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Willingness of university students to continue using e-Learning platforms after compelled adoption of technology: Test of an extended UTAUT model

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Abstract
The COVID-19 pandemic has prompted the adoption of an e-Learning pedagogy. This forced teachers and students to shift to online learning and thus was compelled to adopt online educational technology. Educational institutes have been facing challenges like insufficient infrastructure and a shortage of quality teachers. Online learning can help to address these challenges as online classes can accommodate more students. However, before implementing e-Learning technology management of institutes wants to be sure whether students will adopt new technology. Therefore, the purpose of this study was to unveil which factors are important to adopt new technology if implemented mandatorily. We tested the most popular technology acceptance model the UTAUT to understand students' intentions to continue using the e-Learning system in a mandatory environment. The study used a quantitative approach of research. The participants for this study were selected from a private university in India. The questionnaire for the study was adapted from previous studies. The survey was conducted by sharing an online link while students were attending classes online during the pandemic. Thus, the study utilized a convenience sampling technique. The data were analyzed using structural equation modelling. The findings revealed that the UTAUT model can partially explain the forceful adoption of technology. The study found 'Performance expectancy' and the 'availability of resources' as significant indicators of 'intention for continued usage'. This study recommends educational institutes should ensure students attain academic goals by using e-Learning platforms and ensuring the availability of essential resources to use the e-Learning technology.

Keywords Compelled adoption · e-Learning · Higher education · Mandatory adoption · Online learning · UTAUT Model.

Extended author information available on the last page of the article

1 Introduction

Educational institutions in highly populous countries like India always face various constraints to accommodate the increasing demand to provide quality education to the increasing population. These constraints include – infrastructure, funds, quality teachers etc. (Chattopadhyay, 2013; Dhal, 2020; Modi, 2014; Prakash et al., 2011; Tobenkin, 2022). The government adopted privatization of the education sector to reduce the financial burden of providing education to its large population. Such private institutions are self-funded and are not provided with financial help from the government (Datta & Kundu, 2021).

Due to limited infrastructure, it is challenging for educational institutions to satisfy the increasing demand for quality education. One solution to this constraint is to adopt e-Learning or hybrid learning. e-Learning is offering education through online mode which is characterized by (a) no requirement for physical classroom setup, and (b) the number of students in a class can be more than the conventional face-to-face (F2F) classrooms (Srivastava, 2023). Whereas hybrid learning is the blending of both F2F education and e-Learning. In hybrid learning, some students attend class physically while some students attend virtually at the same time (Raes et al., 2020). Hybrid learning requires specially designed classrooms to serve the purpose. In both approaches, more students can be accommodated in a class than in conventional F2F learning.

e-Learning and hybrid learning both are applications of information technology (IT). The educational institute can mandatorily adopt e-Learning or hybrid learning. However, recent studies documented that users are reluctant to adopt e-Learning; the new technology (G. Singh & Hardaker, 2014; Stanca & Felea, 2015; Yap et al., 2015). Thus, the managers of educational institutions are cautious to leverage technology and transform their institutions into online or hybrid educational institutions. They can be more confident if they understand the antecedents of mandatory implementation of e-Learning or hybrid education.

Various studies are available in the extant literature on adopting technology. Among them, the 'Unified Theory of Acceptance and Use of Technology (UTAUT)' is a widely accepted model in explaining technology acceptance by users (Venkatesh et al., 2012). This model has been tested across various contexts and proven its explanatory power successfully (Venkatesh et al., 2016). The extant studies on the users' adoption of technologies have primarily examined the scenario wherein the users adopted the new technology voluntarily. Although recently few scholars attempted to study technology acceptance in a mandatory environment (Dečman, 2015; Guo, 2022; Khechine et al., 2020; Lehmann et al., 2022; Zhang et al., 2022). None of these studies investigated the Indian educational context. Further, more studies are required to expand the domain of technology acceptance in a mandatory environment. In this study, we used the word 'compelled' instead of the word 'mandatory' because the word 'compelled' is more apt as students were forced to adopt online learning against their will due to the prevailing conditions of the COVID-19 pandemic. Specifically, in the Indian educational context, it is not known whether the constructs of UTAUT are applicable in the context when users are compelled to use the new technology. This knowledge is important for the managers of educational institutes as they can confidently implement e-Learning in their institutes mandatorily. The COVID-19 pandemic has extended an excellent opportunity to test the applicability of the UTAUT model in the forceful adoption of the technology.

The COVID-19 pandemic has prompted the adoption of an online teaching and learning pedagogy. Prior to the pandemic, teaching-learning has been taking place in a Face-to-Face (F2F) physical classroom setting. F2F teaching-learning is also known as synchronous teaching and learning. This F2F format is characterized by a higher level of interaction between learners and teachers. Learners can, not only participate in classroom activities but also clarify their doubts immediately in real time. Thus, the synchronous F2F format is more effective than asynchronous teaching and learning (Daumiller et al., 2021).

The COVID-19 pandemic forced the sudden closure of universities and educational institutes. This compelled both teachers and students to shift to online learning from the F2F format. Thus, they were compelled to adopt online educational technology (e-Learning technology). Therefore, this study was an attempt to test the applicability of the UTAUT model in the forceful adoption of online learning by students. Specifically, we attempted to answer the following research questions:

RQ1: Which factors are important to adopt new technology if implemented mandatorily?
RQ2: Can the UTAUT model explain users' intention to continue using new technology if implemented mandatorily?

To answer the first research question, we conducted an extensive review of extant literature. The second research question is answered by applying covariance-based structural equating modelling for data analysis. The covariance-based structural equation modelling is appropriate for theory testing particularly when the models are relatively simple (Hair et al., 2018).

In this paper, we have comprehensively reviewed the extant literature related to 'online learning', the UTAUT model, and its extension in e-Learning. We have documented the growth of online learning in India. Next, we have discussed the UTAUT model which is the most widely used model to explain users' intention to use new technology and its extended model in mobile learning. Further, we have discussed hypotheses development and in the remaining sections, we have presented results, discussions, and conclusions.

2 Theoretical background

2.1 Online learning (e-Learning)

India has witnessed tremendous growth in online learning in recent years. According to a report by KPMG, the online education market in India is expected to reach $2 billion by 2021, up from $247 million in 2016 (Ankur et al., 2017). This growth can be attributed to the increasing availability of high-speed internet, the proliferation of smartphones, and the government's Digital India initiative, which aims to increase internet connectivity and digital literacy across the country (*Vision & Vision Areas – Digital India*, n.d.).

The online education market in India is dominated by 'edtech' startups, such as BYJU'S, Unacademy, and Vedantu, which have raised millions of dollars in funding from investors such as SoftBank, Sequoia Capital, and Tiger Global Management (M. Singh, 2021). These companies offer a wide range of courses, from primary and secondary education to professional certifications and test preparation. They leverage technology such as artificial intelligence, machine learning, and gamification to provide personalized and engaging learning experiences to students.

Online learning and e-Learning are commonly referred to as the same format of teaching-learning and are often used interchangeably. Although, according to Harriman (2010, as cited in Basak et al., 2018), online learning is one of the types of e-Learning (other types being distance learning, blended learning, and m-learning). The primary emphasis of this study was to understand technology acceptance than understand the types of teaching and learning. Therefore, in this study both the terms, 'online learning' and 'e-Learning' are considered as same.

Various definitions of 'online learning or e-learning' are available in the extant literature. According to Wang et al. (2010, p. 167), "E-learning refers to the use of computer network technology, primarily over or through the internet, to deliver information and instructions to individuals". Akbari et al. (2022, p. 1912) referred e-Learning as "E-learning is the transfer of information and skills via electronic media such as the Internet, intranets, and extranets in well-designed course content with reputable accreditations". Whereas Curtain (2002) defined online learning as-

> use of the internet in some way to enhance the interaction between teacher and student. Online delivery covers both asynchronous forms of interaction such as assessment tools and the provision of web-based course materials and synchronous interaction through email, newsgroups, and conferencing tools, such as chat groups (p. 12).

The use of technology is one of the common factors in most of the available definitions of online learning or e-learning. Adopting online or e-learning therefore essentially requires the adoption of technology (in the context of this study it was educational technology) by teachers and learners.

2.2 UTAUT and extended UTAUT model

There are several models available which explain technology acceptance. However, among them, the UTAUT is the most widely accepted and tested model. The UTAUT has proven its explanatory power in various contexts including educational contexts (Venkatesh et al., 2016). Therefore, we choose the UTAUT model for this study.

UTAUT model (Fig. 1) was synthesized by Venkatesh et al. (2003), by combining eight related theories of technology acceptance. These are the Theory of Planned behavior (TPB), Technology Acceptance Model (TAM), Combined TPB & TAM (C-TAM-TPB), Theory of reasoned action (TRA), Motivational Model (MM), Model

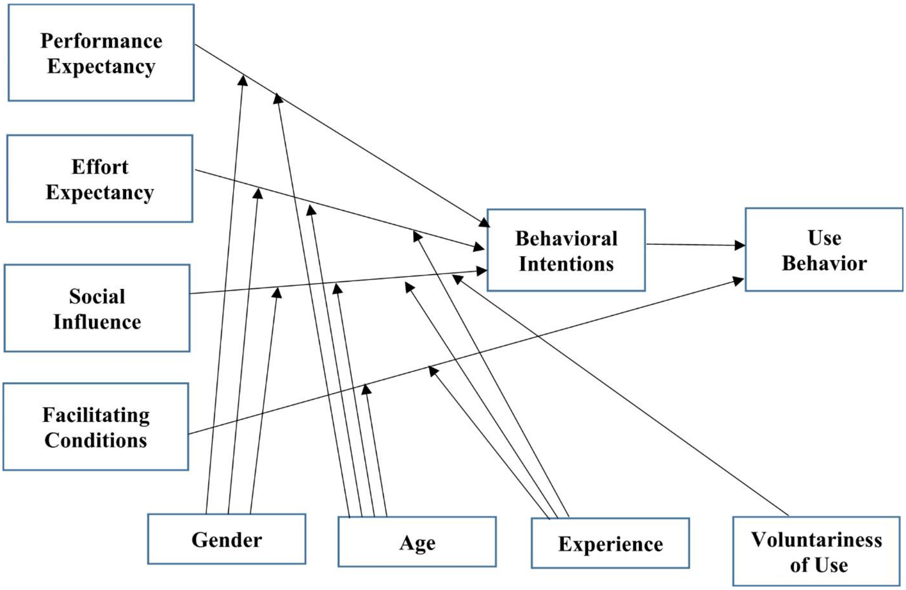

Fig. 1 UTAUT model by Venkatesh et al. (2003)

of PC utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT).

UTAUT has four key constructs; Performance expectancy (PE), Effort expectancy (EE), Social influence (SI), and Facilitating conditions (FC), which predict Intention to Use Technology (ITU). This model has been tested in various contexts and found to be effective in explaining technology acceptance by users. Gender, age, experience, and voluntariness of use were reported to have a moderating effect on the aforementioned four constructs.

Almaiah et al. (2019) extended UTAUT Model for the adoption of mobile learning by adding external factors responsible for the adoption of learning technology by students (Fig. 2).

Our proposed research model is based on the UTAUT model and extended UTAUT model by Almaiah et al. (2019). The COVID-19 pandemic has compelled the premature adoption of several online technologies that are characterized by the lack of human-physical interaction. This is very much essential to curb the spread of the pandemic as it is ensuring social distancing. Students (the study's target group) were forced to use e-Learning systems. Since the adoption was already taken place, we reasoned that the original outcome construct namely 'intention to use' from the UTAUT model was inappropriate in the context of the current study. It was more appropriate to investigate the users' desire to continue using the technology. Therefore, we replaced the construct 'intention to use' with 'Intention to continue use' (ICU) in the proposed research model (Fig. 3). Users' adoption of technology is generally defined as their intention to continue using it (Hsieh et al., 2008).

3 Hypotheses development

For this study we have used two models (a) the UTAUT model by Venkatesh et al. (2003) (Fig. 1) and (b) the extension of the UTAUT model in mobile learning by Almaiah et al. (2019) (Fig. 2). The UTAUT has been mostly accepted technology acceptance model. It has demonstrated effectiveness in elucidating the variability in both the "intention to use technology" and the "actual use of technology", specifically within organizational environments (Venkatesh et al., 2012, p. 157). During longitudinal field studies that observed how employees adopt technology, UTAUT was able to explain "77%" of the variance in the likelihood of "intention to use" technology and "52%" of the variance in the "actual use of technology" (Venkatesh et al., 2016, p. 329). UTAUT model has four constructs performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). Almaiah et al. (2019) extended this model by adding Perceived information quality (PIQ), Perceived compatibility (PCM), Perceived trust (PT), Perceived security (PSE), and Perceived awareness (PA). In the present study, four relevant constructs are used out of nine. The following text provides a detailed explanation of the inclusion and exclusion of the constructs.

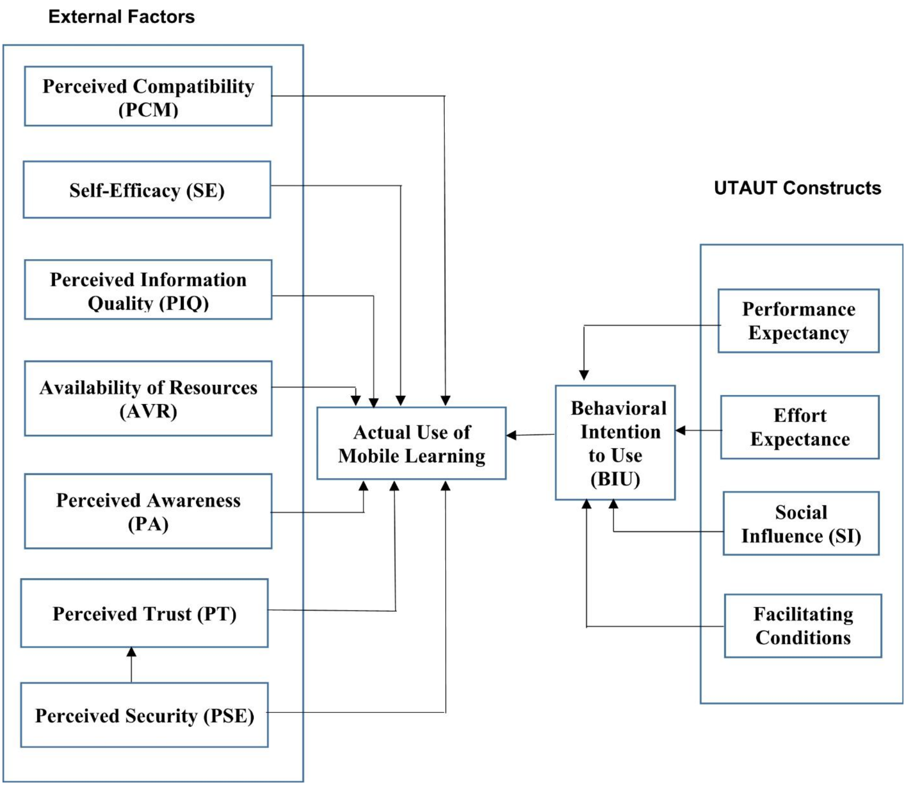

Fig. 2 Model by Almaiah et al. (2019) : Extended UTAUT Model for adoption of mobile learning

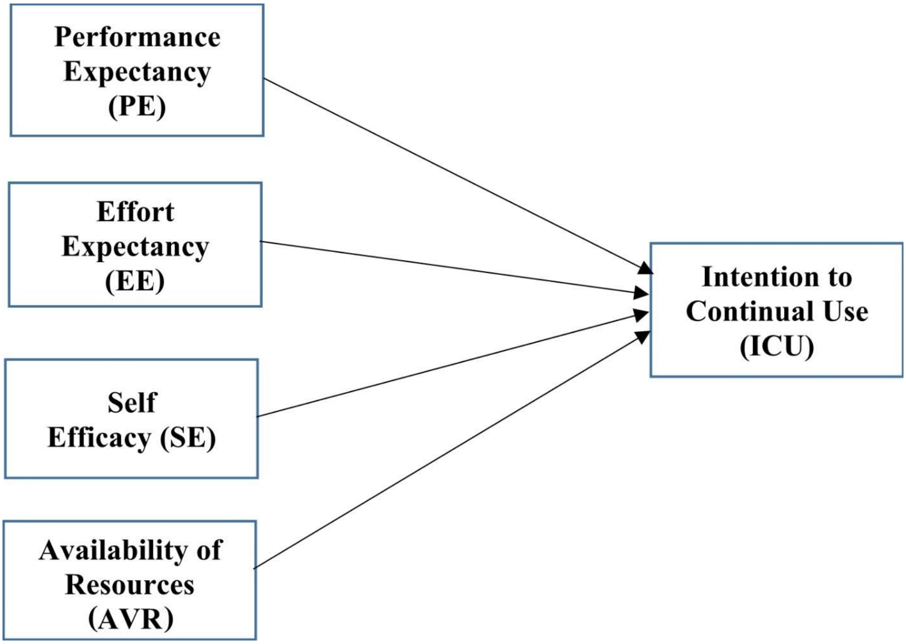

Fig. 3 Research model: Continual use of technology in forceful adoption

3.1 Intention to continue use (ICU)

The context of this study is where students (the study's target group) were forced to use e-Learning technology. Since the adoption was already taken place, we reasoned that the original outcome construct 'intention to use' from the UTAUT model was inappropriate in the context of the current study. It was more appropriate to investigate the users' desire to continue using the technology. Hsieh et al. (2008) referred to users' adoption of technology in general as their intention to continue using it. Therefore, we replaced the construct 'intention to use' with 'Intention to continue use' (ICU) in the proposed research model (Fig. 3).

3.2 Performance expectancy (PE)

Performance expectancy (PE) was described by Venkatesh et al. (2003, p. 447) as "the degree to which an individual believes that using the system will assist him or her in achieving gains in job performance". Based on the above definition, Performance expectancy is defined in the current study as the degree to which students believe that using an e-Learning platform would help them achieve their educational performance goals. Originally, this construct was identified as a predictor of intention to use technology. We used it as a predictor of intention to continue using technology in this study. Many scholars have investigated the impact of performance expectancy on users' attitudes and behavioral intentions. Performance expectancy is a significant indicator of e-Learning technology acceptance by students (Kurt & Tingöy, 2017;

Ngampornchai & Adams, 2016). PE has a favorable impact on attitude and behavioral intention in an e-Learning environment (Olatubosun et al., 2014). Almaiah et al. (2019) reported similar results. Thus, we came up with the following hypothesis:

H_1 Performance Expectancy (PE) has a significant positive effect on the intention to continue using e-Learning platforms post-compelled adoption.

3.3 Effort expectancy (EE)

Effort expectancy is described by Venkatesh et al. (2003, p. 450), as "the degree of ease associated with the usage of the system." The system in this study comprises e-Learning platforms. Many studies have found that effort expectancy is a key factor in deciding whether to use technology (Almaiah & Mulhem, 2019; García Botero et al., 2018; Nikolopoulou, 2018; Venkatesh et al., 2012). Sung et al. (2015) as well as Almaiah et al. (2019) found that effort expectancy is a strong predictor of intention to use a mobile learning system. Similar findings were reported by Kurt and Tingöy (2017), and Ngampornchai and Adams (2016) in the context of e-Learning. Therefore, we proposed the following hypothesis:

H_2 Effort Expectancy (EE) has a significant effect on the intention to continue using e-Learning platforms post-compelled adoption.

3.4 Self-efficacy (SE)

Self-efficacy is one of the most significant components of online learning (Shen et al., 2013). In the context of mobile learning, Almaiah et al. (2019, p. 174,676), defined Self-efficacy (based on the notion of social cognitive theory) as "the degree of users' technological capability to utilize, interact, and transact with learning applications based on past knowledge, experience, and abilities as they feel it is required to do so". Marek et al. (2021) reported that students are not sufficiently techno-savvy as popularly believed and therefore, not comfortable using online learning systems. Thus, being techno-savvy have a positive influence on self-efficacy. Moreover, Self-efficacy has been identified by several researchers as one of the most essential aspects in acceptance of the e-Learning systems (Almaiah et al., 2019). Further, Self-efficacy, according to Chavoshi and Hamidi (2019) influences the intention to use a mobile learning system. Hence, it is recommended that students should have high self-efficacy for a smooth adoption of e-Learning (Sabah, 2016). Therefore, we proposed the following hypothesis:

H_3 Self-efficacy has a significant positive effect on the intention to continue using e-Learning platforms post-compelled adoption.

3.5 Availability of resources (AVR)

The availability of resources is a necessary condition for technology adoption. These resources are hardware and software in the context of e-Learning. The availability of these resources is critical to the success of e-Learning projects (Sarrab et al., 2018). According to Lee (2008), the availability of resources and technical assistance can influence students' acceptance of learning platforms. Students mostly female students prefer to seek personal assistance for issues related to learning technology (Vázquez-Cano et al., 2017). A good internet connection in terms of speed is also crucial, in addition to the hardware and software requirements (Almaiah et al., 2016). Internet connectivity has been a common problem in developing countries (Zigh et al., 2022) like India. Therefore, we proposed the following hypothesis:

H_4 Availability of resources has a significant positive effect on the intention to continue using e-Learning platforms post-compelled adoption.

3.6 Constructs excluded from the study

Two constructs from the original UTAUT model and five constructs from the extended UTAUT model in mobile learning by Almaiah et al. (2019) were excluded from the present study. The rationale for the exclusion is discussed in the following text.

The two constructs from the UTAUT model are (i) Social Influence (SI) and (ii) Facilitating conditions (FC). Social Influence (SI) is defined as the "degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 451). Similarly, facilitating conditions (FC) are defined as the "degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003, p. 453). In the present study, these two constructs SI and FC from UTAUT were initially included. However, due to a lack of reliability and validity, they were dropped. Further, most of the studies which are based on UTAUT excluded Social Influence (SI) and Facilitating conditions (FC) as it is believed that Performance expectancy (PE) and Effort Expectancy (EE) are primary constructs to predict the adoption of technology (Almaiah et al., 2019). Therefore, we believe the exclusion of these two constructs would not affect the outcome of the study.

The original UTAUT model includes four moderators, namely gender, age, experience, and voluntariness of use (Fig. 1). However, many studies that utilize the UTAUT model have excluded these moderators because they are not relevant to the context being studied (Venkatesh et al., 2012). When an organization mandates the use of information systems or technology, the moderators become insignificant (Dwivedi et al., 2019). In this study, the e-Learning system was mandated by the educational institute; therefore, the moderators were not considered.

Almaiah et al. (2019) extended UTAUT Model for the adoption of mobile learning (Fig. 2). The following five external factors used by them were excluded from the present study as they were irrelevant to the context of this study; (i) Perceived information quality (PIQ), (ii) Perceived compatibility (PCM), (iii) Perceived trust (PT), (iv) Perceived security (PSE), and (v) Perceived awareness (PA).

Perceived information quality (PIQ) is defined as "the quality, accuracy, and format of learning content provided by mobile learning applications" (Almaiah et al., 2019, p. 174,676). In the context of the present study, learning platforms were used to conduct live sessions rather than making educational content available on the system. Therefore, the construct PIQ was dropped from this study.

Perceived compatibility (PCM) is the degree to which "an 'Information System' (IS) / 'Information Technology' (IT) innovation is perceived as consistent with the needs and perceptions of potential users" (Almaiah et al., 2019, p. 174,675). Further, Perceived trust (PT) and Perceived security (PSE) are still considered a problem and obstruction to the continued use of technology. In this study, the e-Learning applications were selected by the educational institute and students did not have any choice. Therefore, these constructs were irrelevant. Moreover, Perceived awareness (PA) was irrelevant as users were forced to adopt the learning system irrespective of whether they were aware of the technology.

The resultant proposed research model for the continual use of technology in forceful adoption is depicted in Fig. 3.

4 Methodology

4.1 Sample and data collection

The target population was students engaged in online learning from a private university in India. The data was collected during the pandemic. The participants chosen were from a professional post-graduate school of the university. The study used a quantitative approach to research. To collect the data an online survey form was created, and its link was shared with the students who were attending the academic sessions. One of the limitations of online surveys is researchers have limited control over who would participate in the online survey. Therefore, the sampling approach is a convenience sampling approach. Convenience sampling is common in social science although it threatens the external validity of the research. This is because convenience sampling lacks representation of the population. However, Mullinix et al. (2015) demonstrated that the results of studies wherein samples are chosen using a convenience sampling approach and representative sampling approach are similar. Therefore, we believe although this study utilized convenience sampling the findings are valid.

A total of 267 responses were received. We collected responses for both independent and dependent variables within one survey at the same time. This is the source of common method bias (CMB) which could affect the validity of results. The common method bias can be avoided by procedural control and/or statistical control. While collecting data online, explicit instructions and questions are highly recommended to ensure honest responses and improve internal and external validity (Buhrmester et al., 2018; Clifford & Jerit, 2016; Hunt & Scheetz, 2019; Lowry et al., 2016; Newman et al., 2021; Ward & Meade, 2017). Further, Podsakoff et al. (2012) recommended procedural control of common method bias by providing unambiguous instructions; safeguarding the confidentiality of respondents; avoiding complicated and unclear questions; and keeping the length of the questionnaire short. Following these recommendations first, we explicitly instructed the participants with an appeal to them to participate willingly and answer honestly. We informed them of the purpose of this study. We assured them that the data collected would be used only for the purpose of this study and would not be shared with anyone. We ensured the wording of the questions was simple and understandable and kept the length of the questionnaire sufficiently short. Further, to ensure the confidentiality of respondents we had not included any such questions which reveal their identities like name, email, address, and phone numbers. Thus, exercised procedural control over common method bias ensuring minimum bias and improved internal and external validity of the study.

4.2 Data analysis

Before proceeding to the analysis, we performed a thorough check of all 267 forms which were received. We checked each individual response. 158 responses were excluded from the analysis due to the following reasons - (a) not all questions were answered, (b) "straight line" or "long string" responses. This is the case when a respondent chooses the same response option in series to the multiple scale questions (Ward & Meade, 2017) e.g., a respondent had chosen "Agree" response to all seventeen scale items), and (c) inconsistency in responses. After rigorous inspection, the 109 replies were found to be useful and hence used for data analysis. According to Hair et al. (2018) the sample size should be 15 to 20 observations per variable to attain generalizability. The total variables in the study were five therefore the sample size was considered adequate. The scales employed in this study were adapted from earlier studies, including UTAUT (For detailed discussion please read the section 'Instrument development). The scales' reliability and validity were tested. Covariance-based Structural Equation Modeling software AMOS was used to test the hypotheses.

The demographic details of the participants are presented in Table 1. Total 109 respondents are there, which comprises postgraduate students persuading a professional master's degree from a private university. As presented in Table 2, 70.6% are male and 29.4% are female. In regard to age, 9.2% are in the age group of 20–21, 58.7% are in the age group of 22–23, 22.9% are in the age group of 24–25, and 9.2% are in the age group of 26–27.

The data was analyzed, and the research hypotheses were tested using Covariance-based Structural Equation Modeling (SEM) techniques. The analysis followed the two-step approach developed by Anderson and Gerbing (1988) with the first step focusing on evaluating the validity and reliability of the measurement model, and the second step analyzing the structural model to test the research hypotheses. Similar methodologies are adopted by previous studies (Abbad, 2021; Alshehri et al., 2019; El-Masri & Tarhini, 2017; Salloum & Shaalan, 2019).

Table 1 Demographics of respondents

Demographics	Frequency	Percent
Age		
20–21	10	9.2
22–23	64	58.7
24–25	25	22.9
26–27	10	9.2
Gender		
Male	77	70.6
Female	32	29.4
Area		
Urban	82	75.2
Rural	27	24.8

n = *109*

4.3 Instrument development

In this investigation, five scales were used. Performance expectancy (PE), Effort expectancy (EE), Self-efficacy (SE), Resource availability (AVR), and Intention to continue use (ICU). PE and EE scales were adapted from Almaiah et al. (2019), Alvi (2021), and Venkatesh et al. (2003). The scale of AVR was adapted from Almaiah et al. (2019); Chavoshi and Hamidi (2019); and Brahim and Mohamad (2018). An uninterrupted power supply is a major challenge in rural parts of India (Chambon et al., 2020). Therefore, one item in AVR i.e. 'I always have an uninterrupted power supply to use the e-Learning system' was added by the authors based on the suggestion from the expert panel. The scale of SE was adapted from Almaiah et al. (2019); Olatubosun et al. (2014); and Venkatesh et al. (2003). The ICU scale has three statements. The first statement of the ICU scale, 'I intend to continue using the e-learning system' was adapted from Almaiah et al. (2019) and Hsieh et al. (2008). While remaining two items were adapted from Almaiah et al. (2019). The details of the scale items and their respective sources are presented in Table 2.

A total of 17 items were measured on a 7-point Likert scale (Strongly agree-7 through Strongly disagree – 1). The questionnaire was scrutinized by a panel of ten experts comprises of two students, four academicians (teachers), two experts in e-Learning, and two administrative managers of the institute. As per the suggestions from the panel, we revised the questionnaire, thus face and content validity of the questionnaire was ensured.

5 Data analysis and results

Covariance-based structural equation modelling was used to test the hypotheses. We followed the two-step approach recommended by Anderson and Gerbing (1988). First, we assessed the reliability and validity of the measurement model. All scales used in this study had Cronbach's alpha values greater than 0.7, indicating that they were reliable (Table 3) (Nunnally & Bernstein, 1994). Composite reliability (CR) values over 0.7 and average variance extracted (AVE) values of all scales above 0.5 confirmed the convergent validity. Further, discriminant values (DV) presented on the diagonal in Table 3 are greater than the correlation coefficients of other variables,

Table 2 Scale items and their sources

Construct	Item	Sources
Performance expectancy (PE)	PE1: I find the e-Learning system useful in my study	Almaiah et al. (2019); Alvi (2021); Venkatesh et al. (2003)
	PE2: Using the e-learning system increases the quality of the learning process.	Almaiah et al. (2019); Alvi (2021); Venkatesh et al. (2003)
	PE3: e-learning system help me to improve my educational performance	Almaiah et al. (2019); Alvi (2021); Venkatesh et al. (2003)
Effort Expectancy (EE)	EE1: I find the e-learning system easy to use	Almaiah et al. (2019); Alvi (2021); Venkatesh et al. (2003)
	EE2: It is easy for me to become skilful at using the e-learning system.	Almaiah et al. (2019); Alvi (2021); Venkatesh et al. (2003)
	EE3: Learning to operate the e-learning system is easy for me.	Almaiah et al. (2019); Alvi (2021); Venkatesh et al. (2003)
Availability of Resources (AVR)	AVR1: I have an adequate internet connection to use the e-learning system from anywhere.	Almaiah et al. (2019); Chavoshi and Hamidi (2019); Brahim and Mohamad (2018)
	AVR2: The Internet connection I use is not costly.	Almaiah et al. (2019); Chavoshi and Hamidi (2019); Brahim and Mohamad (2018)
	AVR3: I always have access to a high-speed Internet connection from anywhere to use the e-learning system.	Almaiah et al. (2019); Chavoshi and Hamidi (2019); Brahim and Mohamad (2018)
	AVR4: I always have an uninterrupted power supply to use the e-Learning system.	Authors' Contribution
Self-Efficacy (SE)	SE1: Even if there was no one around to tell me what to do, I could complete my studies or assignment using the e-Learning system	Almaiah et al. (2019); Olatubosun et al. (2014); Venkatesh et al. (2003)
	SE2: I could call someone for help if I got stuck while completing my studies or assignment using the e-Learning system	Almaiah et al. (2019); Olatubosun et al. (2014); Venkatesh et al. (2003)
	SE3: I could complete my studies or assignment using the eLearning system if I had a lot of time to complete the task.	Almaiah et al. (2019); Olatubosun et al. (2014); Venkatesh et al. (2003)
	SE4: If I had just the built-in help facility for assistance, I could complete my studies or assignment using the eLearning system.	Almaiah et al. (2019); Olatubosun et al. (2014); Venkatesh et al. (2003)
Intention to continue use (ICU)	ICU1: I intend to continue using the e-learning system	Almaiah et al. (2019); Hsieh et al. (2008)
	ICU2: I like to use the e-learning system	Almaiah et al. (2019)
	ICU3: I plan to use the e-learning system in the future.	Almaiah et al. (2019)

while maximum shared variance (MSV) values are less than AVE. This satisfied the criteria for discriminant validity. As a result, the scales' reliability and validity were confirmed.

Second, we tested the structural equation model. Structural equation modelling (SEM) is a powerful analytical technique used to examine and evaluate the hypothesized relationships between different variables. It is a comprehensive tool that allows researchers to test complex models and explore the complex interrelationships between multiple variables simultaneously (Hair et al., 2018). In the present study,

Table 3 Reliability and validity of scales

	CR	AVE	MSV	MaxR(H)	AVR	SE	EE	PE	ICU	Cronbach's alpha	Items
AVR	0.842	0.574	0.398	0.858	**0.757**					0.836	4
SE	0.891	0.672	0.632	0.899	0.621	**0.820**				0.891	4
EE	0.838	0.634	0.632	0.845	0.519	0.795	**0.797**			0.839	3
PE	0.868	0.688	0.587	0.874	0.580	0.604	0.763	**0.829**		0.867	3
ICU	0.940	0.841	0.587	0.952	0.631	0.623	0.689	0.766	**0.917**	0.939	3

*Diagonal values are Discriminant Values (DV)

Table 4 Model Fit Summary

Sr. No.	Fit Indices	Observed Value	Criteria of acceptable fit*	Result
1	CMIN / DF (Minimum discrepancy as indexed chi—square)	1.217	<5	Acceptable fit
2	Probability (P) value of chi—square	0.064	≥ 0.05	Acceptable fit
3	GFI (Goodness of Fit)	0.887	>0.9	Unacceptable fit
4	RMR (Root Mean Residual)	0.157	<0.05	Acceptable fit
5	CFI (Comparative Fit Index)	0.982	>0.9 (0.9 – 0.8 borderline fit)	Acceptable fit
6	NFI (Normed Fit Index)	0.910	>0.9	Acceptable fit
7	PNFI (Parsimonious Normed Fit Index)	0.710	>0.5	Acceptable fit
8	Root mean squared error of approximation (RMSEA)	0.045	≤ 0.08	Acceptable fit

**Source*: Hair et al. (2018), Byrne (2016)

the relationship between the UTAUT constructs and extended UTAUT constructs was examined.

We examined the overall model and evaluated its fit using commonly used measures of model fit, which are summarized in Table 4. Except for the GFI, the values of all other fit indices meet the specified parameters, indicating a satisfactory fit to the data. The final model was developed using the non-standardized regression coefficient.

The results of hypothesis testing are shown in Table 5. Performance expectancy (PE) and Availability of resources (AVR) are found to be significant predictors of ICU, but Effort Expectancy (EE) and Self Efficacy (SE) are found to be non-significant (*ns.*). The whole model explains 65% of the variance in the intention to continue using e-Learning platforms ($R^2 = 0.65$). Which is relatively high, although below the recommended level of 70% by Venkatesh et al. (2003).

Path analysis was used to test hypotheses. Table 5 presents the path values (β), standard error (S.E.) critical ratio (C.R.) or *t*-values, and a summary of the hypotheses that were supported and not supported. Two out of four paths were significant as they exceeded a critical ratio of 1.96 and had a *p*-value (**p*) less than 0.05. Performance expectancy (PE) ($\beta = 0.607$, $p < 0.05$) (Hypothesis 1) and Availability of resources (AVR) ($\beta = 0.288$, $p < 0.05$) (Hypothesis 4) significantly impacted students'

Table 5 Result of path analysis

Hypothesis	*β*	*S.E.*	*C.R.*	Result
H_1:PE → ICU	0.607	0.187	3.241	Supported*
H_2:EE → ICU	0.178	0.214	0.831	Not Supported
H_3:SE → ICU	0.121	0.189	0.643	Not Supported
H_4:AVR → ICU	0.288	0.144	1.997	Supported*

*$p<0.05$

intentions to continue using the e-Learning technology. Whereas Effort expectancy (EE) ($\beta=0.178$, *ns*.) (Hypothesis 2) and Self-efficacy (SE) ($\beta=0.121$, *ns*.) (Hypothesis 3) did not significantly affect students' intentions to continue using the e-Learning technology.

6 Discussion

Even though the COVID-19 pandemic forced India's education industry to adopt online learning platforms, students' and instructors' willingness to adopt new technology remained in doubt. This study was an attempt to test the usefulness of the extended UTAUT model in explaining technology acceptance in the context of compelled adoption. To satisfy this objective, Indian students in a private higher education institution were surveyed to understand their willingness to continue using e-Learning platforms. Most students are not comfortable using online learning platforms (Tang et al., 2021) and therefore, their presence and motivation in learning through online mode are significantly challenging (Law et al., 2019; Widjaja & Chen, 2017; Zuo et al., 2022).

The results of the current study are partially consistent with earlier research and provide new insight into the field of technology acceptance specifically under a mandatory environment. Performance expectancy was found to be a significant predictor of continued use of e-Learning platforms. This result is consistent with the findings of Abbad (2021); Almaiah et al. (2019); Olatubosun et al. (2014); and Venkatesh et al. (2003). For students, performance expectancy is the attainment of their educational goals. Students consider e-Learning platforms as a means to achieve their educational goals. Users will not continue to use a system if it fails to meet their expectations. As a result, it is critical for e-Learning system developers to ensure that their systems assist students in achieving their desired educational outcomes.

The availability of resources was found to be an important predictor of the intention to continue using e-Learning platforms in the current study. This result is consistent with the findings of Almaiah et al. (2019); Lee (2008); and Sarrab et al. (2018). This suggests that students will continue to use the e-Learning system if they have all the essential resources. Hardware (devices to access the system, such as smartphones, laptops, and tablets), software (learning management software, video conferencing software etc.), a fast and stable internet connection, and technical assistance are all required. During the informal interactions, teachers (four members of the panel who scrutinized the questionnaire) indicated that students look to them (teachers) for technical assistance and expect teachers to address their technical problems. These expectations were observed to be unpleasant and embarrassing for them, especially for those who were not very tech-savvy.

The study found no significant effect of self-efficacy on the intention to continue using e-Learning platforms. In the extant literature, self-efficacy has been described as both a significant and insignificant predictor of behavioral intention. The findings of this study are consistent with those of Jaradat and Faqih (2014) who found that self-efficacy has no influence on behavioral intentions to use mobile payment technology. However, the findings are inconsistent with the findings reported by Almaiah et al. (2019); Chavoshi and Hamidi (2019); Dash et al. (2022); Sabah (2016); and Shen et al. (2013). The target study population was students pursuing professional postgraduate programs from a higher education institution. Most of the participants were from generation Z (as defined by Dimock, 2019) and were between the age group of 21 to 25 in 2021 (the year when this study was conducted). This generation is known for being more tech-savvy than previous generations (Turner, 2015) and for using social media technology for educational purposes (Mude & Undale, 2023). As a result, we argue that among a technologically savvy population, self-efficacy has no influence on the intention to continue using the technology.

Like the finding of Al-Mamary (2022) this study found effort expectancy is not a significant predictor of intention to continue using e-Learning platforms. Similar findings are reported by Dečman (2015). This result is however inconsistent with the findings of Almaiah et al. (2019), Almaiah and Mulhem (2019), García Botero et al. (2018), Guo (2022), Sultana (2020), Sung et al. (2015), Venkatesh et al. (2012), and Venkatesh et al. (2003). The result of this study showed a strong positive correlation ($r=0.795$, $p<0.001$, Table 3) between Self-efficacy (SE) and Effort expectancy (EE). Lehmann et al. (2022) reported effort expectancy is a significant precursor of self-efficacy. For the generation Z group, self-efficacy was found to be insignificant. As a result, we argue that, as Generation Z is more tech-proficient (Dečman, 2015), neither Self-efficacy nor Effort Expectancy are important predictors of their intention to continue using an e-Learning system in the future.

6.1 Theoretical implications

Our study contributes to the existing body of knowledge on technology acceptance and specifically to the understanding of the adoption of e-Learning by students in a mandatory environment. The uniqueness of this study is the setting of the experiment i.e., mandatory adoption of the technology. Available extant literature mostly studied voluntary adoption. However, studies on compelled adoption are rare. Our study is probably the first in the post-pandemic period which attempted to unveil the factors which are important to adopt new technology if implemented mandatorily (RQ1) in the Indian context. Further, this study attempted to test the extended UTAUT model to understand if it can explain users' intention to continue using new technology if implemented mandatorily (RQ2).

This study contributes to the UTAUT model which is a widely accepted model to understand technology acceptance in various contexts (Almaiah et al., 2019; Dwivedi et al., 2019; Venkatesh et al., 2012). In mandatory adoption of technology, our study confirmed that Performance expectancy is a significant predictor of intention to continue use (Dečman, 2015; Guo, 2022; Lehmann et al., 2022). Furthermore, in a mandatory environment resource availability is a significant predictor of intention to continue use (Lehmann et al., 2022; Zhang et al., 2022). While self-efficacy and effort expectancy both are insignificant.

6.2 Practical implications

The findings of this study provide new insight into the factors that influence students' compelled adoption of e-Learning in higher education. Indian higher education sector faces various challenges including inadequate infrastructure, insufficient funds, shortage of quality teachers etc. (Chattopadhyay, 2013; Dhal, 2020; Modi, 2014; Prakash et al., 2011; Tobenkin, 2022). These can be overcome by adopting either online learning or hybrid learning. The present generation of students is tech-savvy and can adopt new technology for improving their level of knowledge (performance expectancy of users). Based on the findings of this study management of higher education institutions can be more confident in mandating the use of e-Learning systems. e-Educators, implementers, and innovators should ensure that the implementation of technology must help students to achieve their educational goals. They need to promote their online learning by assuring students that their academic expectations would be attained more effectively by adopting the e-Learning system.

Further, the availability of resources to use the technology also need to be ensured. These resources primarily include a digital device (a desktop, a laptop, a smartphone, and a tablet), an uninterrupted internet connection with minimum desired speed, and an uninterrupted power supply. It is critical that students have access to a fast internet connection at all locations from where they participate in online learning. Most of the students attend online sessions through mobile devices. Therefore, e-Learning platforms must be mobile-friendly (Ngampornchai & Adams, 2016). Moreover, policymakers and implementers should not only ensure that necessary resources are available, but also raise awareness and encourage users to use the technology.

7 Limitations and future research

The study includes a few weaknesses, even though the results identified major factors for students' compelled adoption of e-Learning technology. Firstly, the study only focused on students at a private university in India and different results may be obtained when looking at e-learning systems in other universities in India or other developing countries. Therefore, future studies can include students from multiple universities within India and other countries.

Secondly, the moderators such as age, gender, experience, and voluntariness from the original UTAUT model were not considered which could improve the prediction of students' intention to continue using the e-Learning system. Future research can include these moderators to confirm the results of this study. Next, due to the scales' lack of reliability and validity, two constructs, social influence and facilitating conditions, were dropped from the study. As a result, the UTAUT model was tested partially.

Next, the study used self-reported expressions provided by the respondents to measure constructs which may not be precise and may be influenced by bias. Although this study attempted to reduce common method bias by implementing procedural control, it could not be confirmed with a statistical approach. Future studies can exercise more strict control on common method bias to improve the internal and external validity of the research. Further, the survey link was shared with the students available during online sessions. Therefore, the study utilized a convenience sampling technique. This may limit the application of the findings of this study to other populations.

Our study documents that PE and AVR are important factors while EE and SE are insignificant factors to understand students' continual use of e-Learning systems under a mandatory environment. These results have significant implications for future research. First, the students currently pursuing postgraduate higher education (in 2021) are from generation Z. Generation Z is more tech-savvy than previous generations. The findings of this study revealed that earlier theories that were successful in describing previous generations' technology adoption may not be sufficient in understanding the technology acceptance of the generation Z cohort. As a result, it is necessary to conduct additional empirical research and corroborate the conclusions of this study. Second, due to the lack of reliability and validity, the two UTAUT constructs; SI and FC were excluded from this study. It is suggested that a separate study may be conducted to investigate if these two constructs are significant to explain technology acceptance in a similar context so that the overall explanatory power of the model can be improved.

8 Conclusion

The objective of this research was to investigate the factors which are important to adopt new technology if implemented mandatorily and to test whether the most widely accepted UTAUT model can explain users' intention to continue using new technology if implemented mandatorily. These objectives were achieved by studying students' intention to continue using the e-Learning system. The students were from a private higher university in India. The results suggest that students' intention to continue using e-learning systems is predicted by performance expectancy and availability of resources. However, self-efficacy and effort expectancy both are found to be not significant determinants of intention to continue using e-learning systems. Based on these findings universities should ensure students attain their academic goals more effectively by using e-Learning systems. Further, availability of the resources like a digital device, fast internet connection and uninterrupted power supply are crucial determinants for the successful adoption of an e-Learning system.

Implementers should keep in mind that India's internet penetration was only 45% in 2021 (Keelery, 2021), which means that not all students would have access to high-quality internet or even have an internet connection. As a result, we argue that the Indian higher education sector is yet to embrace online learning.

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Declarations

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