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A SEM Approach to Assess M-Learning Intentions Among Students of Design: An Empirical Analysis Using the TRUTAUT Model

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ABSTRACT

Aim/Purpose	This research aims to examine the mobile learning (m-learning) intentions of students pursuing design courses at graduate and undergraduate levels in higher education institutions in a developing country like India. This study integrated the Technology Readiness Index (TRI 2.0) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine students' intentions.
Background	Teaching-learning in design programs at institutions predominantly takes place in design studios. Studios are the place where the constant presence of the educator, along with peers, guides the students in all aspects of creative solutions. This interaction has been hindered during the COVID-19 pandemic. Over the last decade, m-learning has grown in popularity among professionals and students. However, the intentions of students pursuing design courses still need to be evaluated.
Methodology	Using a quantitative approach, a survey of 334 graduate and postgraduate students was held in the National Capital Region of Delhi, India. The students were approached based on a convenience sampling strategy. Structural Equation Modeling (SEM) analysis was carried out to test the formulated hypotheses.
Contribution	This is one of the first studies that empirically measured m-learning intentions of design students in the Indian context using TRUTAUT scales. The study will motivate educators to identify and integrate online content into the

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	design curriculum. This will also help eliminate students' insecurity related to performance in online learning.
Findings	The study found that the technology readiness (TRI) variables (optimism, innovativeness, and discomfort) had no significant relationship with the UTAUT variables. Design students also exhibited some insecurity about performance in their creative field, which is traditionally conducted face-to-face. But all variables of UTAUT had a significant influence, and the model explains 41% of the variance in m-learning intention.
Recommendations for Practitioners	Teachers, as content creators in design education, need to suitably add online content to their subject that facilitates m-learning among students. Institutional administrators should provide adequate infrastructural facilities like stable internet connectivity, computer labs, and technical staff who can help the students with technical issues.
Recommendations for Researchers	The outcome of this TRUTAUT research among design students can be studied in other developing countries to examine design students' intention to adopt m-learning. Researchers can examine the effectiveness of learning through online platforms in design programs.
Future Research	Future studies could improve the model by extending it appropriately and conducting a longitudinal study with interviews and focus group discussions. Also, including teachers' opinions and attitudes toward online learning in design programs is worth exploring.

Keywords: m-learning, design students, UTAUT, technology readiness index, structural equation modeling, TRUTAUT model

INTRODUCTION

The acceptance of e-learning has increased rapidly due to developments in information and communication technology. This is why academics have embraced it and were able to conduct online classes during the COVID-19 period. According to Kumar Basak et al. (2018), e-learning is complementary to traditional teaching methods, and m-learning is a part of e-learning. The availability of inexpensive internet data, the rise in mobile applications, and 4G technology are making remote online work easier. Additionally, the availability of low-cost portable mobile devices with fast processors, high-quality cameras, and the option of flexible on-device and cloud storage is fueling the growth. Mobile phone usage and adoption have reached the grassroots level, and India has also improved its connectivity and availability of Wi-Fi on mobile phones (Kashive & Phanshikar, 2023). These mobile gadgets have even influenced the consumption habits of banking-related products and services (Baptista & Oliveira, 2015; Zhou et al., 2010), health-seeking behavior (Mels, 2018), and mobile learning (Abu-Al-Aish & Love, 2013; Shukla, 2020). Mobile learning, popularly called m-learning, is the distribution of study material by teachers to distant learners, which can be accessed using mobile devices like laptops, personal digital assistants, and smartphones (Abu-Al-Aish & Love, 2013). The user can conveniently reach out to learning materials anytime and anywhere (Al-Adwan et al., 2018, p. 1). Interacting while learning by asking questions to the teacher, listening to live or pre-recorded videos, downloading content, answering quizzes, and submitting assignments can be done online and is easier.

Many studies have been done in the past to understand m-learning intentions (Abu-Al-Aish & Love, 2013; Al-Emran et al., 2020; Al-Rahmi et al., 2022; Huynh et al., 2023). Parsimonious to extended models as frameworks in investigations have been used like the technology acceptance model (TAM) (Al-Rahmi et al., 2022), the combination theory of TAM, TPB, and ECM (Al-Emran et al., 2020), usage of combined TAM and TRI (Bhati et al., 2023), studies based on UTAUT (Al-Hujran et al., 2014;

Shukla, 2020; Srivastava & Bhati, 2022), combined UTAUT and UGT (Thongsri et al., 2018), etc. Studies assessed the viewpoints of teaching staff, undergraduates, and postgraduates on m-learning.

Among the study samples, researchers identified three behavioral intention studies for online learning in the design field (Fu, 2023; Hongwei & Plukphonngam, 2023; Zhang, 2023), all of which focused on students in China in the year 2023, but none on design students in India. The study by Hongwei and Plukphonngam (2023) found both performance and effort expectancy (PE and EE) have a significance on attitude, which in turn significantly impacts the behavioral intention of postgraduate design students to use online guest resources. Zhang's (2023) findings on art and design students' for m-learning revealed a significant impact of perceived usefulness on continuation intention for m-learning. Similar outcomes were reported by Fu (2023) among design students, where he reported a significant impact of PE on behavioral intention (BI). It will be worthwhile to examine the m-learning behavior of design students in the Indian context and check whether they exhibit similar behavioral intentions.

LEARNING IN THE DESIGN DOMAIN

In design programs such as fashion design, architecture, product, and interior design, face-to-face learning is crucial, and the online mode would not be successful (Alnusairat et al., 2020). This is because design programs develop specific skills among students who are supposed to contribute to problems in products and services through innovative solutions with a human-centric approach (Santos et al., 2017). Interactivity between educators, learners, and peers, as well as field visits, play an important role in the outcome. The environment in design studios is different from the old traditional decor. Here, the learners spend long hours in the studio and are actively involved in learning through practice, integrating fundamentals and socially viable designs into their models (Alnusairat et al., 2020). However, the lockdown policies of the coronavirus forced both educators and learners to shift from traditional on-campus design studios to virtual learning. Forced to work remotely without essential resources, such as workshops, design tables, design software, students kept in touch with their educators using various applications on handheld devices. This warrants a study on the intentions of design students for m-learning.

Among the models studied, UTAUT is immensely verified and is used in various educational contexts such as humanities, engineering, management education, and medicine (Nikolopoulou et al., 2020). However, Venkatesh et al. (2012) expressed that UTAUT in itself is not a generalized model for holistically identifying intentions to use a technology. It successfully identifies factors of IS/IT product acceptance and variance in behavioral intentions (Abu-Al-Aish & Love, 2013). However, the psychological components of the user that may be present in the acceptance of information system/information technology (IS/IT) products/services are somehow missing in UTAUT (Dwivedi et al., 2019; Napitupulu, 2017). Therefore, researchers need to add more variables that capture individual characteristics and help explain BI and technology acceptance (Reyes-Mercado et al., 2023). According to Parasuraman (2000), user preparedness for technology adoption is based on personality factors, and hence, he formulated the Technology Readiness Index (TRI), which refers to a person's general mindset regarding beliefs and attitudes toward technology. It addresses all the interrelated features that indicate a person's readiness for a specific technology.

Looking at the existing research, the first gap is the lack of studies that focus on design students. The study aims to provide an enhanced understanding of design students' intention for m-learning and to find the predictors that influence behavioral intention. The second is a theoretical gap that is bridged by integrating TRI as an antecedent with UTAUT to form a TRUTAUT model, which is a fusion of the generic personality traits of TRI and the system-specific dimensions of UTAUT. Thus, the study's research questions are: *what is the m-learning intention of design students*, and *which of the factors of the TRUTAUT model influence m-learning among design domain students*? The primary objective is to investigate the factors of TRUTAUT influencing behavioral intention for m-learning.

The study gains importance in studio-based subjects, such as fashion design, architecture, visual arts, etc., which are based on the exploration and assembly of physical materials (Fingrut & Ng, 2023). Thus, to strengthen the acceptance of online learning among design students, this research will help improve design pedagogy. Educators can find ways to enrich teaching-learning methods by incorporating online videos and inviting online professional art and design communities to engage in two-way online discussion. This will help students, teachers, institutions, and online content providers to enhance the appeal of m-learning among design students.

The next section is a literature review explaining the concept of m-learning, outlining its current state in Inda, with a brief description of UTAUT, TRI, and the rationale for merging TRI with UTAUT. This is followed by the theoretical framework for hypotheses development. Details of the research methodology are then explained. The results based on the SEM analysis are delineated in the next section, followed by an in-depth discussion grounded in the results obtained. The study then provides the conclusion and implications and concludes with limitations and future research.

LITERATURE REVIEW

M-LEARNING CONCEPT

M-learning is the extension of distance education and e-learning (Wang et al., 2009). It is the learning content consumed via wireless technologies such as mobile phones, tablets, PDA, etc. (Shukla, 2020), that a student can use as needed. As a result, m-learning is considered an interface between mobile communication and online learning, making it possible to learn anytime, anywhere, and also enabling the sharing of obtained knowledge with others (Yeap et al., 2016). There has also been a growth in the usage of applications meant for m-learning (Cao & Nguyen, 2022).

Rapid technological innovation has revolutionized the way students in India consume educational content. This significant transition has paved the way for new learning platforms and trusted applications to revitalize two-way communication, greatly benefiting both the educator and the student (Shukla, 2020). However, in addition to the benefits of m-learning, studies have found that the use of technology in education causes worry and anxiety in both teachers and users (Engel et al., 2022). It has been reported by Criollo-C et al. (2021) that the technological infrastructure and the compatibility issues between mobile devices and the learning management system are a concern for the successful implementation of m-learning. From a teacher's perspective, the biggest challenge in m-learning is distinguishing between what the students have learned inside the classroom and what they learn outside and how to strike a balance between the two (Criollo-C et al., 2021). While creating a learning exercise, the teacher has to keep in mind the features of the mobile device (Al-Rahmi et al., 2022) like input and output features (Hamidi & Chavoshi, 2018) and the connectivity of the mobile device to the network to run an application (Suartama et al., 2019). Teachers' ability to deal with m-devices within a classroom is also a limiting factor and cause for concern (Alenazy et al., 2019). This directly influences learners' adaptability and adoption of technology and indirectly affects teaching success via m-learning (Huynh et al., 2023). Hence, it is vital to study the m-learning intentions using a robust and time-tested model.

STATUS OF M-LEARNING IN INDIA

To meet the quality educational requirements of India, Massive Online Open Courses (MOOCs) were offered to students with the launch of the National Program on Technology Enhanced Learning (NPTEL) in 2003 with the support of I.I.T. Madras. Later, India's MOOC, the Study Webs of Active-Learning for Young Aspiring Minds (SWAYAM) portal, was added in 2016 (Das, 2023) and had immense popularity among learners. The University Grants Commission (UGC), the top regulatory body overseeing higher education in India, has allowed the transfer of credits earned from the MOOC courses pursued by the student from the SWAYAM portal (Singh & Kakkar, 2022). To further push digital developments, the Government of India (GoI) launched the Digital India program in July 2015 in a move to transform the country into a digital force. Digital education is also provided under this flagship program. Considering the ubiquitous nature of mobile devices, GoI launched several m-governance and educational applications. A 'Mobile Seva Appstore' has been developed so that citizens can download apps for free. This mobile application store boasts a vast array of m-learning apps offering ample opportunities for learners in the fields of science, commerce, arts, management, journalism, health education, computer science, etc. (Joshi & Bansal, 2017). MOOCs can be pursued through any portable mobile device at the convenience of the student anytime, anywhere. SWAYAM has a repository of more than 300 MOOC courses with an enrollment of over three crore students (Gohain, 2023). However, the challenge is that, though enrollment into MOOCs is encouraging, there was only a 5.74% completion rate among the learners in May 2020 (Singh & Kakkar, 2022), which now stands at 10% (Gohain, 2023).

BRIEF ON UTAUT

The comparison and combination of the main factors of eight previous existing theoretical frameworks culminated in the formulation of UTAUT (Arain et al., 2019). Independent constructs like performance expectancy (PE), social influence (SI), effort expectancy (EE), and facilitating conditions (FC) form the core of UTAUT, influencing the behavioral intention (BI). The model also consists of moderating variables such as experience, age, and gender. It was Venkatesh et al. (2003) who empirically demonstrated the robustness of UTAUT for testing behavioral intentions and use behavior and advocated for continuous validation and testing of the model in varied settings. In the present context, users of mobile devices take advantage of the m-learning systems to carry out learning in their domain area, making UTAUT a suitable choice model for evaluation of intentions (Wang et al., 2009).

Because m-learning differs from the usual environment of IT, the UTAUT core constructs may not adequately capture the special influences of m-learning (Wang et al., 2009). This is also mentioned in a previous study conducted by Pedersen and Ling (2003) on mobile internet services. The authors suggested modifying the traditional acceptance models to examine adoption intentions, including m-learning. After evaluating the design domain area in the context of the developing country, the present researchers added the technology readiness index (TRI) as an antecedent to UTAUT factors.

TECHNOLOGY READINESS INDEX (TRI)

TRI was first formulated by Parasuraman (2000) to determine the extent to which a person is willing to accept technology. Technology readiness (TR) states a person's general state of mind regarding beliefs and attitudes toward technology (Sohaib et al., 2020), which includes both motivating and inhibiting characteristics that define a person's technology usage inclination. On a multi-item scale, TRI originally consisted of 36 items with four dimensions: optimism (OPT), innovativeness (INN), insecurity (INS), and discomfort (DIS). It is noted that OPT and INN enable TR, i.e., individuals are inclined to use technology, and INS and DIS inhibit TR (Parasuraman, 2000), i.e., restrict technology acceptance. Later, Parasuraman and Colby (2015) developed a streamlined TRI 2.0 scale with 16 items to measure the four personality traits. All four variables had 4-items each. The current study utilizes TRI 2.0 scales to accept m-learning.

The TRI has been applied to a variety of contexts and is a popular scale for exploring the behavioral process underlying the acceptance of new technologies (Alsyouf & Ishak Ku, 2017). In the past, TRI has been applied in conjunction with TAM to study the adoption of new technologies among craft, MSME enterprises in Indonesia (Larasati et al., 2017), the role of TR and BI to continue using unmanned convenience stores (H. J. Park & Zhang, 2022), m-health adoption intention among older citizens in combination with TAM (Dash & Mohanty, 2023), e-wallet adoption intention in Malaysia (Leong et al., 2021), assessment of school teachers TR in Turkey (Summak et al., 2010), and association of medical students TR to medical specialization (MacNevin et al., 2021). Thus, findings from past studies suggest that TRI has not been empirically evaluated in the field of design education.

Therefore, further comprehensive empirical validation is needed to examine TR's ability to determine the behavioral intentions of design students, which will be theoretically meaningful.

Justification for Using Merged TRUTAUT

Embedded in the past literature, we find several studies that used this framework. The model was used by Alsyouf and Ishak Ku (2017) to study the acceptance and maintenance of e-health records among nursing staff. Bessadok (2017) discussed readiness to accept e-learning systems that use TRI variables with TAM variables (PU and PEOU) equivalent to PE and EE in the UTAUT model. Similarly, Leong et al. (2021) used TRI variables as antecedents of PE and EE variables to study mobile wallet adoption intention. A cross-country study involving Malaysia, Mexico, and Spain was conducted by Reyes-Mercado et al. (2023) using a merged TR-UTAUT model to examine the adoption of a digital learning environment in business education. In a recent Indian study, Kampa (2023) examines the acceptance of m-learning using TRI variables as antecedents to PU and PEOU.

In the past, some online learning studies conducted on design students have been identified. A study by Iranmanesh and Onur (2022) in the Department of Architecture of a Cyprus-based university compared the viewpoints of students and teachers on the transition from physical to virtual design studios (VDS). Likert scale data were collected from 185 students and 18 teachers. Teachers reported that interaction with students was poorer in the VDS, and group work in the VDS was rated lowest by students. According to the researchers, access to resources, peer relationships, group work, and communication are important influencing factors.

Alnusairat et al. (2020) examined the attitude of 615 undergraduate students in Jordan towards online design studios. Using quantitative measurements, an online survey instrument was made on a 5-point Likert scale. The analysis revealed that students wished for more support during online learning and also reported low levels of satisfaction. Further, Nurunnabi (2023) conducted an online survey among 100 students of interior design programs in the United States to explore online learning perceptions. The survey found that students of interior design valued the ease of online learning, but it also raised issues of the absence of constant contact with their peers and faculty. They reported technical difficulties and raised concerns about the inability to gain hands-on learning experiences that are available in design studios but not in online format. Thus, based on the literature, further research on intentions for m-learning is desirable.

Research Objective

According to the literature, the research objective is to examine the key factors that predict the m-learning intention using TRUTAUT scales.

Theoretical Framework and Hypotheses Formation

In this study, TRI2.0 and UTAUT are merged and used in the model. TRUTAUT indicates that the four constructs of TRI will influence the PE and EE variables of UTAUT, resulting in the adoption intention of m-learning.

Hypotheses on Technology Readiness Index

Optimism and innovativeness

Optimism and innovativeness are motivating traits of TRI. Both these traits motivate individuals to accept the latest technology, and they agree that technology is useful and can be easily used (Kampa, 2023), which will significantly impact their daily work (Bessadok, 2017). The term 'optimism' denotes a favorable opinion on technology characterized by a belief that it helps individuals with enhanced flexibility, efficiency, and control in their daily lives. This positive perception influences their performance by strengthening their belief that using technology would lead to the achievement of their goals. Optimism and performance expectancy are theoretically closely linked through the perspective of technological acceptance and adoption models, like TAM and UTAUT. These models assume that individuals' perceptions regarding technology usefulness and ease of use significantly influence adoption intention and, subsequently, their usage. Further, optimistic individuals' positive outlook extends to their perception of technology, leading them to view technological tasks as less stressful and effortless. In previous studies conducted by Bessadok (2017), Kampa (2023), Leong et al. (2021), and Reyes-Mercado et al. (2023), OPT was found to be significantly related to PE. OPT was also found to have a significant impact on EE in the studies of Kampa (2023), Leong et al. (2021), and Reyes-Mercado et al. (2023) but showed an insignificant association with EE in the study by Bessadok (2017). This requires re-examining these connections for m-learning among design students by following hypotheses:

H1a+: Optimism positively affects performance expectancy.

H1b+: Optimism positively affects effort expectancy.

Innovativeness (INN) is described as a propensity to be at the forefront of technology adoption and a leader in generating new ideas (Parasuraman, 2000). Innovators perceive technology as user-friendly, reducing their perceived effort. Thus, innovativeness drives individuals to take calculated risks in pursuit of performance improvement. INN was significantly associated with PE and EE (Bessadok, 2017; Leong et al., 2021) but showed an insignificant association with EE in the study of Kampa (2023). Thus, the following hypotheses were formed to examine m-learning among design students:

H2a+: Innovativeness positively affects performance expectancy.

H2b+: Innovativeness positively affects effort expectancy.

Insecurity and discomfort

These are inhibiting traits of TRI. Those who have a negative attitude towards technology try to avoid using it in their daily life. As per Parasuraman (2000), insecurity is described as a lack of trust in technology and doubt regarding its ability to function effectively. Discomfort is characterized as the perception of having insufficient control over technology and experiencing a sense of being overwhelmed by it. When tested for the relationship of INS and DIS on PE and EE, conflicting results were again found. Insecurity was found to have an insignificant effect on both PE and EE in the studies of Kampa (2023), Leong et al. (2021), and Reyes-Mercado et al. (2023) but showed a significant relationship with PE and EE in the study of Bessadok (2017). The current researchers hence proposed hypotheses:

H3a-: Insecurity negatively affects performance expectancy, and

H3b-: Insecurity negatively affects effort expectancy.

Likewise, in the studies of Bessadok (2017), Kampa (2023), and Reyes-Mercado et al. (2023), it was found that discomfort has no association with PE and a significant association with EE, leading to the formation of hypotheses:

H4a-: Discomfort negatively affects performance expectancy, and

H4b-: Discomfort negatively affects effort expectancy.

HYPOTHESES ON UTAUT

M-learning intention

Behavioral intention is the dependent variable referred to as the m-learning intention of design students to use online study materials via mobile devices in the current study. It denotes a learner's readiness or inclination to use specific technologies. On the basis of adoption theories and in line with past literature, we expect that m-learning intention will also be significant in the design students.

Performance expectancy (PE)

PE is a key construct in technology adoption and utilization in the UTAUT model and the strongest predictor of BI, according to Venkatesh et al. (2003, 2012). PE pertains to the level to which students of design courses feel that they will achieve the desired level of performance in their academics. Studies by Chelvarayan et al. (2020) and J. Mtebe and Raisamo (2014) found that PE significantly impacts BI, in the setting of online learning using mobile devices. Leong et al. (2021), Arain et al. (2019), and Baptista and Oliveira (2015) all emphasized the significance of PE in UTAUT for predicting BI. Thus, the hypothesis that followed is:

H5: PE significantly influences BI for m-learning.

Effort expectancy (EE)

Past studies suggest that EE indicates the extent to which a learner feels that using online resources for learning purposes will be easy for them (Chen et al., 2021). EE is explained here as the amount to which design students perceive that the use of m-learning is devoid of psychological stress and does not lead to physical exertion. EE was addressed as a direct determinant of BI, with significant association with the UTAUT theory (Abu-Al-Aish & Love, 2013; Al-Emran et al., 2020; Bellaaj et al., 2015; El-Masri & Tarhini, 2017). EE is addressed as PEOU under the TAM theory, thus the researchers hypothesized that:

H6: EE significantly influences BI for m-learning.

Social influence (SI)

In the present context, SI pertains to important others (friends, teachers, professional designers) in the life of design students who endorse the use of m-learning for growth in skills and academic outcomes. SI has also been referred to as subjective norm (SN), which has a significant effect on continuance intention (Al-Emran et al., 2020). Findings from previous research (Arain et al., 2019; El-Masri & Tarhini, 2017; Khechine & Lakhal, 2018) confirm that SI exerts a statistically significant influence on BI. Thus, it could be hypothesized that:

H7: SI significantly influences BI for m-learning.

Facilitating conditions (FC)

FC means the availability of technical infrastructure to users and support for troubleshooting and guidance that facilitates the delivery of m-learning in design studies. This aspect also measures students' confidence in having the requisite knowledge to use mobile learning (Moorthy et al., 2019). In the past, researchers have demonstrated that FC is a significant contributor to BI (Al-Hujran et al., 2014; Leong et al., 2021; Salloum & Shaalan, 2018; Shukla, 2020), leading to the formation of a hypothesis:

H8: FC is a significant predictor of design students' BI for m-learning.

Figure 1 depicts the model derived from the formulated hypotheses.

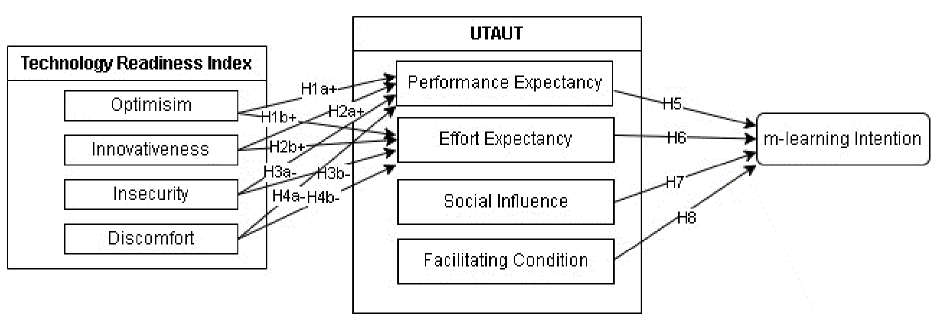

Figure 1. Proposed model for hypotheses testing

RESEARCH METHODOLOGY

To accomplish the objectives, the study adopted a quantitative approach (Thongsri et al., 2018), which is descriptive and cross-sectional, similar to past studies done on m-learning (Cao & Nguyen, 2022; Huynh et al., 2023; Shukla, 2020). A structured questionnaire was prepared to assess the planned research model for the survey. Generalization of the results is possible based on first-hand data collected in quantitative research (L. Cohen et al., 2007).

DATA COLLECTION AND SAMPLING METHOD

Data collection took place in the Delhi National Capital Region (NCR) of India during August and September 2023. This region was chosen because it is one of the most preferred destinations for pursuing higher education among students in India (Singh & Thakur, 2022). It's a hub for many reputed central, state, and private universities and institutions offering programs in various disciplines. We contacted students pursuing graduate and postgraduate programs in design disciplines (architecture, fashion design, interior design, and product design). To collect data, the authors personally visited the design departments of various universities and institutions that offer design programs. With the verbal approval of the head of the department or dean of academics, students pursuing graduate and postgraduate programs in design disciplines who were present at that moment were asked to participate. This type of data collection confirms that the technique is a non-probabilistic convenience sampling method as it provides easy access to respondents, which has also been used in similar previous studies (Bakirtaş & Akkaş, 2020; Bhati et al., 2023; Shukla, 2020). All students who have attended online learning provided by their institutions during the pandemic of COVID-19 or have pursued online learning using mobile devices through the platforms of Coursera, Edx, Simplilearn, Udemy, NPTEL, etc., qualified for participation in the survey. Of the 380 questionnaires distributed, 354 completed responses were received. Upon further review, it was found that 20 students had not attended any online program. Therefore, they were removed from further study, bringing the legible collection to 334 responses. To calculate the sample size for confirmatory factor analysis, the recommendation of Bentler (2006) was chosen, who suggests that the ratio of the sample size with a free parameter should be at least five to one. A similar sample size recommendation was utilized by Pires et al. (2011) in their study to gauge customer usage and acceptance of goods and services that are based on technology. The questionnaire contained 35 measurement items; therefore, 175 samples were needed. However, 200 samples must be collected to use SEM to interpret the collected data (Kline, 2015). Thus, the total number of completed questionnaires collected exceeded the minimum required.

SURVEY INSTRUMENT

A 35-item TRUTAUT instrument was created by combining TRI 2.0 and UTAUT items. There were two sections to the instrument. The first section related to demographic information; students had to indicate their gender, age, level of education, and design course they were enrolled in. The second section comprised 35 statements primarily addressing the factors influencing students' intentions to adopt mobile learning. Participants rated all aspects of the constructs on a Likert scale, ranging from 1 for strongly disagree to 5 for strongly agree.

TRI 2.0 was collaboratively developed by Parasuraman and Colby (2015) and is a 16-item scale. It measures OPT, INN, INS, and DIS, with each construct consisting of 4 items. The authors of the current study have obtained written permission from Rockbridge Associates for academic use of the TRI 2.0 scale (see Appendix). In the UTAUT model, the items for the predictors PE, EE, SI, FC, and BI were all adapted from Samsudeen and Mohamed (2019), Thongsri et al. (2018), and Venkatesh et al. (2003). All predictor variables had four items each, and BI contained three items.

Although the scales were adapted from previously validated research, they required expert validation before proceeding with the pilot study. The instrument was presented to three experts for content and face validity: a professor of consumer behavior, an associate professor of research methodology, and another in the English language department. The researchers notified the experts about the study's aim, the variables used, and the model under study (Izkair & Lakulu, 2023). Since the study was based on the design domain, it is appropriate to consult with the educators in the design domain, too. We met the deans of fashion design, product design, architecture, and interior design. All four deans showed interest in the study topics, but they also expressed concerns, stating that the content delivery is more on the practical side with face-to-face interaction in the design studios. However, they were interested in the findings. After that, the survey instrument was given to ten design students to receive feedback on their comprehension of the language used in the instrument. The experts rated the items for their fit with each of the factors examined: grammar, acceptable word choice, ease of understanding, and clarity of the items. The rating was done using a three-point scale (extremely relevant, relevant, and not relevant). Since no item was deemed irrelevant, all items of the instrument were retained (Lavidas et al., 2022).

DATA ANALYSIS

Step 1: The collected data were used to assess the fit of the model using goodness-of-fit indicators. Reliability tests were conducted for all constructs, including Cronbach's alpha (α) and composite reliability. Convergent validity was evaluated using the average variance extraction (AVE) test to quantify the amount of variance attributable to measurement error. Further, discriminant validity was examined by comparing the square root of the AVE of each latent construct with its inter-construct correlations.

Step 2: Since we combined TRI and UTAUT, we needed a more sophisticated multivariate statistical method. Therefore, statistical analysis was performed on SPSS and SEM on AMOS v23 with the maximum likelihood estimation method at the 5% significance level. SEM is popular because it allows for the examination of assumptions and enables accurate assessment of hypothesized associations. Therefore, it would identify independent variables significantly influencing the intentions of design students.

RESULTS

PARTICIPANTS DEMOGRAPHIC

The data of the study participants regarding gender, age, education level, and program being pursued are presented in Table 1. The sample consists of 63.2% females (n=211) and 36.8% males (n=123). In terms of their age, 62.9% (n=210) lie in the 18 to 21 years age group, followed by students in the age group of 22 to 25 years with a share of 35.3% (n=118). The maximum number of students who are pursuing their graduation program is 71.9% (n=240), and 28.1% (n=94) are in the post-graduation phase. Regarding the design program pursued, 48.8% of students study fashion design, followed by 31.1% in architecture, 11.1% in interior design, and 9% in product design.

Table 1. Demographic profile

Variable	Category	N (%)
Gender	Male	123 (36.8)
	Female	211 (63.2)
Age	18 to 21 years	210 (62.9)
	22 to 25 years	118 (35.3)
	26 years & above	6 (1.8)
Level of education	Pursuing graduation	240 (71.9)
	Pursuing post-graduation	94 (28.1)

Variable	Category	N (%)
Program pursuing	Fashion design	163 (48.8)
	Architecture	104 (31.1)
	Interior design	37 (11.1)
	Product design	30 (9)

MEASUREMENT MODEL ASSESSMENT

Since the scales used in the model were all validated from previous studies, we directly conducted a CFA (George et al., 2020). To assess the fitness of the proposed model, we considered the goodness-of-fit indicators. These include the AGFI-adjusted goodness of fit index, CFI-comparative fit index, IFI-incremental fit index, and RMSEA. The values of these indicators are given in Table 2. The IFI and CFI were all found to have values above 0.9, consistent with recommendations (Hair et al., 2010). The value of chi-square/df is 1.560, below the threshold of 3, and the RMSEA is below the desired range of 0.06 (Hu & Bentler, 1999). Thus, the fit indices validate the acceptable fit of the proposed model to the collected data.

Table 2. Values of fit indices

Fit index	Accepted value	Measurement model	Structural model
$\chi 2/\mathrm{df}$	Less than 3	1.560	1.875
AGFI	0.80 or >	0.859	0.840
IFI	0.90 or >	0.939	0.902
CFI	0.90 or >	0.938	0.901
RMSEA	< 0.06	0.041	0.051

While conducting the CFA, it was found that the factor loadings of the third item SI3 under the construct social influence (SI) and item DIS1 under construct discomfort (DIS) were below the recommended value of 0.50 and hence dropped from the model. The CFA of the measurement model is displayed in Figure 2.

The internal consistency was measured using Cronbach's alpha (α) and composite reliability (CR). The α-values for all the constructs are above 0.70 and, therefore, meet the criteria (Nunnally, 1994). In addition, analytical results show that the CR values were more than 0.70, indicating the achievement of CR (Fornell & Larcker, 1981). While the evaluation of convergent validity was done by examining the AVE values of all constructs, this again was higher than 0.50, which represents a satisfactory convergence value (Fornell & Larcker, 1981; Hair et al., 2017). The model, therefore, demonstrated good convergent validity and reliability. The values of factor loadings, Cronbach's alpha(α), CR, and AVE are presented in Table 3.

A correlation test among the variables was undertaken to measure the inter-variable correlation. Among the UTAUT variables, all the variables exhibited statistically significant positive correlations (Pearson's *r* value ranged from 0.113 to 0.626 at a significance level of 0.05 or less). The analysis of the relationship between TRI and UTAUT variables, as proposed in the model, showed no significant correlation, except for insecurity (M = 3.935. SD = .740), displaying a negative significant correlation with PE ($r = -0.131$, $p<0.05$) and negative insignificant correlation with effort expectancy at a level of 0.05 or less. It should be noted that significant correlations do not guarantee significant causal effects but rather indicate such effects (Pramana, 2018). These outcomes are further verified with path analysis results.

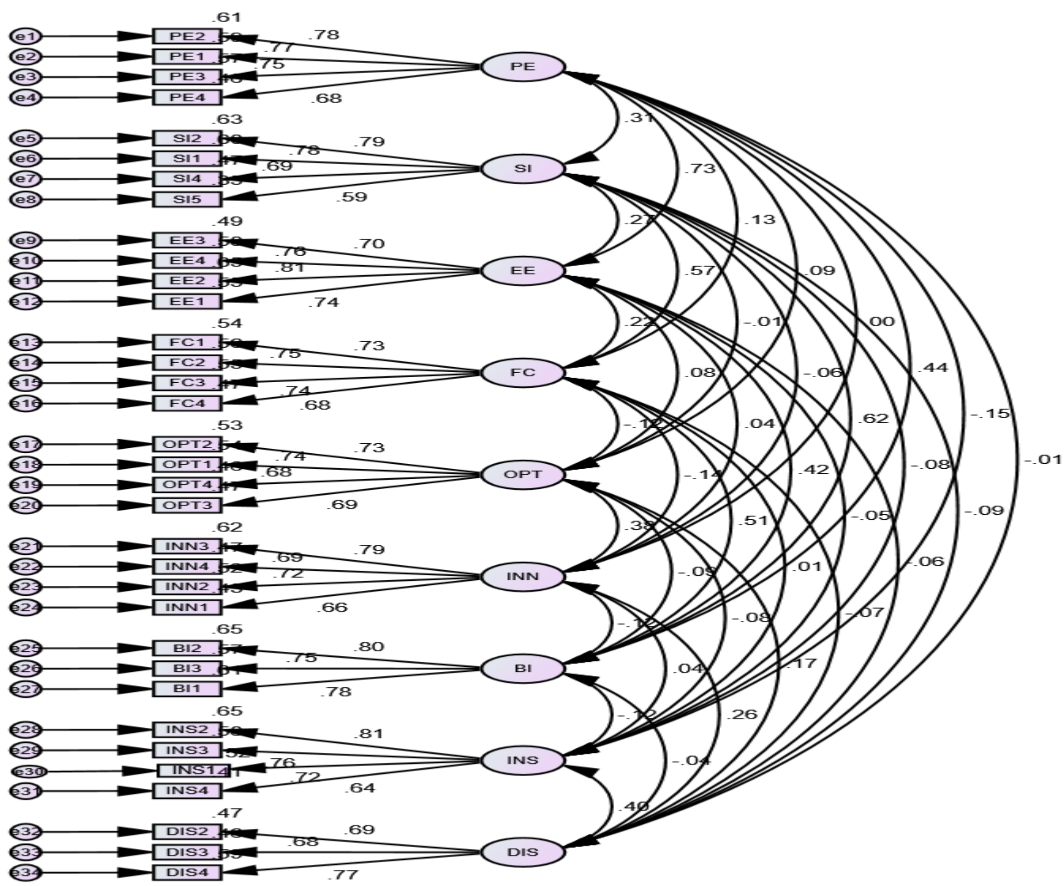

Figure 2. Overall measurement model

Table 3. Assessment of measurement reliability and convergent validity

Construct	Item	Range of factor loading	Ca (α)	Cr	Ave
Performance Expectancy	4 items	0.68 - 0.78	0.831	0.834	0.557
Effort Expectancy	4 items	0.70 - 0.81	0.838	0.839	0.567
Social influence	4 items	0.59 - 0.79	0.803	0.806	0.512
Facilitating Condition	4 items	0.68 - 0.75	0.815	0.818	0.529
Optimism	4 items	0.68 - 0.74	0.798	0.800	0.501
Innovativeness	4 items	0.66 – 0.79	0.803	0.806	0.511
Discomfort	3 items	0.68 – 0.77	0.751	0.756	0.509
Insecurity	4 items	0.64 - 0.81	0.816	0.823	0.540
Behavioral Intention	3 items	0.75 – 0.80	0.821	0.824	0.609

Discriminant validity was assessed by the square root values of AVE obtained from each construct, which were compared with its correlations between constructs (Shukla, 2020). These square root values should surpass the corresponding correlations, and the diagonal values (shown in bold) should exceed the off-diagonal values within the respective rows and columns (Fornell & Larcker, 1981). Table 4 exhibits the achievement of discriminant validity for all constructs.

Table 4. Discriminant validity

Constructs	INS	PE	SI	EE	FC	OPT	INN	BI	DIS
INS	**0.735**								
PE	-0.147	**0.746**							
SI	-0.084	0.314	**0.716**						
EE	-0.047	0.732	0.274	**0.753**					
FC	0.006	0.132	0.572	0.218	**0.727**				
OPT	-0.080	0.090	-0.012	0.078	-0.118	**0.708**			
INN	0.044	0.005	-0.064	0.038	-0.136	0.382	**0.715**		
BI	-0.120	0.444	0.620	0.418	0.510	-0.095	-0.115	**0.780**	
DIS	0.397	-0.011	-0.088	-0.062	-0.075	0.168	0.257	-0.044	**0.713**

Because the data were obtained using a single self-administered survey method, Harman's single-factor test should be used to determine the presence of common method bias (CMB) (Podsakoff et al., 2003). All the components were loaded into a single factor, accounting for 18.065% of the total variance, which is less than the suggested amount of 50%. Thus, no single factor emerged as the dominant factor (Tan et al., 2014), indicating that CMB is absent. Next, the model constructs were tested for the presence of multicollinearity using Variance Inflation Factor (VIF) scores for all constructs. The value of VIF ranged from 1.317 to 1.706, indicating the absence of multicollinearity issues among the constructs, as all values were less than 3.3 (Becker et al., 2015). Since the measurement model achieves the recommended validity and reliability, we proceeded to evaluate the structural model.

Hypotheses Testing (Structural Model Assessment)

As ascertained by the chi-square/df ($\chi 2/df = 1.875$) together with other indices (AGFI = 0.840; IFI = 0.902; CFI = 0.901; RMSEA = 0.051), it indicates an acceptable fit of the structural model to the data, meeting the criteria (Hair et al., 2010; Hu & Bentler, 1999) indicated in Table 2. In addition, the structural model evaluates the path relationships between the independent and dependent constructs in the research model. The hypothesis tests were carried out in AMOS using the SEM procedure, as displayed in Figure 3.

Table 5 depicts the results of the hypothesis tests (estimates, std. error, critical ratio, and p-values). The R-squared value indicates the proportion of exogenous variables that explain the endogenous variable, and it shows the predictive power of a research model (Chen et al., 2021). The model examined predicts an R^2 of 0.41, i.e., 41% of intent for m-learning among design students, which is a moderate effect as per Chin (1998).

The study outcome for TRI motivators, OPT to PE (H1a+), ($\beta = 0.093$, $p>0.05$), OPT to EE (H1b+), ($\beta = 0.028$, $p>0.05$), INN to PE (H2a+) ($\beta = -0.019$, $p>0.05$) and INN to EE (H2b+) ($\beta = 0.018$, $p>0.05$) does not influence the two variables of UTAUT. Among TRI inhibitors, there is a significant relationship between INS and PE (H3a-) ($\beta = -0.172$, $p<0.05$), and INS to EE (H3b-) ($\beta=-0.024$, $p>0.05$) is insignificant. Likewise, DIS to PE (H4a-) ($\beta = 0.037$, $p>0.05$), and DIS to EE (H4b-) ($\beta = -0.032$, $p>0.05$) are also insignificant.

However, according to data analysis, hypotheses H5, H6, H7, and H8 are supported. The results revealed predictors of UTAUT, perceived expectancy (PE) to BI (H5) ($\beta = 0.202$, $p<0.05$), facilitating condition (FC) to BI (H6) ($\beta = 0.458$, $p<0.05$), social influence (SI) to BI (H7) ($\beta = 0.358$, $P<0.05$) and effort expectancy (EE) to BI (H8) ($\beta = 0.243$, $p<0.05$) are all supported in the study. The model displayed a 41% of the variance in BI.

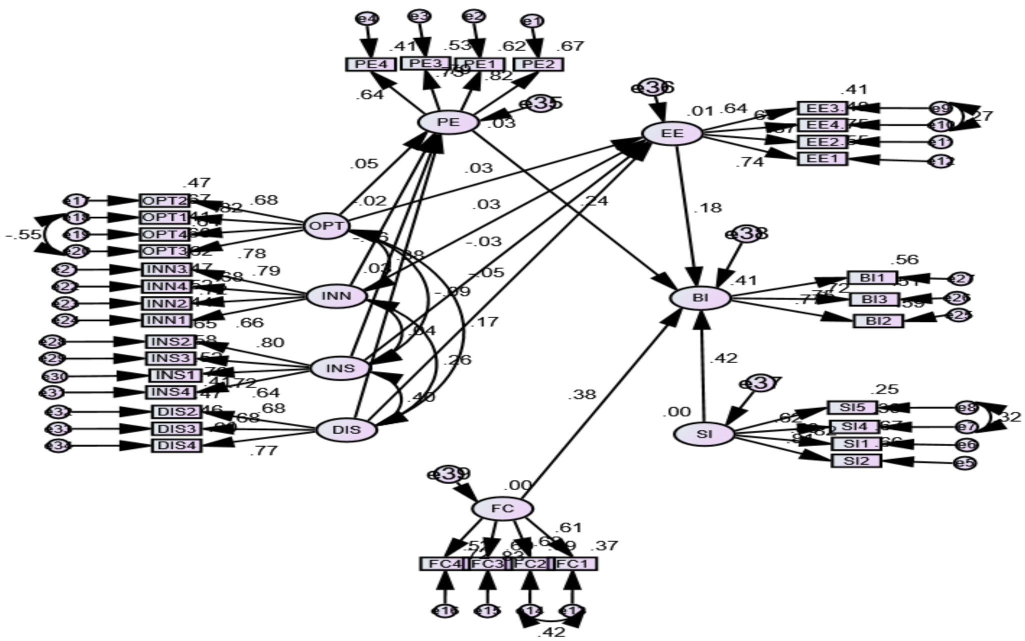

Figure 3. Structural model analysis

Table 5. Outcome of structural model analysis

Hypotheses	Hypothesized path			Estimate	S.E.	C.R.	P-value	Decision
H1a+	PE	<---	OPT	0.093	.122	0.765	.444	Not Supported
H1b+	EE	<---	OPT	0.028	.077	0.368	.713	Not Supported
H2a+	PE	<---	INN	-0.019	.073	-0.258	.796	Not Supported
H2b+	EE	<---	INN	0.018	.046	0.402	.687	Not Supported
H3a-	PE	<---	INS	-0.172	.082	-2.104	.035	Supported
H3b-	EE	<---	INS	-0.024	.051	-0.460	.646	Not Supported
H4a-	PE	<---	DIS	0.037	.089	0.416	.677	Not Supported
H4b-	EE	<---	DIS	-0.032	.056	-0.575	.565	Not Supported
H5	BI	<---	PE	0.202	.050	4.010	***	Supported
H6	BI	<---	FC	0.458	.082	5.570	***	Supported
H7	BI	<---	SI	0.358	.055	6.500	***	Supported
H8	BI	<---	EE	0.243	.081	3.013	.003	Supported

*Note: ***significant at p<0.05*

Next, it is appropriate to calculate the effect size, which is useful for determining "the relative contribution of different factors or the same factor in different circumstances" (Fritz et al., 2011). The values of 0.02, 0.15, and 0.35 suggest small, medium, and large effects, respectively. This is calculated using Cohen f2, which is presented as:

$$f2 = R2/1\text{-}R2$$

In the present study, f2 = 0.833 demonstrated a large effect size (J. Cohen, 2013). The research findings provided crucial insights into the personality traits of design students. They demonstrated a certain level of insecurity in performance when using m-learning. The relationship of TRI variables (optimism, innovativeness, and discomfort) with UTAUT variables (performance and effort expectancy) was found to be insignificant. It can be said that users' technological readiness does not have an impact on the usefulness and ease of use of m-learning among design students. However, all four variables of UTAUT (social influence, facilitation, performance, and effort expectancy) have a significant impact on m-learning intentions.

DISCUSSION

Fewer studies have examined online learning within the field of design education (J. Y. Park, 2011). This paper examines the design students' intention for m-learning guided by TRI 2.0 and UTAUT theory. The relationship of TRI variables with the performance and effort expectancy variables of UTAUT is found to be different, except with a significant relationship of insecurity with performance expectancy. These findings are different from the original TRI formulation (Parasuraman, 2000; Parasuraman & Colby, 2015) and academic literature (Bessadok, 2017; Erdogmus & Esen, 2011). We now discuss each hypothesis and look for a possible explanation.

The hypothesis H1a+ in our study found an insignificant relationship between OPT and PE. This finding is consistent with Mufidah et al.'s (2022) previous study among university students in Malaysia for an online learning management system. Also, an Indonesian study by Larasati et al. (2017) found a similar result for adaptation to new technologies. Similarly, hypothesis H1b+ was also found to be insignificant for the relationship of OPT with EE. This outcome also matches a study in Saudi Arabia by Bessadok (2017) on the acceptance of e-learning systems, as well as a study by Mufidah et al. (2022). Optimism as a personality trait is defined as a person who has a positive vision for technology (Bessadok, 2015). Since design is a creative field, it depends more on the designer's ability to develop creative solutions. This shows that design students are not very optimistic and feel that technology does not facilitate their performance. This is possibly due to design pedagogy being followed in the design programs, which are predominantly studio-based. The critical assessment is based on face-to-face interaction with teachers and peers involving more hands-on activities such as material manipulation, creation of physical models, etc. (Fingrut & Ng, 2023).

Innovativeness (INN) is explained by Parasuraman (2000) as characteristics of an individual who embraces new technologies early on and also plays a role in influencing others' opinions in the adoption of technologies. The hypothesis H2a+ (INN→PE) was found to be insignificant. This outcome is similar to the results of Kampa (2023), who explored the acceptance of m-learning within higher education settings in India. The hypothesis H2b+ (INN→EE) is also not supported, and this outcome is similar to a past study by Mufidah et al. (2022). This explains that design students are not early adopters of technology.

Insecurity is referred to as a sense of suspicion of technology and doubt regarding its effectiveness (Parasuraman, 2000). The construct also explains skepticism towards digital learning and doubts about its content (Kaushik & Agrawal, 2021). Hypothesis H3a- (INS→PE) was found to have a significant relation. This finding has been supported in past studies (Bessadok, 2017; Erdogmus & Esen, 2011). Hence, H3a- is supported. Furthermore, hypothesis H3b- (INS→EE) shows an insignificant relationship. This outcome is consistent with the previous studies (Erdogmus & Esen, 2011; Kampa, 2023; Reyes-Mercado et al., 2023) conducted to examine students' acceptance of the digital environment. Also, in the study by Leong et al. (2021) and Sohaib et al. (2020), the association of insecurity and effort expectancy was insignificant for e-wallet and cryptocurrency adoption, respectively. This shows that design students have a distrust of technology and are skeptical about the technology. Insecure users may be unwilling to make efforts to find out whether technology will benefit them (Sohaib et al., 2020).

Discomfort is explained by Parasuraman (2000) as a perception of being unable to manage the technology and feeling overwhelmed by it. Hypothesis H4a- (DIS→PE) was found to have no statistically significant relationship between discomfort and performance. This finding is supported in the studies of Kampa (2023) for m-learning in India, Reyes-Mercado et al. (2023) for the adoption of a digital learning environment, Amron et al. (2022) on cloud computing acceptance in higher education, and the studies of Erdogmus and Esen (2011) and Galaige et al. (2018) for the effect of technology readiness on technology acceptance. Further, hypothesis H4b- (DIS→EE) also displayed an insignificant relationship. This finding supports past studies (Erdogmus & Esen, 2011; Larasati et al., 2017).

Among architects, Lai and Lee (2020) studied the intention of adopting Building Information Modelling (BIM) technology using TRI and TAM constructs in Malaysia. The study found that optimism, discomfort, and insecurity did not exert a significant impact on adoption. According to Reyes-Mercado et al. (2023), the TRI model is trait-based. Its constructions are based on long-held attitudinal inclinations towards behavior concerning technology rather than perceptions of how a particular technology works. As a result, TRI's proposed dispositional settings are likely to influence how students acquire beliefs when engaging with the digital environment. Therefore, there was an expectation of a relationship between the long-term attitudinal aspects that could influence technological adoption.

The possible explanation for these different results of TRI with UTAUT could be due to the following reasons. First, design education is primarily based on promoting design thinking, stimulating the curiosity of aspiring designers, and enabling debate between designers and stakeholders that promotes critical thinking skills while at the same time developing the next generation of designers into one who is innately more thoughtful and tolerant by nature, should be environmentally conscious, and imaginative to include human touch to solutions (Elçioğlu, 2022). Second, design as a discipline is distinguished by professional practice and collaborative interaction between design students and artifacts (J. Y. Park, 2011), wherein the solution development process is based primarily on face-to-face conversations and little involvement in online forums. The learning and development process is more likely done in design studios, a shared place between the students, educators, and experts, where students share their solutions, which are repeatedly iterated. Third, Ernawati et al. (2022), in the study conducted on students of fashion design, mentioned that competency among students can be developed through instructional pedagogy and through incorporating learning resources like fashion software, e-books, and e-journals that support digital learning. According to Nipyrakis et al. (2023), design courses are considered to be quite challenging tasks that demand a higher level of skills, knowledge, and design solutions embedded with values requiring research-based practical work. This suffices as a reason why TRI dimensions (OPT, INN, and DIS) showed an insignificant relationship with PE and EE among design students due to the inherent characteristics of how design education is being delivered to students by educators.

However, the model predicted 41% of design students' intent for m-learning. The UTAUT variables of the model were found to be significant for m-learning. Recent studies on design students have found that they intend to adopt e-learning. A Chinese study conducted by Hongwei and Plukphonngam (2023) on postgraduate students pursuing design courses discovered a high propensity to have visitors deliver lectures online. Similarly, at Chengdu Textile College in China, students of art and design programs also demonstrated positive intentions for online learning (Fu, 2023), and continued intentions for m-learning were also reported among undergraduate students majoring in art and design at a university based in Chengdu, China (Zhang, 2023).

We evaluated variables of UTAUT as antecedents to BI using hypotheses H5 to H8. The finding of the path coefficient analysis reveals a significant effect of PE on BI ($\beta=0.202$, $p<0.05$), supporting H5. This suggests that students will be inclined towards m-learning if they perceive it as beneficial for enhancing their performance in design education. In other words, the greater the perceived usefulness, the stronger the students' inclination for m-learning (Kampa, 2023). This is similar to past studies that observed PE to be an important predicting variable (Cao & Nguyen, 2022; Shukla, 2020; Tan et al., 2014; Thongsri et al., 2018; Zhang, 2023).

The study further identified EE as a significant predictor of BI for m-learning (EE→BI), supporting H6 (β= 0.243, $p<0.05$). This states that the finding is aligned with prior related studies (Cao & Nguyen, 2022; Huynh et al., 2023; Shukla, 2020; Tan et al., 2014). The results indicate that design students found the use of m-learning very easy and had positive learning experiences with mobile devices. Institutions engaged in design education should provide user-friendly and interactive online forums (Shukla, 2020) that facilitate students' performance and encourage students of diversified design programs to utilize m-learning.

Furthermore, social influence impacts the BI of design students (H7: SI→BI) significantly with β = 0.358 and $p<0.05$. This outcome is similar to earlier studies on m-learning (Al-Hujran et al., 2014; Fu, 2023; Huynh et al., 2023; Shukla, 2020; Tan et al., 2014). Thus, hypothesis H7 is supported. Encouragement by educators, peer group relations, and fellow designers positively impacts a designer's work and adoption intention. The current generation is at ease with computers and other mobile devices (Shukla, 2020); hence, social influence becomes an important factor in the intention to adopt them.

Likewise, FC too showed a significant association with BI (H8: FC→BI) with β = 0.458, and $p<0.05$. The present result reinforces past studies (Huynh et al., 2023; Shukla, 2020). Thus, hypothesis H8 stands accepted. This implies that students believe that they have the requisite technical set-up and support to carry out m-learning, and this supports their behavioral intention for m-learning. If an institution creates a favorable atmosphere, learners will be more likely to employ mobile learning.

Contribution of the Study

The first primary contribution of this research is an empirical verification of the m-learning intention of students pursuing design programs. Second, although there are many studies examining behavioral intention for m-learning based on UTAUT, this research marks a pioneering effort that has used the TRUTAUT model among design students in an Indian context. Third, all four variables of UTAUT have a significant impact on m-learning intentions, which means that value received and gained, ease of use, facilitative infrastructure, and peer group influence in m-learning are critical factors. The model explained 41% of the variance in intentions for m-learning. The study demonstrated that students have positive intentions to learn online, which is similar to three online learning intention studies conducted in China among art and design students.

Fourth, based on the study outcomes, academics should note that the design students have exhibited that they are neither optimistic nor innovative about adopting technology. Therefore, academicians need to adapt their teaching strategies to support students' online learning activities. Academicians should look for opportunities to incorporate online components such as online interaction with design experts, online guest lectures, tracking new technological developments in design studies, etc. Additionally, it also empowers educators to make informed decisions about selecting, implementing, and integrating technological tools and platforms in studio teaching. This will lead to an improvement in the pedagogy of the design programs. This will also help eliminate students' insecurity related to performance in online learning.

Conclusion

The cross-sectional study conducted in the Delhi NCR region of India among design students to identify factors and behavioral intention for adopting m-learning revealed 41% intention. This study uses the two best models, TRI and UTAUT, with each model overcoming the weaknesses of the other (Napitupulu, 2017). The model can predict learners' behavior not only from a system-specific perspective but also from users' psychological aspects. TRUTAUT model for prediction of m-learning behavior among design students is analyzed using SEM technique via IBM SPSS software and AMOS. The closure of academic institutions during COVID-19 has fueled the growth of online education worldwide, and it is now predicted that the e-learning system will be the future solution (Elareshi et al., 2022). TRI 2.0 and UTAUT were developed in Western countries and are well established. However, a study from a developing country with a focus on the design domain was lacking. The findings differ concerning the variables of TRI 2.0. Only the insecurity variable showed a significant negative relationship with performance expectancy. The findings of UTAUT are in line with past studies indicating BI can be predicted for m-learning using UTAUT variables. Based on the research outcome, we propose some implications for increasing m-learning intentions among design students.

IMPLICATIONS

As a theoretical contribution, the current study can provide a deeper insight into the TRUTAUT model from a developing country perspective and help in understanding the m-learning intention of design domain students. The study identified that technology readiness (TRI) variables (optimism, innovativeness, and discomfort) lack a significant relationship with the UTAUT variables (effort and performance expectancy), as observed in past studies. This finding is contrary to the theoretical underpinnings and past studies. Only UTAUT variables validated the design domain students' intentions in an emerging multi-cultural and multi-religious market. This bridges the knowledge gap in the current IS research. The model explained 41% of the variance in BI, and Cohen's f-square effect size of 0.833 also indicated that the results were highly significant.

On the practical side of contribution, academics and online service providers could use the identified variables to build additional strategies for increasing the user base of m-learners. Design students demonstrated a certain level of performance uncertainty when using m-learning. As a result, when implementing online learning, educators and service providers must also consider the design students' perspectives. All parties involved in the creation and delivery of online material must look for opportunities to motivate design students. Second, researchers must look into the resulting outcome of m-learning on the students' learning process (Elnagar et al., 2022). Third, teachers should assess their teaching strategy and chances to incorporate online materials into the course content. Institutional administrators should provide adequate infrastructural facilities like stable internet connectivity, computer labs, and technical staff who can help the students with technical issues. The findings could be useful to decision-makers, academicians, and online service providers who endeavor to implement mobile learning systems.

LIMITATIONS AND FUTURE RESEARCH

Despite important findings, there are still limitations that need to be addressed in the future. First, the study is limited only to the sample area of Delhi NCR region of India. Second, to generalize the study results, a large sample of 334 respondents was used as it was a convenience sampling. However, by covering a larger geographical area and involving more design institutions, the study results can be better generalized. Third, the TRUTAUT model could have been extended to include additional constructs related to the adoption of m-learning. Future studies could improve upon the research method by using a longitudinal study design and incorporating interviews with focus group discussions. Researchers can examine the effectiveness of learning through online platforms in design programs. It is worth exploring the difference in technological readiness (TR) between demographic variables like gender, education level, and design program pursued. This study aimed to design students' intention for m-learning. Future studies could incorporate teachers' opinions and attitudes toward online learning in design programs.

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APPENDIX: LICENSE TO USE TRI 2.0

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