)** | **3.850** | **0.942** |
| **PE1** | 3.894 | 0.914 |
| **PE2** | 3.986 | 0.929 |
| **PE3** | 3.648 | 0.978 |
| **PE4** | 3.890 | 0.947 |
| **Effort Expectancy (PE)** | **3.700** | **1.046** |
| **EE1** | 3.650 | 1.124 |
| **EE2** | 3.600 | 1.011 |
| **EE3** | 3.851 | 1.004 |
| **Social Influence (SI)** | **3.620** | **1.009** |
| **SI1** | 3.658 | 1.000 |
| **SI2** | 3.609 | 1.023 |
| **SI3** | 3.602 | 1.005 |
| **Facilitating Condition (FC)** | **3.721** | **1.072** |
| **FC1** | 3.834 | 1.161 |
| **FC2** | 3.536 | 1.059 |
| **FC3** | 3.710 | 1.029 |
| **FC4** | 3.839 | 1.037 |
| **Hedonic Motivation (HM)** | **3.570** | **1.023** |
| **HM1** | 3.712 | 0.968 |
| **HM2** | 3.511 | 1.044 |
| **HM3** | 3.503 | 1.056 |
| **Price Value (PV)** | **3.570** | **1.123** |
| **PV1** | 3.712 | 1.119 |

| | | |
|---|---|---|
| **PV2** | 3.511 | 1.127 |
| **PV3** | 3.503 | 1.124 |
| **Habit (HT)** | **3.090** | **1.079** |
| **HT1** | 3.124 | 1.032 |
| **HT2** | 2.934 | 1.071 |
| **HT3** | 3.230 | 1.133 |
| **Behavioral Intention (BI)** | **3.380** | **1.067** |
| **BI1** | 3.174 | 1.125 |
| **BI2** | 3.350 | 1.025 |
| **BI3** | 3.617 | 1.050 |
| **Language Competency (LC)** | **3.840** | **0.958** |
| **LC1** | 4.058 | 0.866 |
| **LC2** | 3.824 | 0.957 |
| **LC3** | 3.853 | 0.962 |
| **LC4** | 3.588 | 0.992 |
| **LC5** | 3.911 | 1.015 |
| **Teacher Influence (TI)** | **3.940** | **1.004** |
| **TI1** | 4.106 | 0.87 |
| **TI2** | 3.874 | 1.051 |
| **TI3** | 3.998 | 1.004 |
| **TI4** | 4.017 | 0.972 |
| **TI5** | 3.739 | 1.125 |

**Variable description is given in Tables 4-2-1 to 4-2-10*

Descriptive statistics (see Table 5-13) of the constructs influencing the MOOC adoption intention posited that among existing UTAUT2 constructs, the construct of PE as having the highest mean (3.850) and HT as having the lowest mean (3.090) signifying PE having significant influence on MOOC adoption intention with HT having the least. As regards the extended constructs of LC and TI, LC has a combined mean of 3.840 and TI, 3.940 signifying both the constructs having a major influence on MOOC adoption intention. Analysis further highlighted that among 36 items in the questionnaire, the item TI1 "I believe my teacher is an expert of his subject" of TI construct has the highest mean of 4.106 highlighting positive influence of this item in MOOC adoption intention and the item HT2 "I am addicted to using Online Courses (MOOCs)" of HT construct has the lowest mean (2.934) highlighting insignificant influence of this item on MOOC adoption intention.

### 5.10. Structural Equation Modelling (SEM) Analysis

SEM, a set of statistical techniques, measure and analyze the relations between observed and latent variables. PLS path models are assessed in two steps: the outer model and inner model assessment (Henseler, Ringle and Sinkovics, 2009) as depicted in Figure 5:9.

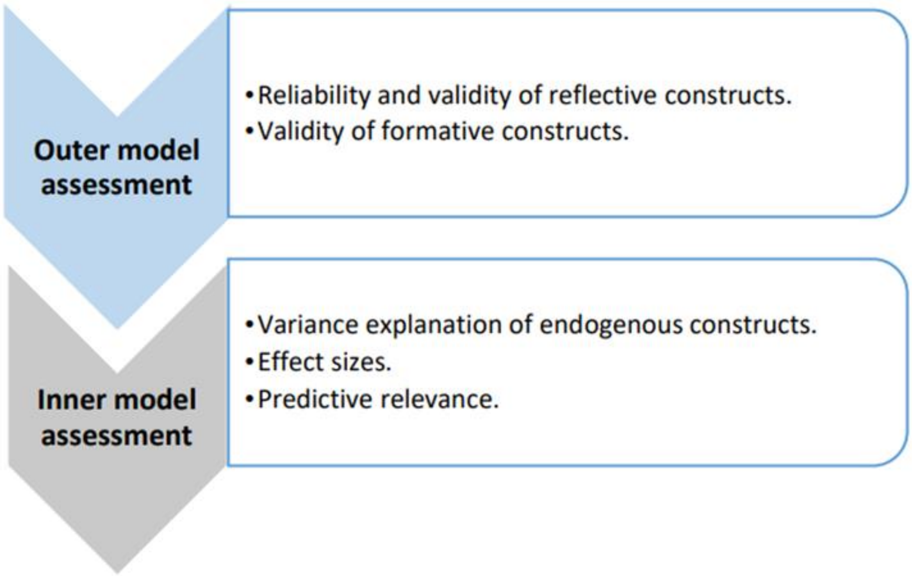



**Figure 5:9:** A two-step process of PLS path model assessment (Henseler, Ringle and Sinkovics, 2009)

Measurement or outer model explains relationships between latent and observed variables whereas, the Structural or inner model describes the correlations between the latent variables (See Figure 5:10).

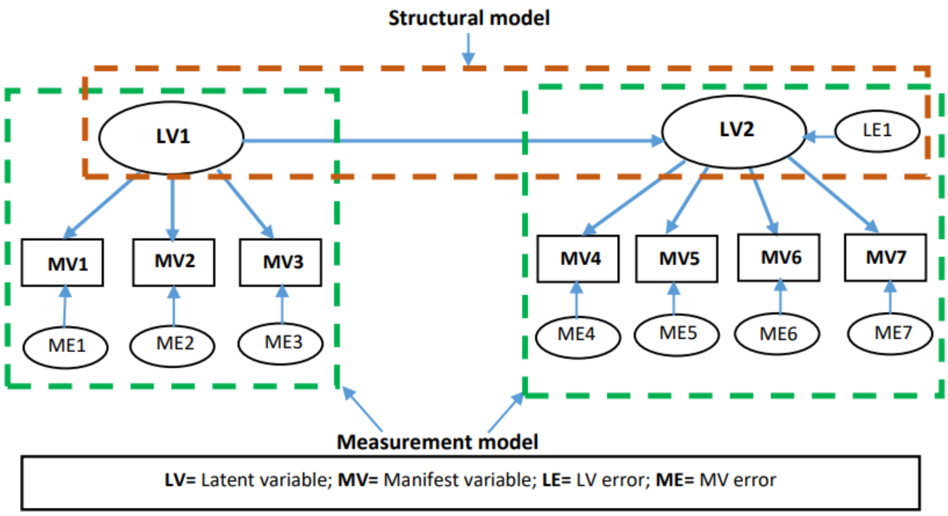



*Figure 5:10: Graphic example of the SEM model.* *Source: Shah and Goldstein (2006)*

Analysis of data was performed in two phases. In the first phase, measurement model was tested and evaluated followed by the assessment and development of structural model in the second phase.

Model validation is defined as "the process of systematic statistical assessment and evaluation of data to confirm whether the model achieves its intended objective or not" (Urbach and Ahlemann, 2010).

### 5.10.1 Measurement model

For data analysis, SPSS 20.0 was employed to carry out data screening tests and run the descriptive statistics to study the demographic variables and second generation (2G) statistical technique namely, Structural Equation Modelling (SEM) was used for modelling causal networks of effects simultaneously rather than step by step" (Lowry and Gaskin, 2014). SEM has found many takers in the recent year on account of its enhanced capability to measure the reliability and validity of multi-items construct. SEM is a mix of exploratory factor analysis and structural path analysis, which makes the simultaneous assessment of both measurement and structural model possible (Hair *et al*., 2014, 2017).

Advantages of SEM are:

1. Assessing the validity of both measurement as well as structural model together.
2. Assessing models comprising of sequence of causes and effects (indirect effects).

Researchers have two methods of SEM to select from viz. variance-based partial least squares (Lohmöller, 1989) and covariance-based SEM (Jöreskog, 1993). CB-SEM is mainly used for confirmation of established theory (i.e., explanation) whereas PLS-SEM is aimed at optimising the explained variance of the dependent latent variables" (Hair, Ringle and Sarstedt, 2011).

The PLS based SEM technique was used for primary data analysis and to assess and evaluate the proposed model on account of reasons listed below -

1. It runs on large and small sample sizes with no restrictions on data normality (Chin, 1998).
2. PLS-SEM is deemed fit to appraise complex models and validate its predictive ability (Hair *et al*., 2014, 2017).
3. CB-SEM is recommended for the confirmatory research (assessing and evaluating established theories) whereas PLS-SEM is advised to be used for the exploratory research (developing or testing new theories) (Hair, Ringle and Sarstedt, 2011; Henseler et al., 2014; Lowry and Gaskin, 2014; Sarstedt et al., 2014). In the current work, PLS-SEM was used because the topic under investigation is novel in the context of MOOCs in Indian settings, and the new proposed model has two additional constructs.
4. The study's objective is to investigate the variables influencing behavioural intention to use MOOCs. PLS-SEM is advised for the current investigation since it is prediction driven as opposed to CB-SEM, which is parameter oriented.
5. PLS-SEM can handle complex models having large number of latent and observed constructs, indicator variables, and the causal relationships (Hair, Ringle and Sarstedt, 2011)

Analysis was performed using SmartPLS 3.0 software (Ringle et al., 2015).

In PLS-SEM, the measurement model depicts associations between the observed data and the latent variables, which are used to calculate the constructs' reliability and validity (see Table 5-15). Cronbach's alpha, composite reliability (CR), and average variance retrieved were used to assess each construct's internal consistency and item reliability (AVE).

**Table 5-14: Construct Operationalization**

| Variable and Construct | Mean | SD | Factor Loading | VIF |
|---|---|---|---|---|
| **Performance Expectancy (PE) (α=0.870, CR=0.911, AVE=0.720)** | | | | |
| PE1 | 3.894 | 0.914 | 0.850 | 2.230 |
| PE2 | 3.986 | 0.929 | 0.878 | 2.664 |
| PE3 | 3.648 | 0.978 | 0.833 | 1.917 |
| PE4 | 3.890 | 0.947 | 0.833 | 2.106 |
| **Effort Expectancy (PE) (α=0.868, CR=0.919, AVE=0.790)** | | | | |
| EE1 | 3.650 | 1.124 | 0.867 | 2.118 |
| EE2 | 3.600 | 1.011 | 0.903 | 2.427 |
| EE3 | 3.851 | 1.004 | 0.897 | 2.309 |
| **Social Influence (SI) (α=0.884, CR=0.928, AVE=0.812)** | | | | |
| SI1 | 3.658 | 1.000 | 0.886 | 2.388 |
| SI2 | 3.609 | 1.023 | 0.912 | 2.638 |
| SI3 | 3.602 | 1.005 | 0.905 | 2.518 |
| **Facilitating Condition (FC) (α=0.723, CR=0.833, AVE=0.565)** | | | | |
| FC1 | 3.834 | 1.161 | 0.749 | 1.379 |
| FC2 | 3.536 | 1.059 | 0.868 | 2.690 |
| FC3 | 3.710 | 1.029 | 0.845 | 2.485 |
| FC4 | 3.839 | 1.037 | 0.481 | 1.079 |
| **Hedonic Motivation (HM) (α=0.910, CR=0.943, AVE=0.847)** | | | | |
| HM1 | 3.712 | 0.968 | 0.915 | 2.832 |
| HM2 | 3.511 | 1.044 | 0.929 | 3.521 |
| HM3 | 3.503 | 1.056 | 0.917 | 2.969 |
| **Price Value (PV) (α=0.763, CR=0.862, AVE=0.676)** | | | | |
| PV1 | 3.712 | 1.119 | 0.816 | 1.509 |
| PV2 | 3.511 | 1.127 | 0.791 | 1.561 |
| PV3 | 3.503 | 1.124 | 0.859 | 1.576 |
| **Habit (HT) (α=0.725, CR=0.841, AVE=0.639)** | | | | |
| HT1 | 3.124 | 1.032 | 0.752 | 1.408 |
| HT2 | 2.934 | 1.071 | 0.790 | 1.517 |
| HT3 | 3.230 | 1.133 | 0.853 | 1.385 |
| **Behavioral Intention (BI) (α=0.888, CR=0.930, AVE=0.817)** | | | | |
| BI1 | 3.174 | 1.125 | 0.889 | 2.272 |

| | | | | |
|---|---|---|---|---|
| BI2 | 3.350 | 1.025 | 0.925 | 3.105 |
| BI3 | 3.617 | 1.050 | 0.897 | 2.672 |
| **Language Competency (LC) (α=0.771, CR=0.845, AVE=0.524)** | | | | |
| LC1 | 4.058 | 0.866 | 0.695 | 1.418 |
| LC2 | 3.824 | 0.957 | 0.825 | 1.996 |
| LC3 | 3.853 | 0.962 | 0.775 | 1.872 |
| LC4 | 3.588 | 0.992 | 0.674 | 1.278 |
| LC5 | 3.911 | 1.015 | 0.633 | 1.316 |
| **Teacher Influence (TI) (α=0.707, CR=0.810, AVE=0.472)** | | | | |
| TI1 | 4.106 | 0.870 | 0.500 | 1.244 |
| TI2 | 3.874 | 1.051 | 0.794 | 1.822 |
| TI3 | 3.998 | 1.004 | 0.815 | 1.971 |
| TI4 | 4.017 | 0.972 | 0.759 | 1.620 |
| TI5 | 3.739 | 1.125 | 0.491 | 1.235 |

**Variable description is given in Tables 4-2-1 to 4-2-10*

Reliability criterion recommends that Cronbach's alpha, Composite reliability (CR) values should be greater than 0.7, and AVE's critical value should be greater than 0.5 (Fornell and Larcker, 1981).

Reliability is calculated by Cronbach's alpha, also known as the coefficient alpha. The consistency of a study's findings is how reliable it is. Similar to Cronbach's alpha, Composite Reliability is a metric for evaluating the internal consistency of scale components. Measures of convergent validity include Average Variance Extracted (AVE). Convergent validity evaluates how closely two measures that are supposed to evaluate the same construct are related, and Variance Inflation Factors (VIF) assesses multicollinearity, which occurs when independent variables in a regression model have strong correlations with one another. Multicollinearity happens when a model's correlate predictors give duplicate information about the response. Multicollinearity is problematic if the VIF score is more than 4.0. (Hair et al., 2010).

The values of Cronbach's alpha and CR were above 0.7, as shown in Table 5-15, indicating that all the constructs had reliable and internal consistent values (Nunnally, 1978) making sure the internal consistency and reliability of all the constructs.

The level of relationship between two measures that are supposed to be evaluated for the same construct is known as convergent validity. The factor loading of each construct is used to evaluate the convergent validity of each construct. Except for the construct of TI, which has a borderline AVE value of 0.472, all constructs' convergent validity is confirmed by the observation that their AVE values are higher than the benchmarked value of 0.5 (Hair et al., 2014). The Fornell-Larcker criterion and the Cross loadings test are the two methods used to evaluate discriminant validity, which examines how dissimilar one construct is from another (Hulland 1999). The Fornell and Larcker (1981) criterion, which states that a construct shares more variance with its assigned indicators than with any other construct, is used to evaluate the discriminant validity. Each construct's AVE should be higher than the square root of the construct's highest correlation with any other variable (Fornell and Larcker, 1981). Table 5-15 displays the correlation matrix for the constructs, where the primary diagonals are the average extracted variance's square roots (AVE).

**Table 5-15: Discriminant Validity of the constructs in the measurement model**

| 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** |

Note: Bold digits represent the square roots of AVEs.

Table 5-15 results suggests that the requirement of discriminant validity was satisfied as each item loading is greater than all of its cross-loadings excepting that of PV i.e. the cross loadings of PV is greater with the construct of Habit.

The indicator's cross loadings must be higher than all of its cross loadings with other constructs, which is the second criterion for discriminant validity (Chin 1998). Both tests validate the discriminant validity of the constructs in the model, and the cross-loading findings are summarised in Table 5-16.

**Table 5-16: Cross loading test for discriminant validity of constructs**

| Constructs | BI | EE | FC | HT | HM | LC | PE | PV | SI | TI |
|---|---|---|---|---|---|---|---|---|---|---|
| **BI1** | 0.889 | 0.366 | 0.547 | 0.704 | 0.547 | 0.459 | 0.478 | 0.709 | 0.458 | 0.333 |
| **BI2** | 0.925 | 0.417 | 0.602 | 0.646 | 0.582 | 0.480 | 0.544 | 0.648 | 0.491 | 0.392 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **BI3** | 0.897 | 0.414 | 0.550 | 0.555 | 0.538 | 0.484 | 0.576 | 0.542 | 0.447 | 0.337 |
| **EE1** | 0.355 | 0.867 | 0.484 | 0.291 | 0.214 | 0.291 | 0.265 | 0.203 | 0.244 | 0.101 |
| **EE2** | 0.408 | 0.903 | 0.482 | 0.295 | 0.315 | 0.282 | 0.377 | 0.251 | 0.341 | 0.164 |
| **EE3** | 0.410 | 0.897 | 0.486 | 0.280 | 0.311 | 0.304 | 0.403 | 0.237 | 0.339 | 0.142 |
| **FC1** | 0.506 | 0.550 | 0.749 | 0.411 | 0.292 | 0.526 | 0.342 | 0.317 | 0.305 | 0.357 |
| **FC2** | 0.513 | 0.410 | 0.868 | 0.361 | 0.298 | 0.406 | 0.305 | 0.327 | 0.333 | 0.326 |
| **FC3** | 0.495 | 0.369 | 0.845 | 0.309 | 0.296 | 0.439 | 0.353 | 0.255 | 0.336 | 0.299 |
| **FC4** | 0.345 | 0.276 | 0.481 | 0.295 | 0.417 | 0.444 | 0.456 | 0.317 | 0.380 | 0.213 |
| **HM1** | 0.588 | 0.327 | 0.419 | 0.443 | 0.915 | 0.404 | 0.605 | 0.468 | 0.454 | 0.331 |
| **HM2** | 0.531 | 0.256 | 0.346 | 0.472 | 0.929 | 0.367 | 0.563 | 0.492 | 0.436 | 0.279 |
| **HM3** | 0.576 | 0.291 | 0.389 | 0.486 | 0.917 | 0.379 | 0.509 | 0.519 | 0.456 | 0.286 |
| **HT1** | 0.463 | 0.221 | 0.337 | 0.752 | 0.371 | 0.300 | 0.336 | 0.667 | 0.331 | 0.229 |
| **HT2** | 0.470 | 0.252 | 0.353 | 0.790 | 0.365 | 0.302 | 0.278 | 0.675 | 0.344 | 0.214 |
| **HT3** | 0.704 | 0.294 | 0.406 | 0.853 | 0.463 | 0.350 | 0.419 | 0.799 | 0.392 | 0.271 |
| **LC1** | 0.336 | 0.251 | 0.409 | 0.241 | 0.298 | 0.695 | 0.443 | 0.192 | 0.336 | 0.247 |
| **LC2** | 0.474 | 0.326 | 0.558 | 0.349 | 0.344 | 0.825 | 0.466 | 0.311 | 0.370 | 0.505 |
| **LC3** | 0.345 | 0.239 | 0.477 | 0.203 | 0.261 | 0.775 | 0.405 | 0.174 | 0.297 | 0.504 |
| **LC4** | 0.404 | 0.159 | 0.389 | 0.376 | 0.339 | 0.674 | 0.326 | 0.341 | 0.302 | 0.357 |
| **LC5** | 0.300 | 0.198 | 0.296 | 0.240 | 0.248 | 0.633 | 0.360 | 0.215 | 0.318 | 0.241 |
| **PE1** | 0.486 | 0.326 | 0.383 | 0.371 | 0.474 | 0.485 | 0.850 | 0.351 | 0.480 | 0.283 |
| **PE2** | 0.482 | 0.332 | 0.397 | 0.338 | 0.501 | 0.473 | 0.878 | 0.298 | 0.490 | 0.279 |
| **PE3** | 0.528 | 0.357 | 0.390 | 0.437 | 0.538 | 0.431 | 0.833 | 0.426 | 0.549 | 0.276 |
| **PE4** | 0.495 | 0.327 | 0.424 | 0.342 | 0.547 | 0.491 | 0.833 | 0.323 | 0.515 | 0.333 |
| **PV1** | 0.572 | 0.248 | 0.384 | 0.761 | 0.460 | 0.329 | 0.386 | 0.816 | 0.397 | 0.257 |
| **PV2** | 0.469 | 0.148 | 0.218 | 0.626 | 0.422 | 0.177 | 0.230 | 0.791 | 0.244 | 0.163 |
| **PV3** | 0.667 | 0.234 | 0.363 | 0.812 | 0.442 | 0.334 | 0.383 | 0.859 | 0.363 | 0.256 |
| **SI1** | 0.428 | 0.310 | 0.384 | 0.395 | 0.443 | 0.432 | 0.533 | 0.362 | 0.886 | 0.318 |
| **SI2** | 0.484 | 0.327 | 0.390 | 0.399 | 0.439 | 0.395 | 0.525 | 0.369 | 0.912 | 0.236 |
| **SI3** | 0.478 | 0.307 | 0.421 | 0.417 | 0.439 | 0.391 | 0.567 | 0.388 | 0.905 | 0.247 |
| **TI1** | 0.171 | 0.153 | 0.232 | 0.130 | 0.226 | 0.372 | 0.338 | 0.087 | 0.269 | 0.500 |
| **TI2** | 0.327 | 0.095 | 0.294 | 0.212 | 0.245 | 0.376 | 0.224 | 0.212 | 0.217 | 0.794 |
| **TI3** | 0.298 | 0.110 | 0.359 | 0.202 | 0.203 | 0.391 | 0.209 | 0.191 | 0.141 | 0.815 |
| **TI4** | 0.306 | 0.070 | 0.291 | 0.215 | 0.247 | 0.367 | 0.235 | 0.224 | 0.211 | 0.759 |
| **TI5** | 0.208 | 0.149 | 0.199 | 0.291 | 0.216 | 0.337 | 0.256 | 0.230 | 0.228 | 0.491 |

To summarize, assessment established that the measurement model fulfilled the benchmarked quality criteria. Hence, the next step is to evaluate the structural model.

### 5.10.2 Structural model

The Structural or inner model describes the correlations between the latent variables (See Figure 5:9). The Table 5-17 below explain the criteria used to evaluate the structural model in this study.

**Table 5-17: The criteria used to evaluate the structural model.**

| Criterion | Description | Proposed threshold value | Reference |
|---|---|---|---|
| Coefficient of determination ($R^2$) | "Measure the explained variance of a latent variable relative to its total variance (Urbach and Ahlemann, 2010) | Substantial: values around 0.670, Moderate: values around 0.333, Weak: values around 0.190 | Chin (1998), Ringle (2004) |
| Path coefficient (β) | Provide estimates of the algebraic sign, magnitude, and significance of hypothesised coorelations between the latent variables | Sign: + or -, Magnitude: the effect of exogenous variable on endogenous variable increases as the value of path coefficient increases. Significance: $p<0.05$ | Huber et al. (2007) |
| Effect size: Cohen's $f2$ | "Measure if an independent latent variable has substantial impact on a dependent latent variable (Urbach and Ahlemann, 2010) | Too weak: below 0.020, Small: between 0.020 and 0.150, Medium: between 0.150 and 0.350, Large: above 0.350 | Cohen (1998), Chin (1998), Ringle (2004) |
| Predictive relevance ($Q^2$) | Measure how well observed values are reproduced by the model | Q2>0 | Stone (1974), Geisser (1975), Fornell and Cha (1994) |

To determine the relationship between the constructs, the PLS findings of the structural model (Fig. 5:10) were assessed using reliability and validity evaluations of the model that were measured and values that were in accordance with benchmarked norms. Table 5-18 shows the findings of the path coefficient and T-Statistics value. PLS path models produce squared multiple correlations (R2) for each latent construct to reflect the fit of the model to the hypothesized associations, and structural model is evaluated by measuring the path coefficients (β value), which does not require data normality. Using the bootstrapping process, hypotheses are checked for relevance (Chin, 1998). Along with the T-statistics values, Table 5-18 also lists the β values for the postulated path coefficients. According to the findings, the intention to use MOOCs is strongly predicted by the construct of PV.

The relation between PV and BI is statistically significant with β = 0.316 and has a positive impact on BI towards MOOC adoption intention which is in accordance with the existing literature (Raman and Don, 2013; Venkatesh *et al*., 2012). However, it contradicts the results of El-Masri and Tarhini, 2017. The change in BI is in proportion to PV with a coefficient of 0.316. This indicates that a variation in PV by a value of 100 points will bring about change in BI, by 31 points. Therefore, H6 is accepted. Other variables having significant influence on intention to adopt MOOCs are PE (β = 0.127) and EE (β = 0.066) which is in accordance with the prior literature (Fianu *et al.,* 2018; Venkatesh *et al.,* 2003; Al-Adwan, 2020). Therefore, H1-H2 are accepted. In line with the existing literature, FC (β = 0.238) and HM (β = 0.145) also have significant positive impact on BI of Gen Z towards MOOC adoption corroborating the findings of existing studies (Brown and Venkatesh, 2005; Raman and Don, 2013; Tseng *et al*., 2019). Thus, H4-H5 are accepted. The relationship between SI and BI is not statistically significant with β = 0.02 and T-value = 0.60, which is not supporting the extant literature (Raman and Don, 2013; Persada *et al.*, 2019; Chaiyasoonthorn et al., 2021). However, supporting the studies of Jeng and Tzeng (2012) and Fianu *et al.* (2018). Hence H3 is rejected. The independent variable of HT ((β = 0.121) has an insignificant impact on BI, which is not in accordance with the results of Gupta and Dogra, (2017) and in line with the results of Raman and Don, (2013), therefore H7 is rejected. LC doesn't have a clear relationship with BI with β = 0.035 contradicting extant literature (Aldahdouh and Osório, 2016; Raja and Kallarakal, 2020) and substantiating the results of Barak *et al.* (2015). Hence H8 is rejected. TI does not have a statistically major influence on BI with β = 0.044 thus not supporting the results of extant literature (Huang *et al*., 2019; Hoi and Mu, 2021; Al-Adwan *et al.,* 2021). Therefore, H9 is rejected.

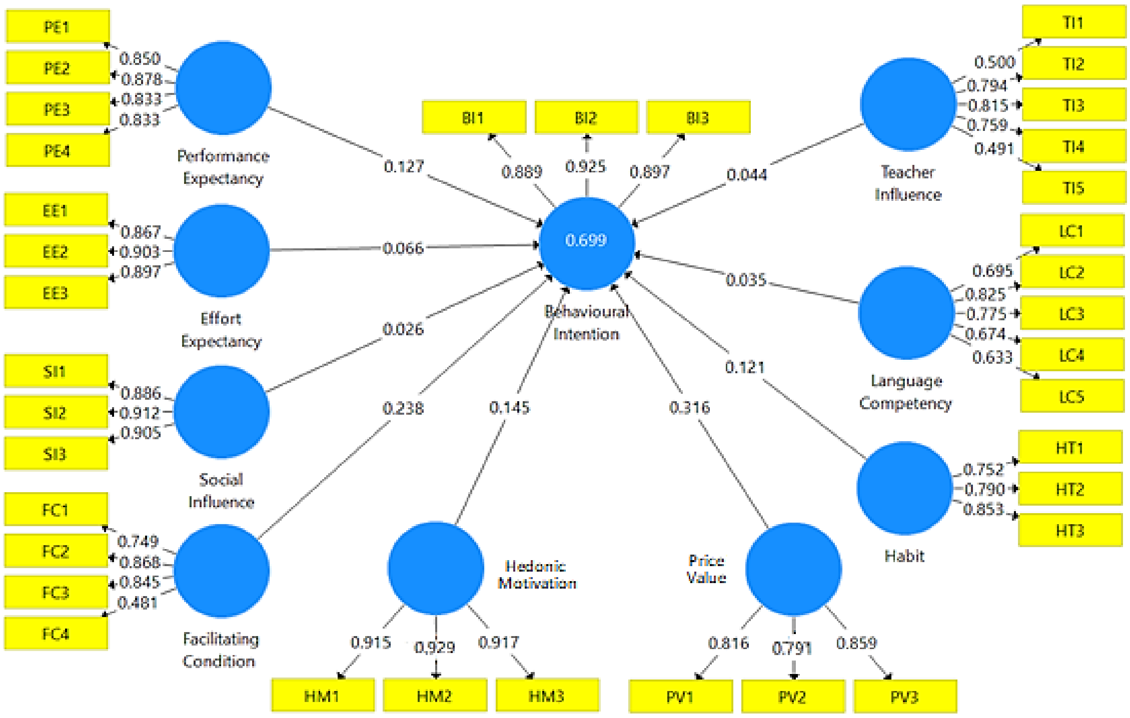



*Figure 5:11: Structural model.*

**Table 5-18: Path coefficient and T-Statistics value**

| Hypothesis | Path | β Values | P Values | Decision |
|---|---|---|---|---|
| H1 | PE -> BI | 0.127 | 0.005 | Accepted |
| H2 | EE -> BI | 0.066 | 0.039 | Accepted |
| H3 | SI -> BI | 0.026 | 0.547 | Rejected |
| H4 | FC-> BI | 0.238 | 0.000 | Accepted |
| H5 | HM->BI | 0.145 | 0.001 | Accepted |
| H6 | PV-> BI | 0.316 | 0.000 | Accepted |
| H7 | HT-> BI | 0.121 | 0.084 | Rejected |
| H8 | LC-> BI | 0.035 | 0.355 | Rejected |
| H9 | TI -> BI | 0.044 | 0.181 | Rejected |

**Measuring the value of $R^2$**: According to "PLS path models," squared correlation values of 0.75, 0.50, and 0.25 are regarded as high, medium, and low, respectively (Hair et al., 2014). An independent construct's impact on the dependent construct is described by $R^2$ statistics. The dependent construct's $R^2$ value is 0.69, as shown in figure 2, which is larger than 0.50 and near to 0.75; as a result, the $R^2$ value is regarded as being of medium to high value.

**Effect size $f^2$**: Effect sizes quantify how each independent variable affects the dependent variable. When an independent variable is excluded from the PLS path model, it analyses the variance in squared correlation values to determine if the independent variable has a significant impact on the value of the dependent variable or not. Effect size $f^2$ (Chin, 1998) is calculated using the following formula -

$$\mathbf{f^2 = R^2\,included - R^2 excluded / 1 - R^2\,included}$$

The influence of independent variable is high at the structural level if $f^2$ is 0.35 and it is medium if $f^2$ is 0.15 and low if $f^2$ is 0.02 (Cohen 1988). Interpretation of the analysed data is as shown in Table 5-19.

**Table 5-19: Effect size $f^2$**

| Independent Construct | Dependent Construct | Effect Size | Inference |
|---|---|---|---|
| Effort Expectancy | | 0.010 | Small Effect |
| Facilitating Condition | | 0.088 | Medium Effect |
| Habit | | 0.008 | Small Effect |
| Hedonic Motivation | | 0.036 | Medium Effect |
| Language Competency | Behavioral Intention | 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 |

While other constructs have a moderate impact, the independent predictor constructs FC (0.088), HM (0.036), and PV (0.059) have a medium impact on the dependent construct of BI to adopt MOOC.

**Model's predictive relevance:** The calculation of $Q^2$ Statistics is used to assess the PLS path model's validity. A measure of prediction accuracy is the $Q^2$ value (Stone, 1974; Geisser, 1974). By reproducing the observed values provided in the model itself using blind folding techniques, the model is able to anticipate and predict (Henseler et al., et al 2009). In structural models, a value of $Q^2$ greater than zero indicates that the model has predictive relevance, whereas a value of $Q^2$ less than zero indicates that the model lacks predictive relevance. The values of 0.02, 0.15, and 0.35 indicate that an independent construct has a moderate, medium, or substantial predictive relevance for a chosen dependent construct, respectively, to support predictive relevance. The $Q^2$ effect size indicating the model's predictive relevance and inference is shown in Table 5-20. The predictive relevance $Q^2$ effect size of each exogenous component in the model is 0.552, indicating that the constructs have a significant predictive impact on behavioral intention to enrol in MOOCs.

**Table 5-20: Predictive relevance of the model by cross validated redundancy approach**

| **Construct** | **Type of Latent Construct** | **SSO** | **SSE** | **$Q^2$ (=1-SSE/SSO)** |
|---|---|---|---|---|
| Behavioral Intention | Endogenous | 1449.000 | 649.430 | 0.552 |
| Effort Expectancy | Exogenous | 1449.000 | 1449.000 | |
| Facilitating Condition | Exogenous | 1932.000 | 1932.000 | |
| Habit | Exogenous | 1449.000 | 1449.000 | |
| Hedonic Motivation | Exogenous | 1449.000 | 1449.000 | |
| Language Competency | Exogenous | 2415.000 | 2415.000 | |
| Performance Expectancy | Exogenous | 1932.000 | 1932.000 | |
| Price Value | Exogenous | 1449.000 | 1449.000 | |
| Social Influence | Exogenous | 1449.000 | 1449.000 | |
| Teacher Influence | Exogenous | 2415.000 | 2415.000 | |

In short, the measurement of the structural model explains that the structural model fulfils the benchmarked quality standard. Thus, the forthcoming step is to analyse and evaluate the hypothesised educational characteristics of students impacting behavioral intention to adopt MOOCs.

### 5.10.3 Analysis of Variance (ANOVA) test

An ANOVA was performed to study the impact of educational characteristics of students on the behavioral intention towards MOOC adoption. Educational characteristics refer to the course stream enrolled, the type of institution, and the nature of the degree. First, the factors of MOOC adoption and behavioral intention towards MOOCs differ significantly across the course streams of Gen Z students were analysed and evaluated. Higher education institutions across the country run several courses. The learning derived from these courses and the changing demand for these courses in line with the industry requirements influence students’ intention toward MOOC adoption. As a result, the first section of this hypothesis makes an effort to analyse the influence of students' course streams on their behavioural intention to adopt MOOCs.

To begin with, we established the normality of data by conducting Levene's test resulting in a *p*-value greater than 0.05, in case of all constructs (see Table 5-21). The F-test is used by Levene's test to evaluate the null hypothesis that the variance is the same for all groups. A p-value of less than.05 indicates that the assumption should be rejected.

Table 5-21: Test of Homogeneity of Variances

| | Levene Statistic | df1 | df2 | Sig. |
|---|---|---|---|---|
| Performance Expectancy | .615 | 4 | 478 | .652 |
| Effort Expectancy | .431 | 4 | 478 | .786 |
| Social Influence | .945 | 4 | 478 | .438 |
| Facilitating Conditions | .151 | 4 | 478 | .962 |
| Hedonic Motivation | 2.095 | 4 | 478 | .080 |
| Price Value | .390 | 4 | 478 | .816 |
| Habit | .655 | 4 | 478 | .624 |
| Behavioral Intention | .580 | 4 | 478 | .677 |
| Language Competency | .247 | 4 | 478 | .911 |
| Teacher Influence | 1.453 | 4 | 478 | .215 |

Subsequently, we measured the mean of all the factors across the course streams which is depicted in Table 5-22. The table shows that students pursuing management/administration courses have the highest mean for PE (3.91), SI (3.69), PV (3.33), HT (3.19), BI (3.51), LC (3.92) and TI (4.03). However, students pursuing science and any other (Arts and Humanities, Designing, Languages, Music etc.) course have the highest mean score of 4.14 and 3.86 for EE and FC respectively and students pursuing commerce having highest mean score of 3.64 in case of HM.

Table 5-22: Mean of Course stream

| | | N | Mean | Std. Deviation | Std. Error |
|---|---|---|---|---|---|
| Performance Expectancy | Science | 19 | 3.776 | 1.007 | 0.231 |
| | Engineering | 85 | 3.806 | 0.822 | 0.089 |
| | Commerce | 75 | 3.890 | 0.739 | 0.085 |
| | Management/ Administration | 238 | 3.914 | 0.804 | 0.052 |
| | Any other | 66 | 3.686 | 0.748 | 0.092 |
| | Total | 483 | 3.855 | 0.800 | 0.036 |
| Effort Expectancy | Science | 19 | 4.140 | 0.788 | 0.181 |
| | Engineering | 85 | 3.510 | 0.952 | 0.103 |
| | Commerce | 75 | 3.751 | 0.870 | 0.100 |
| | Management/ Administration | 238 | 3.713 | 0.962 | 0.062 |
| | Any other | 66 | 3.717 | 0.864 | 0.106 |
| | Total | 483 | 3.701 | 0.931 | 0.042 |
| Social Influence | Science | 19 | 3.351 | 1.189 | 0.273 |
| | Engineering | 85 | 3.557 | 0.926 | 0.100 |
| | Commerce | 75 | 3.627 | 0.960 | 0.111 |
| | Management/ Administration | 238 | 3.691 | 0.850 | 0.055 |
| | Any Other | 66 | 3.540 | 0.955 | 0.118 |
| | Total | 483 | 3.623 | 0.910 | 0.041 |
| Facilitating Conditions | Science | 19 | 3.816 | 0.953 | 0.219 |
| | Engineering | 85 | 3.603 | 0.812 | 0.088 |
| | Commerce | 75 | 3.757 | 0.797 | 0.092 |
| | Management/ Administration | 238 | 3.723 | 0.788 | 0.051 |
| | Any Other | 66 | 3.864 | 0.726 | 0.089 |
| | Total | 483 | 3.730 | 0.793 | 0.036 |
| Hedonic Motivation | Science | 19 | 3.263 | 0.927 | 0.213 |
| | Engineering | 85 | 3.537 | 0.977 | 0.106 |
| | Commerce | 75 | 3.644 | 0.797 | 0.092 |
| | Management/ Administration | 238 | 3.629 | 1.002 | 0.065 |
| | Any Other | 66 | 3.429 | 0.816 | 0.100 |
| | Total | 483 | 3.574 | 0.943 | 0.043 |
| Price Value | Science | 19 | 3.088 | 1.053 | 0.242 |
| | Engineering | 85 | 3.231 | 0.927 | 0.101 |
| | Commerce | 75 | 3.267 | 1.004 | 0.116 |

| | | | | | |
|---|---|---|---|---|---|
| | Management/ Administration | 238 | 3.339 | 0.995 | 0.065 |
| | Any Other | 66 | 2.934 | 0.998 | 0.123 |
| | Total | 483 | 3.244 | 0.993 | 0.045 |
| Habit | Science | 19 | 2.860 | 1.073 | 0.246 |
| | Engineering | 85 | 3.039 | 0.843 | 0.091 |
| | Commerce | 75 | 3.151 | 0.916 | 0.106 |
| | Management/ Administration | 238 | 3.193 | 0.836 | 0.054 |
| | Any Other | 66 | 2.823 | 0.831 | 0.102 |
| | Total | 483 | 3.096 | 0.866 | 0.039 |
| Bevavioural Intention | Science | 19 | 3.404 | 1.022 | 0.234 |
| | Engineering | 85 | 3.322 | 0.968 | 0.105 |
| | Commerce | 75 | 3.387 | 0.904 | 0.104 |
| | Management/ Administration | 238 | 3.517 | 0.970 | 0.063 |
| | Any other | 66 | 2.960 | 0.892 | 0.110 |
| | Total | 483 | 3.382 | 0.965 | 0.044 |
| Language Competency | Science | 19 | 3.737 | 0.859 | 0.197 |
| | Engineering | 85 | 3.635 | 0.697 | 0.076 |
| | Commerce | 75 | 3.917 | 0.698 | 0.081 |
| | Management/ Administration | 238 | 3.923 | 0.666 | 0.043 |
| | Any other | 66 | 3.797 | 0.679 | 0.084 |
| | Total | 483 | 3.847 | 0.692 | 0.032 |
| Teacher Influence | Science | 19 | 3.958 | 0.876 | 0.201 |
| | Engineering | 85 | 3.671 | 0.764 | 0.083 |
| | Commerce | 75 | 3.979 | 0.654 | 0.076 |
| | Management/ Administration | 238 | 4.033 | 0.628 | 0.041 |
| | Any other | 66 | 3.952 | 0.663 | 0.082 |
| | Total | 483 | 3.947 | 0.683 | 0.031 |

Finally, One-way ANOVA analysis was conducted with the assumption that mean of the factors of MOOC adoption and behavioral intention towards MOOC differ significantly across the course streams of Gen Z students. From the Table 5-23, it is clear that the computed value of F is greater between the course streams for the factors of HT (2.95), BI (4.53), LC (3.15) and TI (4.59). Correspondingly, the observed p-value of HT (0.02), BI (0.001), LC (.014), and TI (0.01) for these factors is below the chosen alpha of 0.05 (0.000 < 0.05). Thus, the hypothesis is partially accepted, suggesting significant difference between course streams for the factors of HT, BI, LC and TI.

Table 5-23: One-way ANOVA test on Course stream

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Performance Expectancy | Between Groups | 3.133 | 4 | .783 | 1.227 | .299 |
| | Within Groups | 305.212 | 478 | .639 | | |
| | Total | 308.345 | 482 | | | |
| Effort Expectancy | Between Groups | 7.014 | 4 | 1.753 | 2.039 | .088 |
| | Within Groups | 410.989 | 478 | .860 | | |
| | Total | 418.003 | 482 | | | |
| Social Influence | Between Groups | 3.314 | 4 | .828 | 1.000 | .407 |
| | Within Groups | 396.107 | 478 | .829 | | |
| | Total | 399.420 | 482 | | | |
| Facilitating Conditions | Between Groups | 2.757 | 4 | .689 | 1.097 | .357 |
| | Within Groups | 300.359 | 478 | .628 | | |
| | Total | 303.116 | 482 | | | |
| Hedonic Motivation | Between Groups | 4.421 | 4 | 1.105 | 1.246 | .290 |
| | Within Groups | 423.942 | 478 | .887 | | |
| | Total | 428.363 | 482 | | | |
| Price Value | Between Groups | 8.990 | 4 | 2.247 | 2.304 | .058 |
| | Within Groups | 466.234 | 478 | .975 | | |
| | Total | 475.223 | 482 | | | |
| Habit | Between Groups | 8.726 | 4 | 2.181 | 2.953 | .020 |
| | Within Groups | 353.163 | 478 | .739 | | |
| | Total | 361.889 | 482 | | | |
| Behavioral Intention | Between Groups | 16.422 | 4 | 4.105 | 4.536 | .001 |
| | Within Groups | 432.673 | 478 | .905 | | |
| | Total | 449.095 | 482 | | | |
| Language Competency | Between Groups | 5.940 | 4 | 1.485 | 3.153 | .014 |
| | Within Groups | 225.123 | 478 | .471 | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Total | 231.063 | 482 | | | |
| Teacher Influence | Between Groups | 8.324 | 4 | 2.081 | 4.596 | .001 |
| | Within Groups | 216.418 | 478 | .453 | | |
| | Total | 224.742 | 482 | | | |

To know further as to which course stream has a significant impact on factors influencing MOOC adoption intention, we ran post hoc test (table 5-24). Result posits that there is a major difference between the students pursuing management/administration and any other courses (0.028) on the factor of PV towards MOOC adoption intention. Similarly, the study posits that there is a major difference between the students pursuing management/administration courses and any other courses (0.018) on the factor of HT towards MOOC adoption intention. Study highlights significant difference between the learners pursuing management/administration courses and any other courses (0.000) on the factor of BI towards MOOC adoption intention. Lastly the study posits that there is major difference between students pursuing engineering and commerce (0.033), engineering and management/administration (0.000) on the factor of TI towards MOOC adoption intention.

Table 5-24: Multiple Comparisons (Post hoc test)

| Dependent Variable | (I) Participant Education Stream | (J) Participant Education Stream | Mean Difference (I-J) | Std. Error | Sig. |
|---|---|---|---|---|---|
| PE | Science | Engineering | -0.030 | 0.203 | 1.000 |
| | | Commerce | -0.114 | 0.205 | 0.981 |
| | | Management/Administration | -0.138 | 0.191 | 0.951 |
| | | Any Other | 0.091 | 0.208 | 0.992 |
| | Engineering | Science | 0.030 | 0.203 | 1.000 |
| | | Commerce | -0.084 | 0.127 | 0.964 |
| | | Management/Administration | -0.108 | 0.101 | 0.822 |
| | | Any Other | 0.120 | 0.131 | 0.890 |
| | Commerce | Science | 0.114 | 0.205 | 0.981 |
| | | Engineering | 0.084 | 0.127 | 0.964 |
| | | Management/Administration | -0.024 | 0.106 | 0.999 |
| | | Any Other | 0.204 | 0.135 | 0.553 |
| | Management/Administration | Science | 0.138 | 0.191 | 0.951 |
| | | Engineering | 0.108 | 0.101 | 0.822 |

| | | | | | |
|---|---|---|---|---|---|
| | | Commerce | 0.024 | 0.106 | 0.999 |
| | | Any Other | 0.228 | 0.111 | 0.242 |
| | Any Other | Science | -0.091 | 0.208 | 0.992 |
| | | Engineering | -0.120 | 0.131 | 0.890 |
| | | Commerce | -0.204 | 0.135 | 0.553 |
| | | Management/Administration | -0.228 | 0.111 | 0.242 |
| EE | Science | Engineering | 0.631 | 0.235 | 0.058 |
| | | Commerce | 0.389 | 0.238 | 0.476 |
| | | Management/Administration | 0.427 | 0.221 | 0.301 |
| | | Any Other | 0.423 | 0.241 | 0.403 |
| | Engineering | Science | -0.631 | 0.235 | 0.058 |
| | | Commerce | -0.241 | 0.147 | 0.471 |
| | | Management/Administration | -0.203 | 0.117 | 0.414 |
| | | Any Other | -0.207 | 0.152 | 0.652 |
| | Commerce | Science | -0.389 | 0.238 | 0.476 |
| | | Engineering | 0.241 | 0.147 | 0.471 |
| | | Management/Administration | 0.038 | 0.123 | 0.998 |
| | | Any Other | 0.034 | 0.157 | 1.000 |
| | Management/Administration | Science | -0.427 | 0.221 | 0.301 |
| | | Engineering | 0.203 | 0.117 | 0.414 |
| | | Commerce | -0.038 | 0.123 | 0.998 |
| | | Any Other | -0.004 | 0.129 | 1.000 |
| | Any Other | Science | -0.423 | 0.241 | 0.403 |
| | | Engineering | 0.207 | 0.152 | 0.652 |
| | | Commerce | -0.034 | 0.157 | 1.000 |
| | | Management/Administration | 0.004 | 0.129 | 1.000 |
| SI | Science | Engineering | -0.206 | 0.231 | 0.900 |
| | | Commerce | -0.276 | 0.234 | 0.763 |
| | | Management/Administration | -0.340 | 0.217 | 0.521 |
| | | Any Other | -0.190 | 0.237 | 0.931 |
| | Engineering | Science | 0.206 | 0.231 | 0.900 |
| | | Commerce | -0.070 | 0.144 | 0.989 |
| | | Management/Administration | -0.134 | 0.115 | 0.773 |
| | | Any Other | 0.016 | 0.149 | 1.000 |
| | Commerce | Science | 0.276 | 0.234 | 0.763 |
| | | Engineering | 0.070 | 0.144 | 0.989 |
| | | Management/Administration | -0.064 | 0.121 | 0.984 |
| | | Any Other | 0.086 | 0.154 | 0.980 |
| | | Science | 0.340 | 0.217 | 0.521 |

| | | | | | |
|---|---|---|---|---|---|
| | Management/Administration | Engineering | 0.134 | 0.115 | 0.773 |
| | | Commerce | 0.064 | 0.121 | 0.984 |
| | | Any Other | 0.150 | 0.127 | 0.760 |
| | Any Other | Science | 0.190 | 0.237 | 0.931 |
| | | Engineering | -0.016 | 0.149 | 1.000 |
| | | Commerce | -0.086 | 0.154 | 0.980 |
| | | Management/Administration | -0.150 | 0.127 | 0.760 |
| FC | Science | Engineering | 0.213 | 0.201 | 0.828 |
| | | Commerce | 0.059 | 0.204 | 0.998 |
| | | Management/Administration | 0.093 | 0.189 | 0.988 |
| | | Any Other | -0.048 | 0.206 | 0.999 |
| | Engineering | Science | -0.213 | 0.201 | 0.828 |
| | | Commerce | -0.154 | 0.126 | 0.737 |
| | | Management/Administration | -0.120 | 0.100 | 0.754 |
| | | Any Other | -0.261 | 0.130 | 0.265 |
| | Commerce | Science | -0.059 | 0.204 | 0.998 |
| | | Engineering | 0.154 | 0.126 | 0.737 |
| | | Management/Administration | 0.034 | 0.105 | 0.998 |
| | | Any Other | -0.107 | 0.134 | 0.931 |
| | Management/Administration | Science | -0.093 | 0.189 | 0.988 |
| | | Engineering | 0.120 | 0.100 | 0.754 |
| | | Commerce | -0.034 | 0.105 | 0.998 |
| | | Any Other | -0.141 | 0.110 | 0.705 |
| | Any Other | Science | 0.048 | 0.206 | 0.999 |
| | | Engineering | 0.261 | 0.130 | 0.265 |
| | | Commerce | 0.107 | 0.134 | 0.931 |
| | | Management/Administration | 0.141 | 0.110 | 0.705 |
| HM | Science | Engineering | -0.274 | 0.239 | 0.781 |
| | | Commerce | -0.381 | 0.242 | 0.513 |
| | | Management/Administration | -0.366 | 0.225 | 0.480 |
| | | Any Other | -0.166 | 0.245 | 0.961 |
| | Engineering | Science | 0.274 | 0.239 | 0.781 |
| | | Commerce | -0.107 | 0.149 | 0.952 |
| | | Management/Administration | -0.092 | 0.119 | 0.939 |
| | | Any Other | 0.108 | 0.155 | 0.957 |
| | Commerce | Science | 0.381 | 0.242 | 0.513 |
| | | Engineering | 0.107 | 0.149 | 0.952 |
| | | Management/Administration | 0.016 | 0.125 | 1.000 |
| | | Any Other | 0.215 | 0.159 | 0.658 |

| | | | | | |
|---|---|---|---|---|---|
| | Management/Administration | Science | 0.366 | 0.225 | 0.480 |
| | | Engineering | 0.092 | 0.119 | 0.939 |
| | | Commerce | -0.016 | 0.125 | 1.000 |
| | | Any Other | 0.200 | 0.131 | 0.548 |
| | Any Other | Science | 0.166 | 0.245 | 0.961 |
| | | Engineering | -0.108 | 0.155 | 0.957 |
| | | Commerce | -0.215 | 0.159 | 0.658 |
| | | Management/Administration | -0.200 | 0.131 | 0.548 |
| PV | Science | Engineering | -0.144 | 0.251 | 0.979 |
| | | Commerce | -0.179 | 0.254 | 0.955 |
| | | Management/Administration | -0.251 | 0.235 | 0.823 |
| | | Any Other | 0.153 | 0.257 | 0.976 |
| | Engineering | Science | 0.144 | 0.251 | 0.979 |
| | | Commerce | -0.035 | 0.156 | 0.999 |
| | | Management/Administration | -0.108 | 0.125 | 0.911 |
| | | Any Other | 0.297 | 0.162 | 0.356 |
| | Commerce | Science | 0.179 | 0.254 | 0.955 |
| | | Engineering | 0.035 | 0.156 | 0.999 |
| | | Management/Administration | -0.072 | 0.131 | 0.982 |
| | | Any Other | 0.332 | 0.167 | 0.271 |
| | Management/Administration | Science | 0.251 | 0.235 | 0.823 |
| | | Engineering | 0.108 | 0.125 | 0.911 |
| | | Commerce | 0.072 | 0.131 | 0.982 |
| | | Any Other | .40459* | 0.137 | 0.028 |
| | Any Other | Science | -0.153 | 0.257 | 0.976 |
| | | Engineering | -0.297 | 0.162 | 0.356 |
| | | Commerce | -0.332 | 0.167 | 0.271 |
| | | Management/Administration | -.40459* | 0.137 | 0.028 |
| HT | Science | Engineering | -0.180 | 0.218 | 0.923 |
| | | Commerce | -0.291 | 0.221 | 0.679 |
| | | Management/Administration | -0.334 | 0.205 | 0.480 |
| | | Any Other | 0.036 | 0.224 | 1.000 |
| | Engineering | Science | 0.180 | 0.218 | 0.923 |
| | | Commerce | -0.112 | 0.136 | 0.924 |
| | | Management/Administration | -0.154 | 0.109 | 0.616 |
| | | Any Other | 0.216 | 0.141 | 0.542 |
| | Commerce | Science | 0.291 | 0.221 | 0.679 |
| | | Engineering | 0.112 | 0.136 | 0.924 |
| | | Management/Administration | -0.042 | 0.114 | 0.996 |

| | | | | | |
|---|---|---|---|---|---|
| | | Any Other | 0.328 | 0.145 | 0.160 |
| | Management/Administration | Science | 0.334 | 0.205 | 0.480 |
| | | Engineering | 0.154 | 0.109 | 0.616 |
| | | Commerce | 0.042 | 0.114 | 0.996 |
| | | Any Other | .37004* | 0.120 | 0.018 |
| | Any Other | Science | -0.036 | 0.224 | 1.000 |
| | | Engineering | -0.216 | 0.141 | 0.542 |
| | | Commerce | -0.328 | 0.145 | 0.160 |
| | | Management/Administration | -.37004* | 0.120 | 0.018 |
| BI | Science | Engineering | 0.082 | 0.241 | 0.997 |
| | | Commerce | 0.017 | 0.244 | 1.000 |
| | | Management/Administration | -0.113 | 0.227 | 0.987 |
| | | Any Other | 0.444 | 0.248 | 0.379 |
| | Engineering | Science | -0.082 | 0.241 | 0.997 |
| | | Commerce | -0.065 | 0.151 | 0.993 |
| | | Management/Administration | -0.195 | 0.120 | 0.483 |
| | | Any Other | 0.362 | 0.156 | 0.141 |
| | Commerce | Science | -0.017 | 0.244 | 1.000 |
| | | Engineering | 0.065 | 0.151 | 0.993 |
| | | Management/Administration | -0.130 | 0.126 | 0.840 |
| | | Any Other | 0.427 | 0.161 | 0.062 |
| | Management/Administration | Science | 0.113 | 0.227 | 0.987 |
| | | Engineering | 0.195 | 0.120 | 0.483 |
| | | Commerce | 0.130 | 0.126 | 0.840 |
| | | Any Other | .55721* | 0.132 | 0.000 |
| | Any Other | Science | -0.444 | 0.248 | 0.379 |
| | | Engineering | -0.362 | 0.156 | 0.141 |
| | | Commerce | -0.427 | 0.161 | 0.062 |
| | | Management/Administration | -.55721* | 0.132 | 0.000 |
| LC | Science | Engineering | 0.102 | 0.174 | 0.978 |
| | | Commerce | -0.180 | 0.176 | 0.844 |
| | | Management/Administration | -0.186 | 0.164 | 0.787 |
| | | Any Other | -0.060 | 0.179 | 0.997 |
| | Engineering | Science | -0.102 | 0.174 | 0.978 |
| | | Commerce | -0.282 | 0.109 | 0.073 |
| | | Management/Administration | -.28739* | 0.087 | 0.009 |
| | | Any Other | -0.162 | 0.113 | 0.605 |
| | Commerce | Science | 0.180 | 0.176 | 0.844 |
| | | Engineering | 0.282 | 0.109 | 0.073 |

| | | | | | |
|---|---|---|---|---|---|
| | | Management/Administration | -0.005 | 0.091 | 1.000 |
| | | Any Other | 0.120 | 0.116 | 0.837 |
| | Management/Administration | Science | 0.186 | 0.164 | 0.787 |
| | | Engineering | .28739* | 0.087 | 0.009 |
| | | Commerce | 0.005 | 0.091 | 1.000 |
| | | Any Other | 0.126 | 0.095 | 0.681 |
| | Any Other | Science | 0.060 | 0.179 | 0.997 |
| | | Engineering | 0.162 | 0.113 | 0.605 |
| | | Commerce | -0.120 | 0.116 | 0.837 |
| | | Management/Administration | -0.126 | 0.095 | 0.681 |
| TI | Science | Engineering | 0.287 | 0.171 | 0.446 |
| | | Commerce | -0.021 | 0.173 | 1.000 |
| | | Management/Administration | -0.075 | 0.160 | 0.990 |
| | | Any Other | 0.006 | 0.175 | 1.000 |
| | Engineering | Science | -0.287 | 0.171 | 0.446 |
| | | Commerce | -.30808* | 0.107 | 0.033 |
| | | Management/Administration | -.36218* | 0.085 | 0.000 |
| | | Any Other | -0.281 | 0.110 | 0.083 |
| | Commerce | Science | 0.021 | 0.173 | 1.000 |
| | | Engineering | .30808* | 0.107 | 0.033 |
| | | Management/Administration | -0.054 | 0.089 | 0.974 |
| | | Anyother | 0.027 | 0.114 | 0.999 |
| | Management/Administration | Science | 0.075 | 0.160 | 0.990 |
| | | Engineering | .36218* | 0.085 | 0.000 |
| | | Commerce | 0.054 | 0.089 | 0.974 |
| | | Anyother | 0.081 | 0.094 | 0.908 |
| | Any Other | Science | -0.006 | 0.175 | 1.000 |
| | | Engineering | 0.281 | 0.110 | 0.083 |
| | | Commerce | -0.027 | 0.114 | 0.999 |
| | | Management/Administration | -0.081 | 0.094 | 0.908 |

Secondly, the factors of MOOC adoption and behavioral intention towards MOOC differ significantly across the Gen Z students' Institution type were analysed and evaluated.

India which boasts of several State Universities, Deemed to be Universities, Central Universities, Private Universities offering different UG and PG courses across all streams of study, have students with different demographic, socio-economic background and all of them come to attain higher education with varied reasons. Every university has its own management, culture and way of governance which is believed to influence the behavioral intention of students studying in it towards things around. Therefore, in the second section of this hypotheses, the study endeavours to analyse the impact of respondents' institution type on the behavioral intention toward MOOC adoption. Normality of the data distribution was established using Levene's test (see Table 5-25).

**Table 5-25: Test of Homogeneity of Variances**

| | Levene Statistic | df1 | df2 | Sig. |
|---|---|---|---|---|
| Performance Expectancy | .615 | 4 | 478 | .652 |
| Effort Expectancy | .431 | 4 | 478 | .786 |
| Social Influence | .945 | 4 | 478 | .438 |
| Facilitating Conditions | .151 | 4 | 478 | .962 |
| Hedonic Motivation | 2.095 | 4 | 478 | .080 |
| Price Value | .390 | 4 | 478 | .816 |
| Habit | .655 | 4 | 478 | .624 |
| Behavioral Intention | .580 | 4 | 478 | .677 |
| Language Competency | .247 | 4 | 478 | .911 |
| Teacher Influence | 1.453 | 4 | 478 | .215 |

Subsequently, we measured the mean of all the factors across the institution type covered in the sample which is depicted in Table 5-26. The table shows that students pursuing courses in the institution of national repute have the highest mean for PE (4.18), EE (4.14), SI (3.86), PV (3.50), HT (3.20), LC (4.09), and TI (4.25). However, students pursuing courses in the central university and institution of eminence have the highest mean score of 4.15 and 3.76 for FC and HM, respectively.

Table 5-26: Mean of Institution type

| | | N | Mean | Std. Deviation | Std. Error |
|---|---|---|---|---|---|
| Performance Expectancy | Private College/University | 182 | 3.846 | 0.819 | 0.061 |
| | State University | 155 | 3.858 | 0.815 | 0.065 |

| | | | | | |
|---|---|---|---|---|---|
| | Deemed University | 51 | 3.765 | 0.889 | 0.125 |
| | Central University | 57 | 3.833 | 0.693 | 0.092 |
| | Institution of Eminence (IOE) | 13 | 3.750 | 0.700 | 0.194 |
| | Institution of National Repute | 25 | 4.180 | 0.619 | 0.124 |
| | Total | 483 | 3.855 | 0.800 | 0.036 |
| Effort Expectancy | Private College/University | 182 | 3.659 | 0.904 | 0.067 |
| | State University | 155 | 3.572 | 1.021 | 0.082 |
| | Deemed University | 51 | 3.765 | 0.883 | 0.124 |
| | Central University | 57 | 4.012 | 0.740 | 0.098 |
| | Institution of Eminence (IOE) | 13 | 3.333 | 0.943 | 0.261 |
| | Institution of National Repute | 25 | 4.147 | 0.758 | 0.152 |
| | Total | 483 | 3.701 | 0.931 | 0.042 |
| Social Influence | Private College/University | 182 | 3.590 | 0.932 | 0.069 |
| | State University | 155 | 3.615 | 0.929 | 0.075 |
| | Deemed University | 51 | 3.699 | 0.803 | 0.113 |
| | Central University | 57 | 3.684 | 0.793 | 0.105 |
| | Institution of Eminence (IOE) | 13 | 3.154 | 1.059 | 0.294 |
| | Institution of National Repute | 25 | 3.867 | 0.986 | 0.197 |
| | Total | 483 | 3.623 | 0.910 | 0.041 |
| Facilitating Conditions | Private College/University | 182 | 3.603 | 0.809 | 0.060 |
| | State University | 155 | 3.660 | 0.818 | 0.066 |
| | Deemed University | 51 | 3.814 | 0.672 | 0.094 |
| | Central University | 57 | 4.156 | 0.620 | 0.082 |
| | Institution of Eminence (IOE) | 13 | 3.423 | 0.739 | 0.205 |
| | Institution of National Repute | 25 | 4.150 | 0.700 | 0.140 |
| | Total | 483 | 3.730 | 0.793 | 0.036 |
| Hedonic Motivation | Private College/University | 182 | 3.599 | 0.972 | 0.072 |
| | State University | 155 | 3.518 | 0.988 | 0.079 |

| | | | | | |
|---|---|---|---|---|---|
| | Deemed University | 51 | 3.556 | 0.990 | 0.139 |
| | Central University | 57 | 3.538 | 0.726 | 0.096 |
| | Institution of Eminence (IOE) | 13 | 3.769 | 0.917 | 0.254 |
| | Institution of National Repute | 25 | 3.747 | 0.824 | 0.165 |
| | Total | 483 | 3.574 | 0.943 | 0.043 |
| Price Value | Private College/University | 182 | 3.319 | 0.975 | 0.072 |
| | State University | 155 | 3.260 | 0.968 | 0.078 |
| | Deemed University | 51 | 3.281 | 1.023 | 0.143 |
| | Central University | 57 | 2.854 | 0.966 | 0.128 |
| | Institution of Eminence (IOE) | 13 | 3.051 | 1.193 | 0.331 |
| | Institution of National Repute | 25 | 3.507 | 1.028 | 0.206 |
| | Total | 483 | 3.244 | 0.993 | 0.045 |
| Habit | Private College/University | 182 | 3.152 | 0.864 | 0.064 |
| | State University | 155 | 3.123 | 0.861 | 0.069 |
| | Deemed University | 51 | 3.157 | 0.885 | 0.124 |
| | Central University | 57 | 2.830 | 0.805 | 0.107 |
| | Institution of Eminence (IOE) | 13 | 2.718 | 1.070 | 0.297 |
| | Institution of National Repute | 25 | 3.200 | 0.822 | 0.164 |
| | Total | 483 | 3.096 | 0.866 | 0.039 |
| Behavioral Intention | Private College/University | 182 | 3.394 | 0.994 | 0.074 |
| | State University | 155 | 3.419 | 0.981 | 0.079 |
| | Deemed University | 51 | 3.288 | 1.024 | 0.143 |
| | Central University | 57 | 3.193 | 0.873 | 0.116 |
| | Institution of Eminence (IOE) | 13 | 3.205 | 0.800 | 0.222 |
| | Institution of National Repute | 25 | 3.773 | 0.718 | 0.144 |
| | Total | 483 | 3.382 | 0.965 | 0.044 |
| Language Competency | Private College/University | 182 | 3.836 | 0.699 | 0.052 |
| | State University | 155 | 3.808 | 0.740 | 0.059 |

| | | | | | |
|---|---|---|---|---|---|
| | Deemed University | 51 | 3.733 | 0.669 | 0.094 |
| | Central University | 57 | 3.986 | 0.580 | 0.077 |
| | Institution of Eminence (IOE) | 13 | 3.815 | 0.802 | 0.222 |
| | Institution of National Repute | 25 | 4.096 | 0.487 | 0.097 |
| | Total | 483 | 3.847 | 0.692 | 0.032 |
| Teacher Influence | Private College/University | 182 | 3.941 | 0.694 | 0.051 |
| | State University | 155 | 3.916 | 0.668 | 0.054 |
| | Deemed University | 51 | 3.969 | 0.750 | 0.105 |
| | Central University | 57 | 3.912 | 0.686 | 0.091 |
| | Institution of Eminence (IOE) | 13 | 3.862 | 0.585 | 0.162 |
| | Institution of National Repute | 25 | 4.256 | 0.561 | 0.112 |
| | Total | 483 | 3.947 | 0.683 | 0.031 |

Finally, One-way ANOVA analysis was done with the assumption that mean of the factors of MOOC adoption and behavioral intention towards MOOC differ significantly across the Gen Z students' Institution type. From the Table 5-27, it is clear that the computed value of F is greater between the course streams for the factors of EE (3.63), FC (6.41), and PV (2.47). Correspondingly, the observed p-value of EE (0.003), FC (0.000), and PV (0.032) for these factors is below the chosen alpha value of 0.05 (0.000 < 0.05). Hence, the research hypothesis is partially accepted, suggesting major difference between the type of institutions for the factors of EE, FC, and PV.

Table 5-27 One-way ANOVA test on Institution type

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Performance Expectancy | Between Groups | 3.242 | 5 | .648 | 1.014 | .409 |
| | Within Groups | 305.103 | 477 | .640 | | |
| | Total | 308.345 | 482 | | | |
| Effort Expectancy | Between Groups | 15.325 | 5 | 3.065 | 3.631 | .003 |
| | Within Groups | 402.678 | 477 | .844 | | |
| | Total | 418.003 | 482 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Social Influence | Between Groups | 5.068 | 5 | 1.014 | 1.226 | .296 |
| | Within Groups | 394.353 | 477 | .827 | | |
| | Total | 399.420 | 482 | | | |
| Facilitating Conditions | Between Groups | 19.087 | 5 | 3.817 | 6.411 | .000 |
| | Within Groups | 284.029 | 477 | .595 | | |
| | Total | 303.116 | 482 | | | |
| Hedonic Motivation | Between Groups | 1.926 | 5 | .385 | .431 | .827 |
| | Within Groups | 426.437 | 477 | .894 | | |
| | Total | 428.363 | 482 | | | |
| Price Value | Between Groups | 12.012 | 5 | 2.402 | 2.474 | .032 |
| | Within Groups | 463.211 | 477 | .971 | | |
| | Total | 475.223 | 482 | | | |
| Habit | Between Groups | 7.019 | 5 | 1.404 | 1.887 | .095 |
| | Within Groups | 354.870 | 477 | .744 | | |
| | Total | 361.889 | 482 | | | |
| Behavioral Intention | Between Groups | 6.968 | 5 | 1.394 | 1.503 | .187 |
| | Within Groups | 442.127 | 477 | .927 | | |
| | Total | 449.095 | 482 | | | |
| Language Competency | Between Groups | 3.583 | 5 | .717 | 1.502 | .188 |
| | Within Groups | 227.480 | 477 | .477 | | |
| | Total | 231.063 | 482 | | | |
| Teacher Influence | Between Groups | 2.729 | 5 | .546 | 1.173 | .321 |
| | Within Groups | 222.012 | 477 | .465 | | |
| | Total | 224.742 | 482 | | | |

To know further as to which type of college/university has a significant impact on factors influencing MOOC adoption intention we ran post hoc test (Table 5-28). The findings divulge that there is a major difference between students studying in the state universities and central universities (0.026), state universities and institutions of national repute (0.045) on the factor of EE towards MOOC adoption intention. Similarly, the study reveals that there is a major difference between the students studying in the private college/universities and central universities (0.000) and private college/universities and institutions of national repute (0.012), state universities and central universities (0.001), state universities and institutions of national repute (0.039), central and state universities (0.001), central universities and institutions of eminence (0.033), on the factor of FC towards MOOC adoption intention. The findings also highlight the significant difference between the private universities and central universities (0.024), on the factor of PV towards MOOC adoption intention.

Table 5-28 Multiple Comparisons (Post hoc test)

| Dependent Variable | (I) College/University Type | (J) College/University Type | Mean Difference (I-J) | Std. Error | Sig. |
|---|---|---|---|---|---|
| PE | Private College/University | State University | -.01191 | .08741 | 1.000 |
| | | Deemed University | .08145 | .12671 | .988 |
| | | Central University | .01282 | .12139 | 1.000 |
| | | Institution of Eminence (IOE) | .09615 | .22960 | .998 |
| | | Institution of National Repute | -.33385 | .17059 | .369 |
| | State University | Private College/University | .01191 | .08741 | 1.000 |
| | | Deemed University | .09336 | .12911 | .979 |
| | | Central University | .02473 | .12389 | 1.000 |
| | | Institution of Eminence (IOE) | .10806 | .23093 | .997 |
| | | Institution of National Repute | -.32194 | .17237 | .423 |
| | Deemed University | Private College/University | -.08145 | .12671 | .988 |
| | | State University | -.09336 | .12911 | .979 |
| | | Central University | -.06863 | .15415 | .998 |
| | | Institution of Eminence (IOE) | .01471 | .24848 | 1.000 |
| | | Institution of National Repute | -.41529 | .19526 | .275 |
| | Central University | Private College/University | -.01282 | .12139 | 1.000 |
| | | State University | -.02473 | .12389 | 1.000 |
| | | Deemed University | .06863 | .15415 | .998 |

| | | | | | |
|---|---|---|---|---|---|
| | | Institution of Eminence (IOE) | .08333 | .24581 | .999 |
| | | Institution of National Repute | -.34667 | .19185 | .462 |
| | Institution of Eminence (IOE) | Private College/University | -.09615 | .22960 | .998 |
| | | State University | -.10806 | .23093 | .997 |
| | | Deemed University | -.01471 | .24848 | 1.000 |
| | | Central University | -.08333 | .24581 | .999 |
| | | Institution of National Repute | -.43000 | .27347 | .617 |
| | Institution of National Repute | Private College/University | .33385 | .17059 | .369 |
| | | State University | .32194 | .17237 | .423 |
| | | Deemed University | .41529 | .19526 | .275 |
| | | Central University | .34667 | .19185 | .462 |
| | | Institution of Eminence (IOE) | .43000 | .27347 | .617 |
| EE | Private College/University | State University | .08730 | .10042 | .954 |
| | | Deemed University | -.10537 | .14557 | .979 |
| | | Central University | -.35236 | .13946 | .118 |
| | | Institution of Eminence (IOE) | .32601 | .26377 | .819 |
| | | Institution of National Repute | -.48733 | .19597 | .130 |
| | State University | Private College/University | -.08730 | .10042 | .954 |
| | | Deemed University | -.19266 | .14832 | .786 |
| | | Central University | -.43965* | .14233 | .026 |
| | | Institution of Eminence (IOE) | .23871 | .26530 | .946 |
| | | Institution of National Repute | -.57462* | .19803 | .045 |
| | Deemed University | Private College/University | .10537 | .14557 | .979 |
| | | State University | .19266 | .14832 | .786 |
| | | Central University | -.24699 | .17710 | .730 |
| | | Institution of Eminence (IOE) | .43137 | .28546 | .657 |
| | | Institution of National Repute | -.38196 | .22432 | .531 |

| | | | | | |
|---|---|---|---|---|---|
| | Central University | Private College/University | .35236 | .13946 | .118 |
| | | State University | .43965* | .14233 | .026 |
| | | Deemed University | .24699 | .17710 | .730 |
| | | Institution of Eminence (IOE) | .67836 | .28240 | .157 |
| | | Institution of National Repute | -.13497 | .22040 | .990 |
| | Institution of Eminence (IOE) | Private College/University | -.32601 | .26377 | .819 |
| | | State University | -.23871 | .26530 | .946 |
| | | Deemed University | -.43137 | .28546 | .657 |
| | | Central University | -.67836 | .28240 | .157 |
| | | Institution of National Repute | -.81333 | .31417 | .102 |
| | Institution of National Repute | Private College/University | .48733 | .19597 | .130 |
| | | State University | .57462* | .19803 | .045 |
| | | Deemed University | .38196 | .22432 | .531 |
| | | Central University | .13497 | .22040 | .990 |
| | | Institution of Eminence (IOE) | .81333 | .31417 | .102 |
| SI | Private College/University | State University | -.02531 | .09938 | 1.000 |
| | | Deemed University | -.10960 | .14406 | .974 |
| | | Central University | -.09447 | .13801 | .984 |
| | | Institution of Eminence (IOE) | .43590 | .26103 | .552 |
| | | Institution of National Repute | -.27692 | .19394 | .710 |
| | State University | Private College/University | .02531 | .09938 | 1.000 |
| | | Deemed University | -.08429 | .14678 | .993 |
| | | Central University | -.06916 | .14085 | .996 |
| | | Institution of Eminence (IOE) | .46121 | .26254 | .495 |
| | | Institution of National Repute | -.25161 | .19597 | .794 |
| | Deemed University | Private College/University | .10960 | .14406 | .974 |
| | | State University | .08429 | .14678 | .993 |
| | | Central University | .01514 | .17526 | 1.000 |

| | | | | | |
|---|---|---|---|---|---|
| | | Institution of Eminence (IOE) | .54550 | .28250 | .384 |
| | | Institution of National Repute | -.16732 | .22199 | .975 |
| | Central University | Private College/University | .09447 | .13801 | .984 |
| | | State University | .06916 | .14085 | .996 |
| | | Deemed University | -.01514 | .17526 | 1.000 |
| | | Institution of Eminence (IOE) | .53036 | .27946 | .405 |
| | | Institution of National Repute | -.18246 | .21811 | .961 |
| | Institution of Eminence (IOE) | Private College/University | -.43590 | .26103 | .552 |
| | | State University | -.46121 | .26254 | .495 |
| | | Deemed University | -.54550 | .28250 | .384 |
| | | Central University | -.53036 | .27946 | .405 |
| | | Institution of National Repute | -.71282 | .31091 | .199 |
| | Institution of National Repute | Private College/University | .27692 | .19394 | .710 |
| | | State University | .25161 | .19597 | .794 |
| | | Deemed University | .16732 | .22199 | .975 |
| | | Central University | .18246 | .21811 | .961 |
| | | Institution of Eminence (IOE) | .71282 | .31091 | .199 |
| FC | Private College/University | State University | -.05666 | .08434 | .985 |
| | | Deemed University | -.21070 | .12226 | .517 |
| | | Central University | -.53294* | .11712 | .000 |
| | | Institution of Eminence (IOE) | .17995 | .22153 | .965 |
| | | Institution of National Repute | -.54698* | .16459 | .012 |
| | State University | Private College/University | .05666 | .08434 | .985 |
| | | Deemed University | -.15405 | .12457 | .819 |
| | | Central University | -.47629* | .11953 | .001 |
| | | Institution of Eminence (IOE) | .23660 | .22281 | .896 |
| | | Institution of National Repute | -.49032* | .16631 | .039 |

| | | | | | |
|---|---|---|---|---|---|
| | Deemed University | Private College/University | .21070 | .12226 | .517 |
| | | State University | .15405 | .12457 | .819 |
| | | Central University | -.32224 | .14873 | .255 |
| | | Institution of Eminence (IOE) | .39065 | .23975 | .579 |
| | | Institution of National Repute | -.33627 | .18840 | .476 |
| | Central University | Private College/University | .53294* | .11712 | .000 |
| | | State University | .47629* | .11953 | .001 |
| | | Deemed University | .32224 | .14873 | .255 |
| | | Institution of Eminence (IOE) | .71289* | .23717 | .033 |
| | | Institution of National Repute | -.01404 | .18511 | 1.000 |
| | Institution of Eminence (IOE) | Private College/University | -.17995 | .22153 | .965 |
| | | State University | -.23660 | .22281 | .896 |
| | | Deemed University | -.39065 | .23975 | .579 |
| | | Central University | -.71289* | .23717 | .033 |
| | | Institution of National Repute | -.72692 | .26386 | .067 |
| | Institution of National Repute | Private College/University | .54698* | .16459 | .012 |
| | | State University | .49032* | .16631 | .039 |
| | | Deemed University | .33627 | .18840 | .476 |
| | | Central University | .01404 | .18511 | 1.000 |
| | | Institution of Eminence (IOE) | .72692 | .26386 | .067 |
| HM | Private College/University | State University | .08062 | .10334 | .971 |
| | | Deemed University | .04335 | .14980 | 1.000 |
| | | Central University | .06089 | .14351 | .998 |
| | | Institution of Eminence (IOE) | -.17033 | .27144 | .989 |
| | | Institution of National Repute | -.14777 | .20167 | .978 |
| | State University | Private College/University | -.08062 | .10334 | .971 |
| | | Deemed University | -.03728 | .15263 | 1.000 |
| | | Central University | -.01973 | .14646 | 1.000 |

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|---|---|---|---|---|---|
| | | Institution of Eminence (IOE) | -.25095 | .27301 | .942 |
| | | Institution of National Repute | -.22839 | .20378 | .873 |
| | Deemed University | Private College/University | -.04335 | .14980 | 1.000 |
| | | State University | .03728 | .15263 | 1.000 |
| | | Central University | .01754 | .18225 | 1.000 |
| | | Institution of Eminence (IOE) | -.21368 | .29377 | .979 |
| | | Institution of National Repute | -.19111 | .23084 | .962 |
| | Central University | Private College/University | -.06089 | .14351 | .998 |
| | | State University | .01973 | .14646 | 1.000 |
| | | Deemed University | -.01754 | .18225 | 1.000 |
| | | Institution of Eminence (IOE) | -.23122 | .29061 | .968 |
| | | Institution of National Repute | -.20865 | .22681 | .941 |
| | Institution of Eminence (IOE) | Private College/University | .17033 | .27144 | .989 |
| | | State University | .25095 | .27301 | .942 |
| | | Deemed University | .21368 | .29377 | .979 |
| | | Central University | .23122 | .29061 | .968 |
| | | Institution of National Repute | .02256 | .32331 | 1.000 |
| | Institution of National Repute | Private College/University | .14777 | .20167 | .978 |
| | | State University | .22839 | .20378 | .873 |
| | | Deemed University | .19111 | .23084 | .962 |
| | | Central University | .20865 | .22681 | .941 |
| | | Institution of Eminence (IOE) | -.02256 | .32331 | 1.000 |
| PV | Private College/University | State University | .05847 | .10771 | .994 |
| | | Deemed University | .03764 | .15613 | 1.000 |
| | | Central University | .46488* | .14957 | .024 |
| | | Institution of Eminence (IOE) | .26740 | .28290 | .934 |
| | | Institution of National Repute | -.18799 | .21019 | .948 |

| | | | | | |
|---|---|---|---|---|---|
| | State University | Private College/University | -.05847 | .10771 | .994 |
| | | Deemed University | -.02083 | .15908 | 1.000 |
| | | Central University | .40641 | .15265 | .085 |
| | | Institution of Eminence (IOE) | .20893 | .28454 | .978 |
| | | Institution of National Repute | -.24645 | .21239 | .855 |
| | Deemed University | Private College/University | -.03764 | .15613 | 1.000 |
| | | State University | .02083 | .15908 | 1.000 |
| | | Central University | .42724 | .18994 | .217 |
| | | Institution of Eminence (IOE) | .22976 | .30617 | .975 |
| | | Institution of National Repute | -.22562 | .24059 | .937 |
| | Central University | Private College/University | -.46488* | .14957 | .024 |
| | | State University | -.40641 | .15265 | .085 |
| | | Deemed University | -.42724 | .18994 | .217 |
| | | Institution of Eminence (IOE) | -.19748 | .30288 | .987 |
| | | Institution of National Repute | -.65287 | .23639 | .066 |
| | Institution of Eminence (IOE) | Private College/University | -.26740 | .28290 | .934 |
| | | State University | -.20893 | .28454 | .978 |
| | | Deemed University | -.22976 | .30617 | .975 |
| | | Central University | .19748 | .30288 | .987 |
| | | Institution of National Repute | -.45538 | .33696 | .756 |
| | Institution of National Repute | Private College/University | .18799 | .21019 | .948 |
| | | State University | .24645 | .21239 | .855 |
| | | Deemed University | .22562 | .24059 | .937 |
| | | Central University | .65287 | .23639 | .066 |
| | | Institution of Eminence (IOE) | .45538 | .33696 | .756 |
| HT | Private College/University | State University | .02943 | .09427 | 1.000 |
| | | Deemed University | -.00485 | .13666 | 1.000 |
| | | Central University | .32161 | .13092 | .139 |

| | | | | | |
|---|---|---|---|---|---|
| | | Institution of Eminence (IOE) | .43407 | .24762 | .497 |
| | | Institution of National Repute | -.04799 | .18397 | 1.000 |
| | State University | Private College/University | -.02943 | .09427 | 1.000 |
| | | Deemed University | -.03428 | .13924 | 1.000 |
| | | Central University | .29217 | .13361 | .246 |
| | | Institution of Eminence (IOE) | .40463 | .24905 | .583 |
| | | Institution of National Repute | -.07742 | .18590 | .998 |
| | Deemed University | Private College/University | .00485 | .13666 | 1.000 |
| | | State University | .03428 | .13924 | 1.000 |
| | | Central University | .32645 | .16625 | .365 |
| | | Institution of Eminence (IOE) | .43891 | .26798 | .574 |
| | | Institution of National Repute | -.04314 | .21058 | 1.000 |
| | Central University | Private College/University | -.32161 | .13092 | .139 |
| | | State University | -.29217 | .13361 | .246 |
| | | Deemed University | -.32645 | .16625 | .365 |
| | | Institution of Eminence (IOE) | .11246 | .26510 | .998 |
| | | Institution of National Repute | -.36959 | .20691 | .476 |
| | Institution of Eminence (IOE) | Private College/University | -.43407 | .24762 | .497 |
| | | State University | -.40463 | .24905 | .583 |
| | | Deemed University | -.43891 | .26798 | .574 |
| | | Central University | -.11246 | .26510 | .998 |
| | | Institution of National Repute | -.48205 | .29493 | .576 |
| | Institution of National Repute | Private College/University | .04799 | .18397 | 1.000 |
| | | State University | .07742 | .18590 | .998 |
| | | Deemed University | .04314 | .21058 | 1.000 |
| | | Central University | .36959 | .20691 | .476 |
| | | Institution of Eminence (IOE) | .48205 | .29493 | .576 |

| | | | | | |
|---|---|---|---|---|---|
| BI | Private College/University | State University | -.02558 | .10523 | 1.000 |
| | | Deemed University | .10619 | .15254 | .982 |
| | | Central University | .20079 | .14613 | .743 |
| | | Institution of Eminence (IOE) | .18864 | .27639 | .984 |
| | | Institution of National Repute | -.37956 | .20535 | .436 |
| | State University | Private College/University | .02558 | .10523 | 1.000 |
| | | Deemed University | .13177 | .15542 | .958 |
| | | Central University | .22637 | .14913 | .653 |
| | | Institution of Eminence (IOE) | .21423 | .27799 | .972 |
| | | Institution of National Repute | -.35398 | .20750 | .528 |
| | Deemed University | Private College/University | -.10619 | .15254 | .982 |
| | | State University | -.13177 | .15542 | .958 |
| | | Central University | .09460 | .18557 | .996 |
| | | Institution of Eminence (IOE) | .08245 | .29912 | 1.000 |
| | | Institution of National Repute | -.48575 | .23505 | .307 |
| | Central University | Private College/University | -.20079 | .14613 | .743 |
| | | State University | -.22637 | .14913 | .653 |
| | | Deemed University | -.09460 | .18557 | .996 |
| | | Institution of Eminence (IOE) | -.01215 | .29591 | 1.000 |
| | | Institution of National Repute | -.58035 | .23095 | .122 |
| | Institution of Eminence (IOE) | Private College/University | -.18864 | .27639 | .984 |
| | | State University | -.21423 | .27799 | .972 |
| | | Deemed University | -.08245 | .29912 | 1.000 |
| | | Central University | .01215 | .29591 | 1.000 |
| | | Institution of National Repute | -.56821 | .32920 | .515 |
| | Institution of National Repute | Private College/University | .37956 | .20535 | .436 |
| | | State University | .35398 | .20750 | .528 |
| | | Deemed University | .48575 | .23505 | .307 |

| | | | | | |
|---|---|---|---|---|---|
| | | Central University | .58035 | .23095 | .122 |
| | | Institution of Eminence (IOE) | .56821 | .32920 | .515 |
| LC | Private College/University | State University | .02852 | .07548 | .999 |
| | | Deemed University | .10293 | .10941 | .936 |
| | | Central University | -.14970 | .10482 | .710 |
| | | Institution of Eminence (IOE) | .02088 | .19825 | 1.000 |
| | | Institution of National Repute | -.25974 | .14730 | .491 |
| | State University | Private College/University | -.02852 | .07548 | .999 |
| | | Deemed University | .07441 | .11148 | .985 |
| | | Central University | -.17822 | .10697 | .555 |
| | | Institution of Eminence (IOE) | -.00764 | .19940 | 1.000 |
| | | Institution of National Repute | -.28826 | .14884 | .381 |
| | Deemed University | Private College/University | -.10293 | .10941 | .936 |
| | | State University | -.07441 | .11148 | .985 |
| | | Central University | -.25263 | .13311 | .405 |
| | | Institution of Eminence (IOE) | -.08205 | .21456 | .999 |
| | | Institution of National Repute | -.36267 | .16860 | .263 |
| | Central University | Private College/University | .14970 | .10482 | .710 |
| | | State University | .17822 | .10697 | .555 |
| | | Deemed University | .25263 | .13311 | .405 |
| | | Institution of Eminence (IOE) | .17058 | .21225 | .967 |
| | | Institution of National Repute | -.11004 | .16566 | .986 |
| | Institution of Eminence (IOE) | Private College/University | -.02088 | .19825 | 1.000 |
| | | State University | .00764 | .19940 | 1.000 |
| | | Deemed University | .08205 | .21456 | .999 |
| | | Central University | -.17058 | .21225 | .967 |
| | | Institution of National Repute | -.28062 | .23614 | .842 |

| | | | | | |
|---|---|---|---|---|---|
| | Institution of National Repute | Private College/University | .25974 | .14730 | .491 |
| | | State University | .28826 | .14884 | .381 |
| | | Deemed University | .36267 | .16860 | .263 |
| | | Central University | .11004 | .16566 | .986 |
| | | Institution of Eminence (IOE) | .28062 | .23614 | .842 |
| TI | Private College/University | State University | .02453 | .07457 | .999 |
| | | Deemed University | -.02797 | .10809 | 1.000 |
| | | Central University | .02838 | .10355 | 1.000 |
| | | Institution of Eminence (IOE) | .07912 | .19586 | .999 |
| | | Institution of National Repute | -.31534 | .14552 | .255 |
| | State University | Private College/University | -.02453 | .07457 | .999 |
| | | Deemed University | -.05250 | .11013 | .997 |
| | | Central University | .00385 | .10568 | 1.000 |
| | | Institution of Eminence (IOE) | .05459 | .19699 | 1.000 |
| | | Institution of National Repute | -.33987 | .14704 | .191 |
| | Deemed University | Private College/University | .02797 | .10809 | 1.000 |
| | | State University | .05250 | .11013 | .997 |
| | | Central University | .05635 | .13150 | .998 |
| | | Institution of Eminence (IOE) | .10709 | .21196 | .996 |
| | | Institution of National Repute | -.28737 | .16656 | .516 |
| | Central University | Private College/University | -.02838 | .10355 | 1.000 |
| | | State University | -.00385 | .10568 | 1.000 |
| | | Deemed University | -.05635 | .13150 | .998 |
| | | Institution of Eminence (IOE) | .05074 | .20969 | 1.000 |
| | | Institution of National Repute | -.34372 | .16365 | .289 |
| | Institution of Eminence (IOE) | Private College/University | -.07912 | .19586 | .999 |
| | | State University | -.05459 | .19699 | 1.000 |
| | | Deemed University | -.10709 | .21196 | .996 |

| | | | | | |
|---|---|---|---|---|---|
| | | Central University | -.05074 | .20969 | 1.000 |
| | | Institution of National Repute | -.39446 | .23328 | .538 |
| | Institution of National Repute | Private College/University | .31534 | .14552 | .255 |
| | | State University | .33987 | .14704 | .191 |
| | | Deemed University | .28737 | .16656 | .516 |
| | | Central University | .34372 | .16365 | .289 |
| | | Institution of Eminence (IOE) | .39446 | .23328 | .538 |

Thirdly, the factors of MOOC adoption and behavioral intention towards MOOC differ significantly across the Gen Z students' level of degree were analysed and evaluated.

In this study, Gen Z studying in higher education institutions across various courses and degrees are covered. Students pursuing undergraduate, postgraduate, PhD, and any other degree are covered. The thought process of a student evolves as they move up in the level of education. Thus, in the third section of this hypothesis, the study attempts to analyse the factors of MOOC adoption and behavioral intention towards MOOCs differ significantly across the Gen Z students' level of degree.

At first, we established the normality of data by conducting Levene's test resulting in a *p*-value greater than 0.05, in the case of all the constructs (see Table 5-29).

Table 5-29: Test of Homogeneity of Variances

| Constructs | Levene Statistic | df1 | df2 | Sig. |
|---|---|---|---|---|
| Performance Expectancy | .0490 | 1 | 481 | .825 |
| Effort Expectancy | 1.085 | 1 | 481 | .298 |
| Social Influence | 1.705 | 1 | 481 | .192 |
| Facilitating Conditions | .3990 | 1 | 481 | .528 |
| Hedonic Motivation | 0.714 | 1 | 481 | .399 |
| Price Value | 0.554 | 1 | 481 | .457 |
| Habit | 0.010 | 1 | 481 | .922 |
| Behavioral Intention | 0.787 | 1 | 481 | .375 |

| | | | | |
|---|---|---|---|---|
| Language Competency | 0.249 | 1 | 481 | .618 |
| Teacher Influence | 1.468 | 1 | 481 | .226 |

Subsequently, we measured the mean of all the factors across the level of degrees covered in the sample which is presented in Table 5-30. The table shows that students pursuing post-graduate degree have the highest mean across all the factors viz. PE (3.92), EE (3.75), SI (3.71), FC (3.74), HM (3.65), PV (3.37), HT (3.22), BI (3.49), LC (3.90) and TI (4.05). A postgraduate degree in India is a masters' degree that an individual undertakes after completing an undergraduate degree which is of 3-4 years depending on the program enrolled in. A postgraduate or masters' program is a two-year full-time program. Whereas an undergraduate degree or a bachelor's degree is an educational program conducted after secondary education and is done before the postgraduate education.

Table 5-30: Mean of Level of degree

| | | N | Mean | Std. Deviation | Std. Error |
|---|---|---|---|---|---|
| Performance Expectancy | Undergraduate (Bachelor Program) | 269 | 3.798 | 0.784 | 0.048 |
| | Postgraduate (Master Program) | 214 | 3.925 | 0.816 | 0.056 |
| | Total | 483 | 3.855 | 0.800 | 0.036 |
| Effort Expectancy | Undergraduate (Bachelor Program) | 269 | 3.657 | 0.957 | 0.058 |
| | Postgraduate (Master Program) | 214 | 3.756 | 0.897 | 0.061 |
| | Total | 483 | 3.701 | 0.931 | 0.042 |
| Social Influence | Undergraduate (Bachelor Program) | 269 | 3.551 | 0.946 | 0.058 |
| | Postgraduate (Master Program) | 214 | 3.713 | 0.857 | 0.059 |
| | Total | 483 | 3.623 | 0.910 | 0.041 |
| Facilitating Conditions | Undergraduate (Bachelor Program) | 269 | 3.716 | 0.803 | 0.049 |
| | Postgraduate (Master Program) | 214 | 3.748 | 0.782 | 0.053 |
| | Total | 483 | 3.730 | 0.793 | 0.036 |

| | | | | | |
|---|---|---|---|---|---|
| Hedonic Motivation | Undergraduate (Bachelor Program) | 269 | 3.511 | 0.909 | 0.055 |
| | Postgraduate (Master Program) | 214 | 3.653 | 0.980 | 0.067 |
| | Total | 483 | 3.574 | 0.943 | 0.043 |
| Price Value | Undergraduate (Bachelor Program) | 269 | 3.138 | 0.977 | 0.060 |
| | Postgraduate (Master Program) | 214 | 3.377 | 0.999 | 0.068 |
| | Total | 483 | 3.244 | 0.993 | 0.045 |
| Habit | Undergraduate (Bachelor Program) | 269 | 2.990 | 0.871 | 0.053 |
| | Postgraduate (Master Program) | 214 | 3.229 | 0.844 | 0.058 |
| | Total | 483 | 3.096 | 0.866 | 0.039 |
| Behavioral Intention | Undergraduate (Bachelor Program) | 269 | 3.294 | 0.943 | 0.058 |
| | Postgraduate (Master Program) | 214 | 3.492 | 0.983 | 0.067 |
| | Total | 483 | 3.382 | 0.965 | 0.044 |
| Language Competency | Undergraduate (Bachelor Program) | 269 | 3.804 | 0.707 | 0.043 |
| | Postgraduate (Master Program) | 214 | 3.901 | 0.671 | 0.046 |
| | Total | 483 | 3.847 | 0.692 | 0.032 |
| Teacher Influence | Undergraduate (Bachelor Program) | 269 | 3.859 | 0.701 | 0.043 |
| | Postgraduate (Master Program) | 214 | 4.057 | 0.644 | 0.044 |
| | Total | 483 | 3.947 | 0.683 | 0.031 |

Finally, One-way ANOVA analysis was done with the assumption that mean of the factors of MOOC adoption and behavioral intention towards MOOC differ significantly across the Gen Z students' level of degrees. From the Table 5-31, it is clear that the computed value of F is greater between the level of degrees for the factors of PV (7.01), HT (9.21), BI (5.08) and TI (10.24). Correspondingly, the observed p-value for the factors of PV (0.008), HT (0.003), BI (0.02), and TI (0.001) is below the chosen alpha of 0.05 (0.000 < 0.05). Hence, the research hypothesis is partially accepted, indicating that there is a major difference between the level of degrees for the factors of PV, HT, BI and TI.

Table 5-31: One-way ANOVA test on Level of degree

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Performance Expectancy | Between Groups | 1.919 | 1.000 | 1.919 | 3.013 | 0.083 |
| | Within Groups | 306.425 | 481.000 | 0.637 | | |
| | Total | 308.345 | 482.000 | | | |
| Effort Expectancy | Between Groups | 1.161 | 1.000 | 1.161 | 1.340 | 0.248 |
| | Within Groups | 416.842 | 481.000 | 0.867 | | |
| | Total | 418.003 | 482.000 | | | |
| Social Influence | Between Groups | 3.127 | 1.000 | 3.127 | 3.795 | 0.052 |
| | Within Groups | 396.294 | 481.000 | 0.824 | | |
| | Total | 399.420 | 482.000 | | | |
| Facilitating Conditions | Between Groups | 0.122 | 1.000 | 0.122 | 0.194 | 0.660 |
| | Within Groups | 302.993 | 481.000 | 0.630 | | |
| | Total | 303.116 | 482.000 | | | |
| Hedonic Motivation | Between Groups | 2.407 | 1.000 | 2.407 | 2.718 | 0.100 |
| | Within Groups | 425.956 | 481.000 | 0.886 | | |
| | Total | 428.363 | 482.000 | | | |
| Price Value | Between Groups | 6.831 | 1.000 | 6.831 | 7.015 | 0.008 |
| | Within Groups | 468.393 | 481.000 | 0.974 | | |
| | Total | 475.223 | 482.000 | | | |
| Habit | Between Groups | 6.801 | 1.000 | 6.801 | 9.213 | 0.003 |
| | Within Groups | 355.087 | 481.000 | 0.738 | | |
| | Total | 361.889 | 482.000 | | | |
| Behavioral Intention | Between Groups | 4.698 | 1.000 | 4.698 | 5.085 | 0.025 |
| | Within Groups | 444.397 | 481.000 | 0.924 | | |
| | Total | 449.095 | 482.000 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Language Competency | Between Groups | 1.126 | 1.000 | 1.126 | 2.356 | 0.125 |
| | Within Groups | 229.936 | 481.000 | 0.478 | | |
| | Total | 231.063 | 482.000 | | | |
| Teacher Influence | Between Groups | 4.685 | 1.000 | 4.685 | 10.241 | 0.001 |
| | Within Groups | 220.056 | 481.000 | 0.457 | | |
| | Total | 224.742 | 482.000 | | | |

### 5.11 Summary

This chapter dealt in the findings of the analysis done. It encompasses data screening, the detailing of demographic profile of the respondents, assessment of measurement and structural model using PLS-SEM data analysis technique followed by performing ANOVA to study the influence of educational characteristics of learners on behavioral intention towards MOOC adoption.

# 6 CHAPTER 6: DISCUSSIONS, IMPLICATIONS, AND CONCLUSIONS

## 6.1 Introduction

The objective of this part is to describe data analysis done and to draw inference and implications of research. This study was conducted to investigate the factors influencing MOOC adoption among Gen Z students at Indian HEIs. UTAUT2 was used as a theoretical framework to see if it could be applied to and modified to explain the intention behind MOOC adoption in the Indian context. The proposed model has UTAUT2 extended with two additional factors of LC and TI to assess whether extended theory has better explanatory power. The empirical results supported the applicability and adaptability of UTAUT2 in explaining MOOC adoption intention in the Indian context. The results of testing the hypotheses have shown that PE, EE, FC, PV, and HM had a major influence on MOOC adoption intention amongst Gen Z studying in the HEIs of India whereas the variables of HT, SI, LC and TI had insignificant influence on MOOC adoption intention. The findings of the impact of educational characteristics of the respondents on the factors of MOOC adoption intention have also been discussed followed by the theoretical and practical implications recommended to MOOC developers, policy makers, and instructors. The given recommendation can influence MOOCs providers to adopt newer ways and means to increase MOOC adoption. This was followed by the study limitations and future research avenues, and the concluding comments. The ensuing section will dwell on descriptive statistics of construct items as well as on the inferences of hypothesis testing.

## 6.2. Descriptive Statistics of the Constructs' Items

The study posited Coursera (44.3%) as the most preferred MOOC platform among the respondents followed by Swayam/NPTEL (11.8%), EdX (8.7%), Futurelearn (3.8%), and a mix of other online courses (31.4%) such as Khan academy, Unacademy, UpGrad etc. None of the respondent was found using Udemy, a United States based MOOC platform. Most of the respondent (35.8%) attributed "self-motivation to learn more" as a reason to pursue MOOCs followed by "teacher's instruction" (26.7%), "Free/Economical pricing" (17.5%), "Brand of Institute/university" (14.7%) and remaining (5.2%) attributed reason to pursue MOOCs to peer pressure, friend's advice, and digital marketing by the MOOC providers. These are important findings for the MOOC developers, marketers and instructors to implement to enhance more enrolments in MOOC programs. The study highlighted most of the respondents (43.06%) accessing MOOCs for less than three hours a week followed by respondents accessing it for 3-5 hours (33.13%), 6-8 hours (13.66%) and remaining (10.14%) accessing online courses for more than 8 hours. It is evident from the respondents' feedback that online courses were considered as just a source of complementary knowledge before the on-set of COVID-19 however post pandemic, most of the respondents (49.5%) regarded online courses as an important part of their learning system in comparison to 26.3% respondents saying so before pandemic highlighting significant change in the intention and adoption behavior of the respondents.

**A. Performance Expectancy**

Descriptive statistics (see Table 5-13) of the constructs influencing the MOOC adoption intention highlights that the item "PE2" received the highest mean score (3.986), indicating that the survey participants trust that MOOC courses have the potential to add to their knowledge and skillset thereby aiding them to attain gains in performance in their respective work space. In contrast, item "PE3" has the lowest mean score (3.648). This could be interpreted as the respondents don't see MOOCs to facilitate their academic or career related task faster. Thus, this finding should encourage MOOC marketers to highlight the level of efficiency and productivity build up one can have as a result of learning the subject through MOOCs which in turn will help an individual to complete task efficiently and speedily helping them to secure gains in their area of operation. On the whole, mean of PE items were 3.850, suggesting that the participants concurred on the performance enhancing benefits of learning through MOOCs.

**B. Effort Expectancy**

The findings suggest that for the construct of effort expectancy, the mean of all items is 3.700. This indicates that the respondents agreed to the ease of use of MOOCs. The highest mean was 3.851 for the item "EE3" indicating respondents' affirmation on MOOC's ease of use. While, item "EE2" has the lowest mean (3.600) in relation to other items indicating that the MOOCs developers and the instructors need to improve the level of instructions and interactions between them and the students so that students can have their doubts cleared and clarifications addressed, for their better understanding of the subject and learning outcomes.

### C. Social Influence

For the factor of social influence, the highest mean was 3.658 for the item "SI1" indicating that the respondents confirmed to the influence of important few towards shaping their MOOC adoption intention. In contrast, item "SI3" got the lowest mean (3.602) in comparison to other items suggesting lack of motivation from acquaintances, family and friends, and the reference groups of the respondents. This could be on account of poor MOOC awareness amongst the important few or they are not satisfied with performance or learning outcomes of MOOCs. MOOCs designers and marketers must take cognizance of this and need to liaison more with the academicians in HEIs to understand their concerns related to MOOCs if any and seek their support to popularize MOOCs as an important tool towards value addition amongst Gen Z pursuing higher education. As a whole, mean of all items for the factor of SI was 3.620 indicating that the participants have received moderate level of motivation from reference groups towards enrolling in MOOCs.

### D. Facilitating Condition

For the construct of facilitating condition, mean of all items is 3.721. The highest mean was 3.839 for the item "FC4" indicating that the respondents have a supportive ecosystem extending all possible help to them during the crisis hours thereby influencing MOOC adoption intention. In contrast, item "FC2" has a lowest mean (3.536) in comparison to other items indicating that respondents have issue using MOOCs hence it is of paramount importance for the MOOCs instructors and developers to train the students towards MOOC usage.

### E. Hedonic Motivation

The mean of all items of hedonic motivation is 3.570. The highest mean was 3.712 for the item "HM1" reflecting that the respondents find learning through MOOCs, enjoyable and pleasant. However, on the other hand, item "HM3" got the lowest mean (3.503) in comparison to other items suggesting that MOOCs designers need to introduce more component of fun in learning through MOOCs namely, gamification, simulation etc. to engage and encourage the participants in the learning process.

### F. Price Value

For the construct of price value, the highest mean was 3.712 for the item "PV1" indicating that the respondents consider the pricing of MOOCs they have accessed to be reasonable thereby significantly influencing their MOOC adoption intention. In contrast, item "PV3", got a lowest mean (3.503) in comparison to other items suggesting that the students while findings cost of MOOCs reasonable however are not getting value for money which means that the expected outcome is not in line with the money spent which is a cue for the MOOC developer and the marketers to take cognizance off and create a value proposition having better perceived benefits. In all, the mean of all items is 3.570 which reflects on the importance respondents attached to this construct and role PV plays in influencing MOOC adoption intention.

**G. Habit**

For the construct of habit, the highest mean was 3.230 for the item "HT3" highlighting that the students are mindful of using MOOCs for a value add in their knowledge and skills. On the other hand, item "HT2" got a lowest mean score (2.934) in comparison to other items suggesting that while students acknowledge the importance of MOOCs for the value add in their knowledge and skills and a resulting gain in performance however, are not heavily reliant on it for all the their learnings which indicates that education policy makers, academicians, MOOCs designers, and marketers need to work in tandem to make MOOCs an integral part of the education system which may see our students becoming more accustomed to MOOCs and hence habitual to its usage.

As a whole, mean of all items of habit is 3.090 which is moderate indicating that students acknowledge the use of MOOCs however it hasn't become a part of their habit or daily ritual to refer to it for learning purposes.

**H. Behavioral Intention**

The highest mean was 3.617 for the item "BI3" highlighting that the student's willingness to continue using MOOCs for the knowledge gain. On the other hand, item "BI1" has a lowest mean (3.174) compared to the remaining items indicated that while students intend to continue learning from MOOCs to augment their knowledge, they do not see MOOCs as a part of their daily ritual. Education policy makers and the instructors, on making MOOCs an integral part of students' evaluation matrix, may see MOOCs frequency of usage going up. In all, mean of all items of the factor BI was 3.380, indicating significant role of behavioral intention towards MOOC usage.

**I. Language Competency**

The highest mean was 4.058 for the item "LC1" indicating that the respondents would participate in the learning process if the course is in language which they can understand and relate to. In contrast, item “LC4” got a lowest mean (3.588) in comparison to other items indicating majority of MOOCs are available in English language and the respondent haven’t experienced MOOC delivery in their vernacular language yet hence unable to differentiate its influence on their rapport with their instructors and also it indicates that the interaction between the student and the instructors of MOOCs is limited hence the question of rapport building is ruled out. This finding needs to be taken cognizance off by the MOOCs developers and the instructors so that the enhanced interaction between a student and the instructor results in better learning outcome and more value for money.

Overall, the mean for the construct of language competency of all the items was 3.840 which suggests that the respondents agreed to the significant influence language competency has on the MOOC adoption intention of students.

**J. Teacher Influence**

The highest mean was 4.106 for the item “TI1” indicates that the students hold their teachers as subject matter expert and look up to them to learn and gain knowledge and skills. In contrast, item “TI5” got a lowest mean (3.739) in comparison to other items reflecting on the fact that MOOCs haven’t yet become an integral part of the evaluation matrix of HEIs in India which MOOC developers and the education policy makers must take cognizance off by integrating MOOCs in the course curriculum and assigning weightage to successful MOOC completion. The overall average of all the items was 3.940 which reveals that the respondents of this study concurred to teacher influence towards MOOC adoption intention. Teachers are considered as change agent and bear tremendous influence on students.

The subsequent sub section describes the findings of hypotheses testing.

## 6.2 The Testing of the Hypotheses

The result of testing the hypothesis has shown that most of the hypothesized paths are backed by data. The results offered strong explanation of UTAUT2 in context of MOOCs in Indian settings. The Table 6-1 below highlights the results of hypotheses testing.

Table 6-1: Hypotheses testing and interpretation

| **Hypothesis** | **Definition** | ***P* Value** | **Finding** | **Interpretation** |
|---|---|---|---|---|
| H1 | Performance expectancy influence Gen Z behavioral intention to adopt MOOC. | 0.005 | 0.005 < 0.05 | Significant. H1 accepted. |
| H2 | Effort Expectancy influence Gen Z behavioral intention to adopt MOOC. | 0.039 | 0.039 < 0.05 | Significant. H2 accepted. |
| H3 | Social influence impacts Gen Z behavioral intention to adopt MOOC. | 0.547 | 0.547 > 0.05 | Insignificant. H3 rejected. |
| H4 | Facilitating conditions significantly influence Gen Z to adopt MOOC. | 0.000 | 0.000 < 0.05 | Significant. H4 accepted. |
| H5 | Hedonic motivation influence Gen Z behavioral intention to adopt MOOC. | 0.001 | 0.001 < 0.05 | Significant. H5 accepted. |
| H6 | Price Value influence Gen Z behavioral intention to adopt MOOC. | 0.000 | 0.001 < 0.05 | Significant. H6 accepted. |
| H7 | Habit influence Gen Z behavioral intention to adopt MOOC. | 0.084 | 0.084 > 0.05 | Insignificant. H7 rejected. |
| H8 | Language competency influence Gen Z behavioral intention to use MOOC. | 0.355 | 0.355 > 0.05 | Insignificant. H8 rejected. |
| H9 | Teacher Influence Gen Z behavioral intention to use MOOC. | 0.181 | 0.181 > 0.05 | Insignificant. H9 rejected |

| | | |
|---|---|---|
| H10 | Educational characteristics of students (courses enrolled, nature of degree & type of institution) influence MOOC adoption. | Educational characteristics of the students were found to influence the factors towards MOOC adoption intention |

Five factors namely, PE, EE, FC, HM, and PV had significant influence on MOOC adoption intention. However, the factors of SI, LC, and TI didn't have statistically significant influence on the MOOC adoption intention among Gen Z.

Discussions on research findings construct wise is explained in the following sub section:

A. PE and its influence on BI towards MOOC adoption

The conceptual model posited that PE has a significant influence on BI to use MOOCs (H1). Path coefficient and p value ($\beta$=0.127, $p<0.005$) arrived at, supports the hypothesis. This finding emphatically proves that if an individual achieves his educational goals from MOOCs, then they will continue using MOOCs in the future. Ongoing pandemic also positively impacted respondents' BI to adopt MOOCs on account of its functionality and expected benefits (Adwan, 2020; Mittal *et al*, 2021; Mohan et al., 2020).

B. Effort Expectancy and its influence on behavioral intention towards MOOC adoption

The conceptual model posited that EE has a positive impact on the BI towards MOOC use (H2). Path coefficient and p value ($\beta$=0.066, $p<0.039$) arrived at, supports the hypothesis. This is attributed to the fact that MOOC courses provides ease of use and lesser efforts during the enrolments and while accessing it, owning to its user-friendly design. The results are in accordance with the results of extant literature highlighting the positive influence of EE on BI to use technological innovations (Venkatesh *et al*., 2003; Im et al., 2010). Positive effect of perceived ease of use (Effort Expectancy) on user's BI to adopt MOOC (Al-Adwan, 2020).

C. Social Influence and its influence on behavioral intention towards MOOC adoption

The conceptual model posited that SI has a significant impact on the BI to use MOOCs (H3). Path coefficient and p value ($\beta$=0.026, $p<0.547$) arrived at, rejects the hypothesis. Result revealed statistically insignificant influence of SI on BI which is contrary to the extant literature (Persada *et al*., 2019; Rosaline and Wesley, 2017) and in line with some existing research (Mohan et al., 2020; Jeng and Tzeng, 2012; Fianu *et al.*, 2018). Result of research highlights that Gen Z knowledge of MOOCs is because of their own awareness hence there is no play of external influence on them towards MOOC usage.

D. Facilitating condition and its influence on behavioral intention towards MOOC adoption

The conceptual model posited that facilitating condition has positive influence on BI to use MOOCs (H4). Path coefficient and p value ($\beta$=0.238, $p<0.000$) arrived at, support the hypothesis. Also, FC emerged as one of the strong predictors of MOOC adoption intention. The results are much in accordance with the previous studies suggesting positive effect of FC on BI and use behavior of online learners (Chang *et al.,* 2019; Persada *et al*., 2019; El-Masri and Tarhini, 2017; Fianu et al., 2018) and the adopters of ICT (Šumak and Šorgo, 2016; Rosaline and Wesley, 2017).

E. Hedonic Motivation and its influence on behavioral intention towards MOOC adoption

The conceptual model posited that HM has a significant impact on the BI to use MOOCs (H5). Path coefficient and p value ($\beta$=0.145, $p<0.001$) arrived at, support the hypothesis and indicate HM to be one of the strong predictors of MOOC adoption intention and this confirmation is much in accordance with the existing studies (Mohan et al., 2020; El-Masri and Tarhini, 2017; Yang et al., 2012; Baptista and Oliveira, 2015). Digital friendly Gen Z who prefers living in the virtual world finds MOOCs interesting, exciting, and engaging (Weinswig, 2016).

F. Price Value and its influence on behavioral intention towards MOOC adoption

The conceptual model posited that PV has a positive influence on the BI of Gen Z to use MOOCs (H6). Path coefficient and p value ($\beta$=0.316, $p<0.000$) arrived at, support the hypothesis and indicate that the construct of PV is the most significant independent variable of students' intention to adopt MOOC. This could be attributed to Gen Z students giving extreme importance to the mental transaction between MOOC pricing and the perceived benefits. For profit, MOOC designers and marketers, keep enrolment and access to the content in the course free but charged for the certification which adversely impact the economically weaker students therefore MOOC developers need to keep sensitivity of students towards PV in mind before pricing their course. Study confirms a significant role PV plays in determining Gen Z's BI to adopt technological innovations (Tseng *et al.,* 2019; Gupta, 2019).

G. Habit and its influence on behavioral intention towards MOOC adoption

The conceptual model posited that habit has a positive impact on the BI to use MOOCs (H7). Path coefficient and p value ($\beta=0.121$, $p<0.084$) arrived at reject the hypothesis. This is reflective of students not habituated to using MOOC which can be attributed to majority of HEIs in India haven't formally integrated online learning with offline learning and they are yet to make it as a part of student evaluation criteria. This finding is in accordance with the extant literature by Raman and Don, (2013) and contrary to the prior studies done by Gupta and Dogra (2017) and Mohan et al. (2020).

H. Language competency and its influence on behavioral intention towards MOOC adoption

The conceptual model posited that language competency has a significant influence on the BI to adopt MOOCs (H8). The path coefficient and p value ($\beta=0.035$, $p<0.355$) arrived at, rejects the hypothesis. This suggests that, in contrast to other studies (Aldahdouh and Osório, 2016; Raja and Kallarakal, 2020); and in line with the study by Barak et al., the impact of LC on BI's use of MOOCs is statistically negligible (2015). This shows that students attending HEIs have solid communication skills and are at ease using MOOCs delivered in English language. For them, acceptance of MOOCs is not influenced by language. This information also confirms that the second-largest English-speaking population in the world is found in India (mapsofworld.com).

I. Teacher Influence and its impact on behavioral intention towards MOOC adoption

The conceptual model posited that teacher influence has a significant impact on the BI of Gen Z to adopt MOOCs (H9). The path coefficient and p value ($\beta=0.044$, $p<0.181$) arrived at, rejects the hypothesis. Study indicates that the influence of TI on BI to use MOOCs is insignificant which is contrary to the existing literature (Chang *et al*., 2015; Mohapatra and Mohanty, 2017; Hoi and Mu, 2021; Al-Adwan *et al*., 2021) and in support of study by Ibrahim et al., (2017). This could be attributed to students not getting enough encouragement at college level to pursue MOOCs which seemingly is on account of MOOCs enrolment and completion not being a part of university evaluation criteria.

One-way ANOVA analysis performed to validate assumption that mean of factors of MOOC adoption and behavioral intention differ significantly across the course streams of Gen Z students. From the data it is clear that computed value of F is greater between the course streams for the factors of HT (2.95), BI (4.53), LC (3.15) and TI (4.59). Correspondingly, the observed p-value of HT (0.02), BI (0.001), LC (.014), and TI (0.01) for these factors is below the chosen alpha of 0.05 (0.000 < 0.05). Hence, the research hypothesis is partially accepted, revealing significant difference between the course streams for the factors of HT, BI, LC and TI.

The results (table 5-24) of post hoc test revealed major difference between the students pursuing management/administration and any other courses (0.028) on the factor of PV towards MOOC adoption intention. Similarly, the study reveals that there is a significant difference between the students pursuing management/administration courses and any other courses (0.018) on the factor of HT towards MOOC adoption intention. Study highlights that there is a major difference between the students pursuing management/administration courses and any other courses (0.000) on the factor of BI towards MOOC adoption intention. Lastly the results indicated that there is major difference in students pursuing engineering and commerce (0.033), engineering and management/administration (0.000) on the factor of TI towards MOOC adoption intention.

One-way ANOVA analysis was performed to validate assumption that mean of factors of MOOC adoption and behavioral intention towards MOOC differ significantly across the Gen Z students' Institution type. From the data it is clear that computed value of F is greater between the course streams for the factors of EE (3.63), FC (6.41), and PV (2.47). Correspondingly, the observed p-value of EE (0.003), FC (0.000), and PV (0.032) for these factors is below the chosen alpha of 0.05 (0.000 < 0.05). Thus, the research hypothesis is partially accepted, suggesting that there is a major difference between type of institutions for the factors of EE, FC, and PV.

The result (table 5-28) of post hoc test indicates towards significant difference between the students of state universities and central universities (0.026), state universities and institutions of national repute (0.045) on the factor of EE towards MOOC adoption intention which can be attributed to the difference in training of the students of this institution on MOOC usage which can be strengthened by the respective institutions by training the students. Similarly, study posited that there exist significant difference between the students studying in the private college/universities and central universities (0.000) and private college/universities and institutions of national repute (0.012), state universities and central universities (0.001), state universities and institutions of national repute (0.039), central and state universities (0.001), central universities and institutions of eminence (0.033), on the factor of FC towards MOOC adoption intention which highlights the prevailing gap in the universities of online learning ecosystem which differs from one college too another. The findings also highlight the significant difference between the private universities and central universities (0.024), on the factor of PV towards MOOC adoption intention which can be attributed to stronger economic background of the students studying in the private universities than the central universities.

Finally, one-way ANOVA analysis was performed to validate assumption that mean of the factors of MOOC adoption and behavioral intention towards MOOC differ significantly across the Gen Z students' level of degrees. From the analysed data it is clear that the computed value of F is greater between the level of degrees for the factors of PV (7.01), HT (9.21), BI (5.08) and TI (10.24). Correspondingly, the observed p-value for the factors of PV (0.008), HT (0.003), BI (0.02), and TI (0.001) is below the chosen alpha of 0.05 (0.000 < 0.05). Hence, the research hypothesis is partially accepted, indicating that there is a major difference between the level of degrees for the factors of PV, HT, BI and TI, supporting the extant literature (Al-Ashban and Burney, 2001; Abu-Shanab, 2011; Nasri, 2011; Izogo et al., 2012) and contradicting the study of Laukkanen and Pasanen (2008). No post hoc test was conducted in case of level of degree as in the study we considered only two levels of education, UG and PG.

### 6.3 Implications

The outcome of this study corroborates the appropriateness of UTAUT2 in explaining MOOC adoption intentions in Indian contexts and settings. It provides academicians, instructors, practitioners, education policymakers, institutions of higher education, MOOC designers and developers with knowledge and insights on how to improve MOOC adoption in India and developing countries.

#### 6.3.1 Theoretical implications

An extensive review of previous studies posited that there is no published paper on the explanation of Gen Z adoption of MOOCs using UTAUT2. Thus, the current research adds to the knowledge pool contributing to extant research on online education, specifically MOOCs (Mittal et al., 2021; Persada *et al*., 2019; El-Masri and Tarhini, 2017). The study examined Gen Z characteristics and their MOOC adoption intention, which is one of its kind in India. The study provides empirical evidence highlighting the key role, constructs of PV, HM, FC, PE, and EE played in determining MOOC adoption intention among Gen Z. It also examined the effect of extended constructs of LC and TI on MOOC adoption, but the impact was statistically insignificant, which is contrary to the extant literature (Raja and Kallarakal, 2020; Aldahdouh and Osório, 2016). The present study also examined the role of educational characteristics (courses enrolled, nature of degree & type of institution) and their influence on the factors impacting the behavioral intention towards MOOC adoption. It also adds to the existing knowledge pool, the validated questionnaire items in context of MOOC adoption with the extended factors of LC and TI which can be considered in future research on MOOC adoption. The study validated the applicability and adaptability of UTAUT2 model in explaining MOOC adoption intention amongst Gen Z in the Indian context and settings with the predictive power of 69.9%. This study will act as a foundation for researchers keen on examining the MOOC adoption phenomenon and further working on UTAUT2 to add more predictive power to it by exploring more constructs. This study will also help researchers understand more about the factors impacting the propensity of Gen Z to adopt anything digital as they know digital transformation very well and understand how the use of technological innovations can transform their functioning and enhance their efficiency and productivity at work (dell.com, 2018). Therefore, any researcher keen to study the adoption of emerging consumer centric technologies will find this study helpful.

### 6.3.2 Practical implications

Based on the inferences drawn from the study, the research scholar put forward some suggestions for the education policy makers, MOOC designers and developers, and the instructors on the changes to be incorporated to make MOOCs an important part of the education and students' evaluation matrix at the university level, eventually increasing MOOC adoption among college going students in emerging economies like India to democratize education. Findings posited PV as a key determinant influencing MOOC adoption intention, which MOOC designers and marketers should acknowledge by keeping the price of MOOCs in a way that the students see the perceived benefits of MOOCs more than the price paid. This will result in the increased adoption and usage of MOOCs, which will not only complement offline education but also enable many students belonging to the economically weaker section to receive education. The study establishes that HM has a significant influence on MOOC adoption among Gen Z. Therefore, MOOC designers and developers should look into incorporating the elements of gaming, fun, enhanced peer-to-peer interaction, animations, and simulations etc. to attract the attention of Gen Z (Hone and Said, 2016). Integration of hedonic elements will enhance the playful characteristics of MOOCs, hence reducing monotony among learners and motivating them to enrol in MOOCs (El-Masri and Tarhini 2017; Lee et al. 2015). Facilitating conditions as an influencing factor means that the users of the product feel that they are technologically equipped enough to carry out their work seamlessly and effectively and that the support is around in case the need arises to perform a certain task. The FC significantly influenced the BI of Gen Z to use MOOCs. Thus, all the educators and the support systems engaged in providing online education, esp. MOOCs, must ensure that a complete ecosystem is created in the HEIs in terms of seamless Wi-Fi connection, availability of requisite IT and faculty support so that the students can access and learn from MOOCs without any fuss. The construct of performance expectancy plays a vital role in MOOC enrolment and usage.

The results of the study indicate the need for MOOC designers, developers, and academia to brainstorm and come up with industry relevant courses to increase MOOCs appeal among the students. Courses should be designed in such a way that they can be accessed from any digital device, particularly mobile, laptop, and iPad. MOOC providers should encourage regular communication with learners so as to build a MOOC community with an aim of peer-to-peer interaction and knowledge exchange given the limited interaction that happens between the learners and the MOOC instructors. Designers and developers of MOOCs should work towards ensuring a great experience for the users by adopting the ‘media richness theory’ by Daft and Lengel (1986) combining audio, video, text, and image while creating content. Varied media catches the attention of all the learners with different learning styles viz. auditory, visual, and kinaesthetic, thus helping learners understand and learn from the content of courses. Also, based on the record of learners registered for the courses, MOOC developers using AI algorithms can recommend courses to learners. MOOCs platforms should have discussion or break out rooms that facilitates instantaneous peer to peer interaction for knowledge exchange, doubt clarification etc. Eventually, a synergistic collaboration between HEIs and MOOCs developers would be an important way forward towards MOOC proliferation. The study posited the positive impact of EE on BI to use MOOCs, which can be interpreted as ease of use enhances MOOCs, adoption intention.

It is important to advance the ease of accessing MOOCs by enhancing the features of usability, designing intuitive interfaces for the ease of navigation of learners, searching course content, reading material, and creating learner-friendly interfaces that helps student to access content, upload assignments, and provide ease in online participation and discussion (Fianu et al. 2018). The study posited insignificant influence of the factor of Habit on MOOC adoption intention of Gen Z as the students of this cohort are not habituated to learning from MOOCs yet, and which is an area to work upon for the MOOC providers. They should collaborate with education policy makers and make MOOCs an integral part of course curriculum. According to the findings, social influence has a statistically insignificant effect on Gen Z's BI, implying that the independent variable of social influence has little influence on Gen Z's decision to take MOOCs. MOOC providers and education policy makers should look into the ways to promote the benefits of MOOCs to all the stakeholders who influence a student to exhibit certain behavior. Thus, in this case, there should be regular interaction between MOOC providers and the education policy makers to reach out to teachers, parents, student reference groups, etc. to inform them about the virtue of learning from MOOCs.

The study posited that language competency has an insignificant influence on the MOOC adoption intention, which is on account of sampled students' having a requisite proficiency in the English language, which is the mode of instruction for most of the renowned MOOC providers available in India, hence this result. However, to see a tremendous rise in the adoption of MOOCs in India or any other developing nation, it is recommended to have MOOCs developed in a vernacular language for their widespread acceptability. The study posited an insignificant impact of the teacher influence on BI of Gen Z to use MOOCs, reflecting teachers' lesser familiarity with MOOCs and with online courses not being the part of student evaluation matrix, resulting in a lack of push to students to pursue MOOCs by the teachers. Teachers, considered as nation builders and change agents of society, must encourage, and motivate students to pursue MOOCs and include MOOCs in their course evaluation matrix, motivating them to do MOOC assignments and capstone projects to complement offline learning and to boost their employability by learning new skills. The study revealed that the educational characteristics (courses enrolled, nature of degree & type of institution) of students also impact the factors determining MOOC adoption intention, suggesting these characteristics should be kept in mind by MOOC marketers to increase MOOC enrolment e.g., the majority of students studying in state or central government universities are not from economically strong backgrounds. Therefore, MOOC developers should extend special promotional offers for the financially challenged universities and the students studying there to encourage MOOC adoption.

### 6.4 Limitations and Future Research Directions

Every piece of research has its own set of limitations, and this should act as a future research avenue for scholars. This study applied a cross sectional research method to study Gen Z adoption intention of MOOCs. Thus, it is bereft of studying the behavioral changes in Gen Z, hence longitudinal study is recommended for future research work for better generalizability of findings, besides deploying a probability sampling method for better representation of the population of study. The conceptual model explained 69.9% of the variance in adoption intention, leaving 30.1% unanswered. UTAUT2 needs to be extended with more constructs to improve its explanatory power further. Furthermore, scholars researching on MOOCs can study learners pursuing only online courses to understand their motivations, barriers and challenges faced while enrolling or pursuing MOOCs. This study has drawn samples from the different strata of the institutions having difference in students' fee or price structure and varied facilitating conditions across the campuses which can impact MOOC adoption intention. Thus, this could be another area for scholars to research. As the MOOC completion rate is not encouraging, it makes a strong case to study factors influencing learner satisfaction, engagement, and perceived learning outcomes. Cross cultural study in different countries on MOOC can help in determining the factors impacting MOOC adoption and continuance and the role it plays in furthering education and in bridging the educational divide between the affluent and weaker section of the society.

## 6.5 Conclusion

The models' $R^2$ value of 0.699 highlighted the high predictive power of UTAUT2 in explaining Gen Z's intention to use MOOCs. The outbreak of COVID 19 has a big impact on online education, and the pandemic reinforced the significance of online education complementing offline learning. However, in spite of all the merits, MOOC enrolments and usage are low and not in line with the prevalence of other emerging technologies. Acknowledging the importance of MOOCs in the HEIs and the existing gap in the existing literature on students' MOOC adoption intention, this research work was carried out to explore factors determining MOOC adoption intention in Gen Z by extending the UTAUT2 theory to explain the MOOC adoption phenomenon better. Findings from research show that extended UTAUT2 explains 69.9% of BI to use MOOCs and the constructs of PE, EE, PV, HM, and FC have a statistically significant impact on BI. This research validates the applicability of theory to explain BI of Gen Z to adopt MOOCs. Additionally, by emphasising the statistically insignificant impact of SI, HT, LC, and TI on BI towards MOOC adoption intention, the interpretation of the research diverged from some previous studies. The findings showed that, in addition to the students' educational characteristics, PV is the best predictor of MOOC adoption intention, followed by FC, HM, PE, and EE. The present work adds to the existing work on UTAUT2 by assessing and evaluating its' appropriateness to explain Gen Z's BI towards MOOC adoption. It also shares important recommendations and executable insights to further the cause of online learning, which may come in handy for the MOOCs' designers, developers, marketers, and educators to speed up MOOC enrolments, which is the need of the hour for countries like India to bridge the educational divide to democratize education.

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# APPENDICES

## Appendix A: Questionnaire for the final survey

**Exploring Factors Affecting the Adoption of MOOC* in Generation Z using Extended UTAUT2 Model**

Dear Sir/Madam,

I am doing research on the topic titled "MOOC Adoption in Generation Z". The purpose of reaching out is to take your viewpoint on factors influencing your decision to adopt Massive Open Online Courses (MOOCs) like Coursera, edX, Udemy, upGrad, SWAYAM, NPTEL etc. Kindly spare your valuable 8-10 minutes and fill this form by clicking the box you find as most appropriate and writing answers where desired.

Note:

1. Massive Open Online Courses (MOOCs) is an online course aimed at unlimited participation and open access via the web.

2. This questionnaire is designed to complete my research work. The information thus received will be kept confidential and not to be used for any other purpose.

**Qualifier Question:**

Q1. Qualifier Question: Have you done any online course (MOOCs)? If the answer is "yes" then proceed to complete the survey form.

a) Yes
b) No

**<u>Section: A</u>**

1. On the scale of 1-5, Kindly rate the following attributes based on your opinion.

**(1 - Strongly Disagree, 5 – Strongly Agree)**

| SN | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 1. | Before COVID-19, Online Courses (MOOCs) were considered as just a source of complementary knowledge | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2. | After the onset of COVID-19, Online Courses (MOOCs) are considered as an important and integral part of education | | | | | |

***MOOC stands for massive open online course.** It is an online course aimed at unlimited participation and open access via the web. *MOOCs* provide an affordable and flexible way to learn new skills, advance your career and deliver quality educational experiences at scale.

**2.** How many Online Courses (MOOCs) you have completed while pursuing your UG/PG studies?

a. Less than 3
b. 3-5
c. 6-8
d. More than 8

**3.** Who influenced you to do an online course? (Multi Answer-You can click on more than one answer)

a. Self-motivation to learn more
b. Your teacher's instruction (course has the component of classroom & online learning, both)
c. Your university/college influence to pursue an online course
d. Free/Economical pricing
e. Brand of Institute/University offering MOOCs
f. Any other reason (please specify)

**4.** In which stream you have done your online certification? (Multi Answer-You can click on more than one answer)

a. Arts & Humanities
b. Science (Physics, Chemistry, Biology, Maths, Statistics etc.)
c. Technology (All the engineering and technology courses)
d. Social Science (Psychology, Philosophy, Sociology, Anthropology etc.)
e. Management, Commerce and Economics
f. Languages (english, hindi, regional or foreign)
g. Music
h. Any Other (please specify)

**5.** Which online platform you have used to access your online course (Multi Answer-You can click on more than one answer)

**a.** Coursera
**b.** Udemy
**c.** Swayam/NPTEL

**d.** Edx
**e.** Future learn
**f.** Anyother (please specify)

**6.** How many hours do you access your online course in a week?

a. Less than 3 hours
b. 3-5 hours
c. 6-8 hours
**d.** More than 8 hours

**Section: B**

**7.** On the scale of 1-5, Kindly rate the following attributes based on your opinion.

**(1 - Strongly Disagree, 5 – Strongly Agree)**

| SN | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 1 | I find Online Courses (MOOCs) useful in my studies. | | | | | |
| 2 | Online Courses (MOOCs) increases my chances of achieving knowledge that is important to me. | | | | | |
| 3 | Online Courses (MOOCs) enables me to accomplish my task more quickly. | | | | | |
| 4 | Online Courses (MOOCs) increases my productivity (It adds to my knowledge). | | | | | |
| 5 | How to use Online Courses (MOOCs) is easy for me. | | | | | |
| 6 | My interaction with Online Courses (MOOCs) is clear and understandable. | | | | | |
| 7 | I find Online Courses (MOOCs) easy to use. | | | | | |
| 8 | People who are important to me think that I should use Massive Open Online Courses (MOOCs). | | | | | |
| 9 | People who influence my behaviour think that I should use Massive Open Online Courses (MOOCs). | | | | | |
| 10 | People whose opinions that I value prefer that I use Massive Open Online Courses (MOOCs). | | | | | |
| 11 | I have the resources necessary to use Online Courses (MOOCs) | | | | | |
| 12 | I have the knowledge necessary to use Massive Open Online Courses (MOOCs). | | | | | |
| 13 | Online Courses (MOOCs) is compatible with other technologies (Mobile/Laptops/Tablets) I use. | | | | | |
| 14 | I can get help from others when I have difficulties using Massive Open Online Courses (MOOCs). | | | | | |
| 15 | Using Online Courses (MOOCs) are enjoyable. | | | | | |
| 16 | Using Online Courses (MOOCs) are very entertaining. | | | | | |
| 17 | Using Online Courses (MOOCs) are fun. | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 18 | Online Courses (MOOCs) are reasonably priced. | | | | | |
| 19 | Online Courses (MOOCs) are a good value for the money. | | | | | |
| 20 | At the current price, Online Courses (MOOCs) provides a good value. | | | | | |
| 21 | The use of Online Courses (MOOCs) has become a habit for me. | | | | | |
| 22 | I am addicted to using Online Courses (MOOCs) | | | | | |
| 23 | I must use Massive Open Online Courses (MOOCs). | | | | | |
| 24 | I will always try to use Online Courses (MOOCs) in my daily life. | | | | | |
| 25 | I plan to continue to use Online Courses (MOOCs) frequently. | | | | | |
| 26 | I intend to continue using Online Courses (MOOCs) in the future. | | | | | |

**Section C**

**8.** On the scale of 1-5, Kindly rate the following attributes based on your opinion.
**(1 - Strongly Disagree, 5 – Strongly Agree)**

| SN | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 1 | Students can actively participate in learning if the language of instruction is what they understand well | | | | | |
| 2 | Language used in Online Courses (MOOCs) is important for me to adopt it | | | | | |
| 3 | Language which the students may not be confident with may affect their approach to learning. | | | | | |
| 4 | I find it easy to develop rapport with the teacher delivering Online Courses (MOOCs) in my mother tongue | | | | | |
| 5 | I believe that the Online Courses (MOOCs) if delivered in regional languages will have far wider acceptability | | | | | |

**Section D**

**9.** On the scale of 1-5, Kindly rate the following attributes based on your opinion.

**(1 - Strongly Disagree, 5 – Strongly Agree)**

| SN | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 1 | I believe my teacher is an expert of his subject | | | | | |
| 2 | My teacher is my role model | | | | | |
| 3 | I follow my teacher’s instructions on study related matter | | | | | |
| 4 | My college encourages enrolment in online course (MOOCs) to gain additional knowledge and learn new skills | | | | | |
| 5 | My teachers give additional weightage during evaluation on the successful completion of an online course (MOOCs) | | | | | |

**Section: E**

1. Name (Optional): ____________________________________________________________
2. Age: (a) Less than 20 years (b) 21-25 Years (c) More than 25 Years
3. Gender: (a) Male (b) Female
4. Education (pursuing) (a) Graduate (Bachelor's) (b) Post-Graduate (Master's) (c) PhD (e) Others, please specify
5. Stream: (a) Science (b) Engineering (c) Commerce (d) Management/Administration (e) Others, Specify _____________________
6. College/University: (a) Private College/university (b) State University (c) Deemed University (d) Central University (e) Institution of Eminence (f) Institution of National Repute
7. Institution Name and City ________________________
8. Family Monthly Income: (a) less than Rs 25000 (b) Rs 25001-50000 (c) Rs 50001-75000 (d) Rs 75001 - 100000 (e) More than Rs 100000
9. Challenges you face with online course (MOOCs). Please specify as it will help in improving the design/structure of an online course (Mandatory)________________________________________________

**Thank you for your participation.**

## Appendix B: Dissemination

### (i) Publications:

1. Meet, R. K., & Kala, D. (2021). Trends and future prospects in MOOC researches: A systematic literature review 2013–2020. *Contemporary Educational Technology*, 13(3). https://doi.org/10.30935/cedtech/10986 (Scopus Indexed)

2. Meet, R.K., Kala, D. & Al-Adwan, A.S. Exploring factors affecting the adoption of MOOC in Generation Z using extended UTAUT2 model. Education & Information Technologies (2022). https://doi.org/10.1007/s10639-022-11052-1 (Scopus and SSCI Indexed Journal, IF – 2.917)

### (ii) Paper Presentation International / National Conferences

1. "MOOCs and Millennials", paper presented in the Doctoral Colloquium, 2019 at UPES, Dehradun.

2. "Massive Open Online Courses in Higher Education: Unravelling the journey so far" paper presented in the International Conference on Business Research and Innovation (ICBRI) held during Feb 26th-27th at MDI, Murshidabad.

3. Exploring Factors Affecting the Adoption of MOOC in Generation Z using Extended UTAUT Model" paper presented in the Conference on Excellence in Research and Education (CERE) held during June 18th-20th at IIM, Indore.

### (iii) Domain Specific Certification Courses Done:

1. Attended a 2-Week workshop conducted by Delhi University on "Managing Online Classes and Co-Creating MOOCs" from April 20 to May 6, 2020.

**Authors Biography**

**Prof. Rakesh K. Meet is a practitioner turned educator.**

He is an Area Chair and Assistant Professor (Marketing) at Doon Business School having a rich and diversified Teaching and Corporate experience of 27 years. In his academic tenure he has effectively handled teaching and administrative responsibilities in eminent institutions in regular and visiting roles.

Prior to pursuing career in academics, he had spent 23 years in the corporate world working with Indian & Global Companies of repute like GlaxoSmithKline (fya Novartis Consumer Health), Dabur, HLL Lifecare, Airtel, Reliance and Vodafone in the leadership positions. His last assignment was with Vodafone India limited as Retail Operations Head. He has the distinction of doing triple Master's in Business Management, International Business and Psychology and is currently pursuing Ph.D. in Management from UPES, Dehradun. He has published two papers in peer-reviewed international journals indexed in Scopus, Web of Science and SSCI database. Apart from attending and presenting papers in National and International conferences, Mr. Meet has done certification courses in Digital Marketing, MOOC creation, and Successful Negotiations: Essential Strategies and Skills. His areas of teaching include B2B Marketing, Sales and Distribution Management, Services Marketing, Consumer Behaviour, and Business Environment. Educational technology, Social Media, Gen Z, Sales Efficiency Build Up, Sustainability Management are some of the research areas that interest him. He is a Certified Trainer of Neuro Linguistic Programming and an Assessor of Multiple Intelligences Developmental Scales, certified by Dr. Branton Shearer, Ohio, USA.

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