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MEASUREMENT OF DOCTORAL STUDENTS' INTENTION TO USE ONLINE LEARNING: A SEM APPROACH USING THE TRAM MODEL

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ABSTRACT

Aim/Purpose	The study aims to supplement existing knowledge of information systems by presenting empirical data on the factors influencing the intentions of doctoral students to learn through online platforms.
Background	E-learning platforms have become popular among students and professionals over the past decade. However, the intentions of the doctoral students are not yet known. They are an important source of knowledge production in academics by way of teaching and research.
Methodology	The researchers collected data from universities in the Delhi National Capital Region (NCR) using a survey method from doctoral students using a convenience sampling method. The model studied was the Technology Readiness and Acceptance Model (TRAM), an integration of the Technology Readiness Index (TRI) and Technology Acceptance Model (TAM).
Contribution	TRAM provides empirical evidence that it positively predicts behavioral intentions to learn from online platforms. Hence, the study validated the model among doctoral students from the perspective of a developing nation.
Findings	The model variables predicted 49% of the variance in doctoral students' intent. The TRAM model identified motivating constructs such as optimism and innovativeness as influencing TAM predictors. Finally, doctoral students have positive opinions about the usefulness and ease of use of online learning platforms.

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Recommendations for Practitioners	Academic leaders motivate scholars to use online platforms, and application developers to incorporate features that facilitate ease of use.
Recommendations for Researchers	Researchers can explore the applicability of TRAM in other developing countries and examine the role of cultural and social factors in the intent to adopt online learning.
Future Research	The influence of demographic variables on intentions can lead to additional insights.
Keywords	e-learning, doctoral students, technology acceptance model, technology readiness index, structural equation modeling, online intentions, TRAM model

INTRODUCTION

The growth in information technology (IT) has touched all aspects of human life and its application has been widely accepted and adopted in the education industry as well. Technology has accelerated economic growth and transformed societies through changes in how universities function, particularly in developing nations (Akaslan & Law, 2011). The growth of cloud computing, artificial intelligence, and machine learning has further fueled the growth of information and communication technologies (ICT) (Watanabe et al., 2018). Low internet usage charges coupled with the availability of affordable smartphones and tablets have led to an increase in internet use by students. This has also encouraged educational institutions to use online teaching techniques instead of more conventional ones (Al-Adwan et al., 2021). ICT has opened a whole new world of learning. E-learning is the application of ICT to transmit data for education where course delivery educator and student are operating alone split by time, distance, or both, to improve student performance and learning outcomes (Keller et al., 2007). As per Cidral et al. (2018), e-learning systems offer personalized, flexible learning opportunities at a reduced cost; and enable learning based on the demand of the learner. Due to this, there has been a considerable shift in the focus of education from being teacher-centric to being student-centric. (Al-Fraihat et al., 2020).

Although e-learning initiatives taken by universities and by private players have been successful, the realization of intended goals has been slow to be achieved due to increased e-learning drop-out rates (Al-Fraihat et al., 2020). This is because each user has a different personality trait toward technology (Chen et al., 2009; Mezei et al., 2022), attitude toward continued system usage, and the way the e-learning platform is used (Akaslan & Law, 2011). Moreover, India is a developing country, so there is a digital divide in infrastructural facilities, and universities and institutions lack good infrastructure and are scarce in resources for online learning (Paliwal & Singh, 2021). Moreover, the digitization of libraries is still partial, and in a nascent stage. Funding to acquire online resources in libraries is inadequate, and archival materials are not available, either online or in digital format (Chakraborty & Jana, 2022).

Researchers have argued that continued exploration of information systems (IS) topics in new contexts offers a viable approach to knowledge accumulation (Awad et al., 2022). In the past, academic researchers have explained and interpreted students' awareness, attitudes, and intentions for e-learning systems at both undergraduate and postgraduate levels (Abu-Al-Aish & Love, 2013; Bellaaj et al., 2015; Olasina, 2019; Salloum & Shaalan, 2019). There are also well-documented studies on the perception of academicians (Abu-Shanab & Ababneh, 2015; Srivastava & Singh Bhati, 2020; Summak et al., 2010) and technology readiness concerning e-services system adoption by consumers (C.-H. Lin et al., 2007), professional students (Ling & Moi, 2007), students pursuing MBA (van der Rhee et al., 2007), and primary school teachers (Summak et al., 2010). What is missing, however, is a detailed study that provides a current state of intentions of doctoral students to learn from online platforms. Doctoral students are an important source of knowledge production (Uzuner, 2008). Their contribution is unique because they help in enrichment by expanding and reforming the existing knowledge in core areas of the discipline (Liu, 2004, p. 2). During the research journey, a Ph.D. scholar accesses online library resources (e-books, article databases, and e-journals), uses data analysis software, bibliographic software, writing software, conducts plagiarism checks, etc. Finally, the research work must be presented through academic writing that is formal, impersonal, and contain factual evidence that requires citations and references in a structured format (Bouchrika, 2022). To be able to apply all this in theses, doctoral students need to learn some or all of these aspects during the research journey, for which many doctoral students have to learn from online platforms. As stated by Lavidas et al. (2023), discovery of factors that might explain the intentions for e-learning in higher education is still an important and rising area. This paper responds to this need; that is, to identify the intentions of the doctoral students to learn online. This will help the academicians, management of educational institutions, online content curators, etc., to find techniques to help doctoral students maintain their learning and continue to contribute to the body of fundamental knowledge (Flowerdew, 2000)

There are many empirical studies on TAM and its expansion, but fewer studies have been conducted that involve the simultaneous assessment of personality traits and perceptual variables. User characteristics can influence their intention for online learning and, in turn, their desire to use products and services that are enabled by technology. As a result, integrating Parasuraman (2000) proposed technological readiness (TR) as an antecedent to perceptual variables of TAM could aid in understanding the usage willingness. The current researchers used the combined framework of TRI and TAM, commonly known as TRAM, to examine what constructs and significant relationships exist between doctoral students related to learning through online platforms. Delhi NCR was used to conduct the study as it has the best higher education infrastructure that attracts students from all over India (Singh, 2022). The study also validates the TRAM model for e-learning. There are three ways in which this study complements literature. First, this research offers opportunities for both academics and e-service providers to communicate and motivate future academicians to continue learning themselves voluntarily. Second, according to the literature that is currently available to researchers, there are numerous studies on technology adoption using TAM and UTAUT, while studies based on the TRAM model for online learning in India are very few. This demonstrates the knowledge gap in existing research on the underuse of TRAM in the context of intentions for online learning among doctoral students. Third, understanding how people perceive technology generally will help the findings be more broadly applicable.

The following sections detail the review of literature, research variables, hypotheses, and model, leading to research methodology, data analysis, discussions, implications, conclusion, and finally suggestions for additional research are given last.

LITERATURE REVIEW

E-LEARNING CONCEPT

E-learning improves teaching and learning by facilitating the knowledge and information flow between academics and students in educational institutions (Abu-Shanab & Ababneh, 2015). The online platforms provide access to interactive tools, and the latest information, allowing students to conduct their research on a topic of their choice (Paine, 2022). Students can access these learning materials anywhere, anytime using portable devices such as smartphones, iPads, and laptops thus allowing the mobility of the learner facilitated by technology (Al-Adwan et al., 2018). Further, e-learning makes it possible to accommodate a large number of students in a session allowing the academician to reach a larger group, removing the barrier of traditional teaching and learning. Previous researchers have tried to pinpoint the variables influencing intentions of online learning (Abu-Shanab & Ababneh, 2015; Akaslan & Law, 2011; Al-Fraihat et al., 2020; Amin & Zaman, 2021; Boateng et al., 2016; Cidral et al., 2018; Kanwal & Rehman, 2017).

Technology Acceptance Model (TAM)

Many academics have conducted studies in the management information system (MIS) in the past to determine the elements that influence computer use. One of the most successful intention-based models used by researchers is the TAM, created by Davis (1989) to explain and predict acceptance of computing technologies (Abbad et al., 2009). TAM consists of three variables: perceived ease of use (PEU), perceived usefulness (PU), and behavioral intent, which aid in the prediction of users' intentions to embrace and employ technology (Abu-Shanab & Ababneh, 2015). TAM was adapted from the Theory of Reasoned Action (TRA) and is specially designed to predict the adoption of information systems. It is also considered to be a perfect model to examine student adoption of e-learning (Abbad et al., 2009).

Technology Readiness Index (TRI)

The TRI was evolved by Parasuraman (2000) to estimate the technology readiness (TR) of individuals. Parasuraman (2000) defined TRI as "people's intention to embrace and use new technologies for accomplishing goals in home life and at work." TRI has two dimensions, namely motivators and inhibitors. These two dimensions are further divided into four constructs. Motivators include optimism (OPT) and innovativeness (INN), and negative inhibitors include discomfort (DIS) and insecurity (INS). TRI 1.0 was initially created with 36 items based on the Likert scale (Parasuraman, 2000), to assess people's mental maps for the use of newer technologies. Later, it was reduced to 16 items using the same constructs and called TRI 2.0 (Parasuraman & Colby, 2014). TRI expresses a set of viewpoints about technology, but it does not represent someone's proficiency with it. (Walczuch et al., 2007). As per Parasuraman and Colby (2014) "TR is an individual-level characteristic that does not vary in the short term, nor does it change suddenly in response to a stimulus." The four constructs of TRI, as defined by Kuo et al. (2013) and Parasuraman and Colby (2014), are as follows:

- Optimism refers to "a positive view of technology and a belief that it offers people increased control, efficiency, and flexibility in their lives." Individuals that view technology with positiveness are labeled as optimistic and are ready for online learning.
- Innovativeness is "a tendency to be an early adopter of technology and opinion leader." Innovative people are considered to be thought leaders and pioneers in the technology space among their peers for online learning.
- Discomfort refers to "a perception of being unable to control the technology and a feeling of being overwhelmed by it." In the present study, it is explained as having anxiety, feeling uneasiness, and being nervous while learning online (Kaushik & Agrawal, 2021).
- Insecurity is "suspicion of technology and doubt about its capability to work." Unsecured individuals mistrust technology. For our study, the construct is explained as "disbelief in learning digitally and suspicious about its contents" (Kaushik & Agrawal, 2021).

Since its inception, TRI study areas have included self-service technologies (J.-S. C. Lin & Hsieh, 2007), online services (Massey et al., 2007), mobile data services (Chen et al., 2013), acceptance of ERP applications in micro, small and medium enterprises (MSME) (Larasati et al., 2017), travelers' satisfaction with travel technologies (Wang et al., 2017), internet banking (Pires et al., 2011), assessment of TR of academicians (Badri et al., 2014; Summak et al., 2010), and TR of professional students (Lai, 2008; Ling & Moi, 2007). Based on available literature support, the present researchers utilized TRI 2.0 scale items to measure doctoral students' readiness for online learning.

Technology Readiness and Acceptance Model (TRAM)

E-learning falls within the e-service context offered by universities and private service providers. Owing to the high level of consumer interaction required to co-produce services, TAM may not alone be sufficient to fully describe the technology adoption behavior of doctoral students (C.-H. Lin et al., 2007). Consequently, it is essential to use a model that incorporates specific individual traits related to personality that impact a person's inclination to adopt a certain technology. TRI, which measures the personality traits of an individual, has been used in the past to measure inclinations for the use of technology. Certain personality factors may result in a person using a particular technology in a particular area but do not imply that he/she will use it in a different situation (Pires et al., 2011). TRI and TAM development was done to explain how people adopt new technologies (Davis, 1989; Parasuraman, 2000). Second, they differ conceptually as TRI explains technological acceptance through individuals' innate tendencies, whereas TAM does so through system-specific perceptions. So, integrating TRI into TAM makes theoretical sense. TRAM combines the general dimensions of the TRI consisting of optimism, innovativeness, discomfort, and insecurity with the TAM variables, consisting of PEU, PU, and intention to use.

C.-H. Lin et al. (2007) combined TR and TAM, leading to the formation of the TRAM model. They proposed that TR's influence on usage intention is mediated by PEU and PU (variables of TAM) and identified a significant association between TR and willingness to use in the e-service environment. Using TAM and TRI, Walczuch et al. (2007) investigated financial services offered in Belgium. Indian studies conducted by Gurung and Goswami (2022) used the TRAM model to study the teacher's preparedness for synchronous online teaching, and Raman and Aashish (2021) utilized the TRAM model to verify users' intentions for sports and fitness wearable devices. Similarly, Pillai et al. (2020) studied customers' intention to shop from artificial intelligence-powered retail outlets, and Sivathanu (2019) examined the usage intentions for open banking technology. Additionally, Kamble et al. (2019) used a mix of TAM, TRI, and the theory of planned behavior (TPB) to research the adoption of blockchain technology among practitioners of the supply chain in India. A Malaysian study by Alsyouf and Ku Ishak (2017) stressed the importance of studying TR constructs in medical settings for technology adoption. As a result, this study incorporates the TR constructs as an antecedent to independent variables of TAM to better understand doctoral students' utilization intention for online learning platforms. The recommendation of the TRI's creators, earlier research, and the current researchers' objective all served as the foundation to use TRAM.

OBJECTIVE OF THE RESEARCH

Based on the literature review support, studies based on the TRAM model are very few and are from different perspectives in the Indian context. This highlights the lacunae in the stream of research about the under-use of TRAM, particularly concerning studies of online learning intentions among doctoral students Therefore, the present study attempts to examine TRAM factors with the doctoral student's intention to learn online.

RESEARCH VARIABLES, HYPOTHESES, AND MODEL

TAM emerged as the most trustworthy IS model to explain usage behavior (Walczuch et al., 2007). It assists in determining people's desire to adopt or use technology with the help of two variables, PEU and PU. Eventually, these two variables were employed in many study models under various names. Based on earlier studies, we were able to put forth a sound basis for the TRAM model for statistical evaluation with various hypotheses given below.

INTENTIONS FOR E-LEARNING (IEL)

IEL is the dependent variable in the present study. It is an attitude that the TAM theory classifies as a behavioral intention variable (Aisyah & Eszi, 2020). It is formulated with two core determinants of perception, i.e., PEU and PU. According to TRAM, in our study, the behavioral intention of doctoral students relates to their decision to adopt online platforms for learning during their research journey. In our model and consistent with the adoption theory, we expect that intention for e-learning would be significant among doctoral students.

Perceived Ease of Use and Perceived Usefulness

According to Davis (1989), PU is a measure of how much a stakeholder thinks using a technology-enabled system has enhanced their individual or group performance or organizational performance. The second most important construct in TAM is PEU, the extent to which users believe they would not incur a large amount of work or will face additional burdens while using a system (Abu-Shanab & Ababneh, 2015). Additionally, it is postulated that PU is affected by PEU because the effort saved through improved usability can be used to improve performance by allowing a person to complete other important tasks with the same amount of effort (Yi et al., 2003). Several pieces of research have examined the relationship between PU and PEU and support that they are important determinants in the relationship (Abu-Shanab & Ababneh, 2015; Khorasani & Zeyun, 2014; C.-H. Lin et al., 2007; Tarhini et al., 2013) with behavioral intentions to use online learning. We, therefore, formulate the following hypotheses:

H1: Doctoral students' PU for online learning has a significant impact on their intentions to use.

H2: Doctoral students' PEU for online learning has a significant impact on their intentions to use.

H3: Doctoral students' PEU for online learning has a significant impact on PU.

Effect of Optimism (OPT) on PU and PEU

Optimism is stated as "a positive view of technology and a belief that offers people increased control, flexibility, and efficiency in their lives" (Parasuraman & Colby, 2001). It aids in capturing favorable attitudes toward technology (Panday, 2018). Nonetheless, it is discovered that those who are optimistic choose paths that are more helpful in accomplishing their goals (Walczuch et al., 2007). They feel that technology is the way forward to accomplishing more useful tasks and that it is also easy to use. (Alsyouf & Ku Ishak, 2017). Chen et al. (2009) evaluated the effect of OPT on PU and PEOU in their study of continuation intent when using self-service technologies and found them to be significant. We, therefore, propose the following hypotheses:

H4a: Doctoral students' PEU is positively influenced by optimism.

H4b: Doctoral students' PU is positively influenced by optimism.

Effect of Innovativeness (INN) on PU and PEU

INN is described as "a tendency to be a technology pioneer and thought leader" (Parasuraman & Colby, 2001). Similar to OPT, it is an influencing dimension that gauges how much a person believes themselves to be technological trailblazers (Panday, 2018). This dimension tells that all those individuals who have a high degree of innovative ability will generally look forward to the acceptance of new technologies and enjoy using them (Yi et al., 2003). INN is a very crucial element in cognitive absorption related to PEU and PU (Agarwal & Karahanna, 2000). A past study by Leong et al. (2021) found INN to be positively related to both PEU and PU. However, the study by Walczuch et al. (2007) found a mixed relationship between PU and PEU. But Chen et al. (2009), while evaluating the effect of INN on PU and PEU, found no relationship in their study. Therefore, it has become imperative to study the effect of INN on PEU and PU leading to the formulation of the hypotheses:

H5a: Doctoral students' PEU is positively influenced by innovativeness.

H5b: Doctoral students' PU is positively influenced by innovativeness.

Effect of Insecurity (INS) on PU and PEU

Insecurity is described as "distrust of technology and skepticism about its ability to work properly" (Parasuraman & Colby, 2001). This inhibitory dimension stresses fears and concerns that a person will have when conducting a technology-based transaction (Panday, 2018). The current study views insecurity as something where an individual expresses doubt and uncertainty about optimal functioning (Parasuraman, 2000). People with high levels of insecurity lack confidence and always feel that technologies are risky (Alsyouf & Ku Ishak, 2017). This dimension was evaluated on PU and PEU (Chen et al., 2009) to check intent for self-service technologies, and for the adoption of e-wallets by Leong et al. (2021). To test the relationships, the hypotheses drawn are:

H6a: Doctoral students' PEU is negatively influenced by insecurity.

H6b: Doctoral students' PU is negatively influenced by insecurity.

Effect of Discomfort (DIS) on PU and PEU

Discomfort is stated as "a perceived lack of control over technology and a feeling of being overwhelmed by it" (Parasuraman & Colby, 2001). When faced with technology, some people experience fear and anxiety (Panday, 2018), which is typically measured by this inhibitory dimension. People who are uneasy with technology believe that it controls them and is not meant for ordinary people (Parasuraman, 2000). Such people become apprehensive about the use of technology (Alsyouf & Ku Ishak, 2017). Both Kuo et al. (2013) and Walczuch et al. (2007) found that discomfort had a significant impact on PEU and had no impact on PU. To find the relationship between DIS on PEU and PU, we hypothesize as follows:

H7a: Discomfort negatively influences the PEU of doctoral students.

H7b: Discomfort negatively influences the PU of doctoral students.

Figure 1 is the proposed model created for empirical testing.

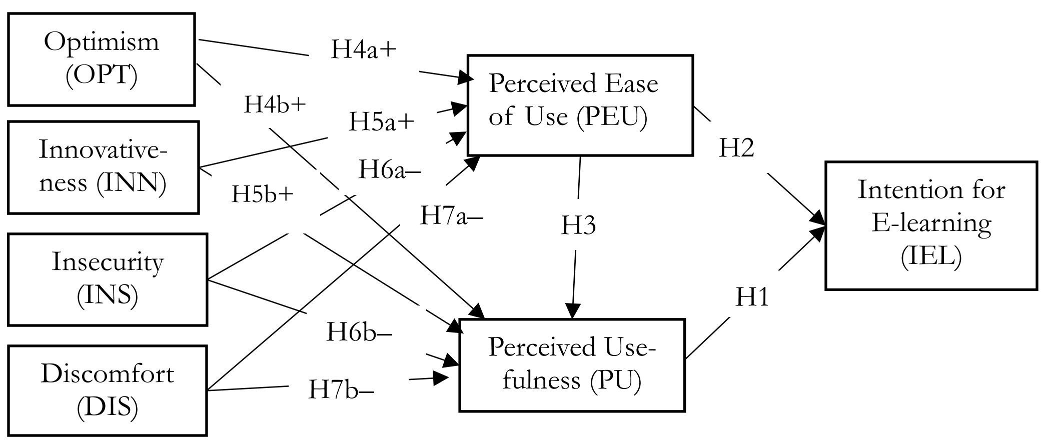

Figure 1. Research model for testing

Research Methodology

To accomplish the study objective, TRAM was used. A quantitative research approach similar to past studies (Larasati et al., 2017; Mufidah et al., 2022; Panday, 2018) using a structured close-end research instrument was used to evaluate the research model. Moreover, quantitative research, enables data collection and analysis, thus enabling generalization, i.e., the results of a particular group may reflect society as a whole in terms of content, samples, and patterns (Cohen et al., 2007)

Research Instrument

TRI 2.0 and TAM constructs made up of closed-ended questions were combined to generate a 26-item TRAM instrument. The instrument had two sections. The first concerns demographic factors; scholars were supposed to mark their gender, age, research stream, and the type of university where they are pursuing their doctoral program. The next section had 26 statements, which were mainly about factors influencing intentions for e-learning. All construct items were scored using a Likert scale of 1 being strongly disagreed to 5 strongly agreeing.

TRI 2.0 is a multi-item scale consisting of 16 items (1-16) for measuring OPT, INN, INS, and DIS. Each construct consists of 4-items. The developer of TRI (Parasuraman, 2000) collaborated with Charles Colby, Chief Methodologist at Rockbridge Associates, Inc. leading to the formation of TRI 2.0 (Parasuraman & Colby, 2014). "These questions comprise the Technology Readiness Index 2.0 which is copyrighted by A. Parasuraman and Rockbridge Associates, Inc., 2014. This scale may be duplicated only with written permission from the authors." The present authors have obtained the requisite permission (see Appendix). The second tool consists of TAM constructs developed by Davis (1989). It measures perceived ease of use (PEU-3 items), perceived usefulness (PU-4 items), and intention for e-learning (IEL-3 items), after minor modifications according to the study background. They were listed from items 17 to 26 in the research instrument.

Before the conduct of the pilot study, the instrument was checked for face and content validity. The items were checked by two professors, one working in the languages and the other in the management department, for correctness of grammar, use of appropriate words, clarity of statement to facilitate understanding, and item fit to each of the factors under study. A 3-point scale (not relevant, relevant, very relevant) was used for the assessment procedure. Following this scoring process, all items were retained in the final instrument, as no item was scored as not relevant (Lavidas et al., 2022). The instrument was then subjected to a pilot test. The outcome of the pilot study showed that all items had requisite loading except INS4 from construct insecurity. Due to inadequate factor loading, INS4 was excluded and, thus, construct insecurity finally had 3 items, resulting in 25 measurement items in the final instrument.

Sampling and Data Collection

The instrument was administered to doctoral students who are pursuing Ph.D. from central, state, and private universities located in Delhi National Capital Region, India. As the number of scholars pursuing doctoral programs was not known, we visited university libraries and departments (commerce, management, arts, education, and science) to collect data. Only those participants who were available at that particular time were included in the study. This way of selecting participants for the study confirms that the method is convenience sampling and is consistent with past studies (Bakirtaş & Akkaş, 2020; Lavidas et al., 2023; Shukla, 2021). Data collection took place between September and November 2022. The time required by each scholar averaged 15-20 minutes. This technique facilitated direct communication with the scholars, allowing us to explain the goals of the study, allay concerns, and give guidance for filling out the questionnaire. We managed to receive 323 complete responses out of 360 distributed to doctoral students. The sample size decision for the study was based on 10 cases per variable rule-of-thumb as suggested by Bentler and Chou (1987) and Nunnally (1994). Since the instrument had 25 measurement items, the required sample size was 250. However, the minimum sample size required for analysis with Structural Equation Modeling (SEM) is 200 (Kline, 2015). Therefore, the sample size collected is larger than the minimum required.

Data Screening: Reliability and Validity

Data collected through the TRAM questionnaire was checked for missing entries and found to be good to proceed further. In the second step, data was exported to SPSS v24 and was checked for reliability and validity. Cronbach alpha was used for reliability testing. After that, confirmatory factor analysis was performed on the data to determine its convergent and discriminant validity, and then SEM analysis for path coefficients using AMOS was performed. The p-value of <0.05 was used to assess whether there exists a statistically significant relation between the TRAM variables.

DATA ANALYSIS AND RESULTS

RESPONDENTS' PROFILE

Table 1 lists the profile of the scholars who participated in the study. Out of 323 scholars who took part in the study, female scholars were 52.7% (n=170), while 47.3% were male (n=153). Maximum doctoral students were between 21 and 30 years of age. The scholars pursuing a doctoral program were from commerce (12.38%), management (25.38%), arts (21.67%), education (20.12%), and the science stream (20.43%). These doctoral students belonged to central universities (20%), state universities (23.66%), and private universities (53.33%).

Table 1. Study participants' characteristics

VARIABLE	CATEGORY	N (%)
Gender	Male scholars	153 (47.3)
	Female scholars	170 (52.7)
Age (years)	21-30	168 (52.0)
	31 - 40	120 (37.15)
	41 & above	35 (10.83)
Doctoral scholar's research stream	Commerce	40
	Management	82
	Arts	70
	Education	65
	Science	66
Type of university	Central university	3 (20)
	State university	4 (23.66)
	Private university	8 (53.33)

SEM

A two-step process was used to validate the suggested empirical model and test the suggested hypotheses. Step one involved performing a confirmatory factor analysis to determine whether the model reaches a sufficient level of fitness for assessment of validity and reliability issues in the constructs. Step two involved testing the hypotheses (structural model).

MEASUREMENT MODEL EVALUATION

Since we used established scales for the TRAM model, we directly proceeded to confirmatory factor analysis (George et al., 2020) using AMOS V23. The fit indices computed for the measurement and structural model to verify the convergent validity of the scales were found to have a sufficient fit for the collected data. The Tucker Lewis Index (TLI), Incremental Fit Indices (IFI), and Comparative Fit Index (CFI) values were all found above 0.9, satisfying the criteria (Anderson & Gerbing, 1988; Hair et al., 2010). The chi-square normalized by degree of freedom is less than 3, and the root mean square error of approximation (RMSEA) less than 0.06 (Hair et al., 2010), ensuring a good fit of the model with the data. These results are shown in Table 2.

Table 2. Fit indices of the model

FIT INDEX	RECOMMENDED VALUE	MEASUREMENT MODEL	STRUCTURAL MODEL
$\chi2$/ df	Less than 3	2.074	2.133
AGFI	0.80 or above	0.852	0.851
TLI	0.90 or above	0.931	0.927
IFI	0.90 or above	0.946	0.943
CFI	0.90 or above	0.946	0.942
RMSEA	Less than 0.06	0.058	0.059

CFA, shown in Figure 2, was performed to determine the validity and reliability of the model's reflective constructs. Convergent validity, which describes how converging all items in a particular construct are, was determined by values of factor loading (FL), composite reliability (CR), Cronbach's alpha (CA), and AVE. The factor loadings in all constructs were above 0.5 matching the specifications of Hair et al. (2010) except for item INS4 hence was dropped from further study.

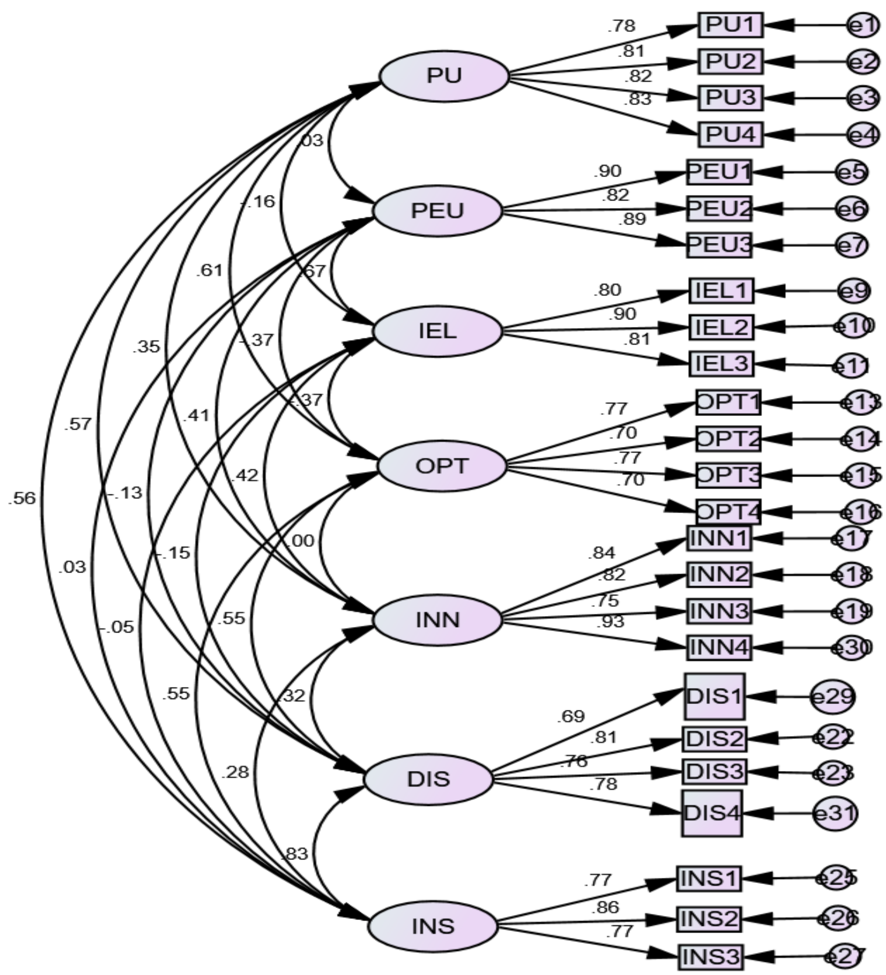

Figure 2. Overall measurement model

The CA test was used to determine the construct reliability. Each construct's reliability score was greater than 0.70 and met the thresholds proposed by Nunnally (1994). The CR for all constructs is above 0.7, indicating construct reliability (Fornell & Larcker, 1981). Calculation of average variance extract (AVE) resulted in values above the acceptable value of 0.5 (Fornell & Larcker, 1981). Thus, the value of AVE >=0.5 denotes that the proposed model's construct elements have all reached a reasonable level of convergence. Table 3 presents CA, CR, and convergent validity values.

Table 3. Outcome of measurement scales

CONSTRUCT	ITEM	FACTOR LOADING	CRONBACH'S ALPHA (CA)	CR	AVE
Perceived Usefulness	PU1	0.780	0.903	0.884	0.656
	PU2	0.808			
	PU3	0.825			
	PU4	0.827			
Perceived Ease of Use	PEU1	0.901	0.805	0.904	0.759
	PEU2	0.819			
	PEU3	0.892			
Intentions for E-Learning	IEL1	0.801	0.844	0.877	0.705
	IEL2	0.901			
	IEL3	0.814			
Optimism	OPT1	0.766	0.820	0.822	0.537
	OPT2	0.699			
	OPT3	0.767			
	OPT4	0.696			
Innovativeness	INN1	0.836	0.820	0.903	0.701
	INN2	0.819			
	INN3	0.755			
	INN4	0.930			
Discomfort	DIS1	0.694	0.898	0.845	0.578
	DIS2	0.806			
	DIS3	0.761			
	DIS4	0.776			
Insecurity	INS1	0.767	0.875	0.841	0.639
	INS2	0.858			
	INS3	0.769			

The researchers examined the square root of the AVE derived for each construct to test discriminant validity. Table 4 displays the discriminant validity results. Intercorrelation between the latent constructs is shown by off-diagonal values, while diagonal values are the squared roots of the AVE. These square roots of AVE should be greater than off-diagonal values present in respective rows and columns (Fornell & Larcker, 1981). Since the square root values of the AVE are higher compared to the corresponding values in columns and rows, discriminant validity appears to be satisfied for all constructs.

Table 4. Discriminant validity results

Construct	INS	PU	PEU	IEL	OPT	INN	DIS
INS	**0.799**						
PU	0.56	**0.81**					
PEU	0.026	0.026	**0.871**				
IEL	-0.054	-0.161	0.673	**0.84**			
OPT	0.554	0.611	-0.37	-0.373	**0.733**		
INN	0.284	0.354	0.407	0.416	-0.002	**0.837**	
DIS	0.627	0.567	-0.129	-0.146	0.547	0.323	**0.76**

Structural Model Evaluation

The hypothesis testing and the association between the constructs were based on standardized paths. Figure 3 displays the outcome of the structural model. R^2 for the perceived usefulness is 0.54 and for perceived usability is 0.41. The proposed model predicts an R^2 of 0.49, i.e., 49% of the intent of online learning. The information in Table 5 is consequently supportive of the current study model's predictive validity.

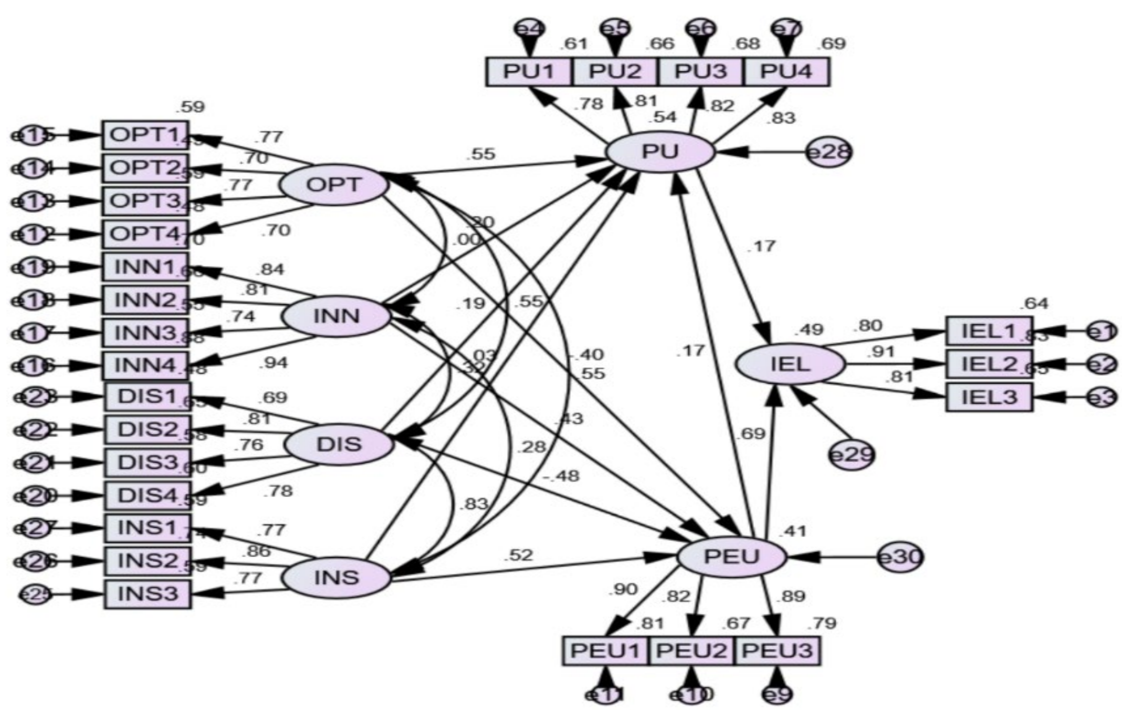

Figure 3. Path coefficients of the structural model

Table 5. Outcome of the analysis

Hypotheses	Hypothesized Path	Estimate	S.E.	t-value	p-value	Decision
H1	IEL<---PU	0.128	0.038	3.386	***	Supported
H2	IEL<---PEU	0.531	0.046	11.647	***	Supported
H3	PU<---PEU	0.168	0.071	2.36	0.018	Supported
H4a+	PEU<---OPT	0.416	0.083	5.000	***	Supported
H4b+	PU<---OPT	0.575	0.091	6.334	***	Supported
H5a+	PEU<---INN	0.429	0.061	7.089	***	Supported
H5b+	PU<---INN	0.207	0.063	3.289	0.001	Supported
H6a–	PEU<---INS	0.571	0.148	3.851	***	Not Supported
H6b–	PU<---INS	0.036	0.142	0.251	0.802	Not Supported
H7a–	PEU<---DIS	-0.478	0.137	-3.486	***	Supported
H7b–	PU<---DIS	0.196	0.13	1.501	0.133	Not Supported

Note: Estimate=standardized regression weights, ***significant at $p<0.01$

DISCUSSION

To address the primary research issues of the study, we proposed and tested the TRAM model, which includes the TAM and TRI 2.0 scales. The study leverages both the system design and the individual characteristics. The suggested model predicted 49% of the variance, allowing researchers to investigate the variables that affect doctorate students' intention to engage in online learning.

Results obtained confirm that PU had a significantly positive effect on research scholar intent for e-learning leading to acceptance of H1. This finding is comparable to those of Azizi et al. (2020). Also, Tarhini et al. (2013) found that PU is a significant factor in developing countries in determining intentions for e-learning, which is also similar to the context of the present study. Similar results were obtained from C.-H. Lin et al. (2007), who used the TRAM model to measure consumers' willingness to accept e-services. Therefore, the use of online learning is considered useful among doctoral students.

Our study also found that PEU had a significant positive effect on the doctoral students' intention for e-learning leading to acceptance of H2. Our findings are comparable to those of earlier studies (Azizi et al., 2020; C.-H. Lin et al., 2007; Tarhini et al., 2013). Similarly in a Malaysian study conducted by Khorasani and Zeyun (2014), PEU had a strong impact on students' intentions for web-based learning. Therefore, PEU is an important predictor of doctoral students' intentions for e-learning.

The results of our study continued to reveal a significant association between PEU and PU leading us to accept H3. This finding is similar to past studies conducted on e-learning adoption in Pakistan (Kanwal & Rehman, 2017), student acceptance of e-learning in Garamsar, Iran (Mahmodi, 2017), and on web-based learning system by Khorasani and Zeyun (2014). This reinstates that the constructs PEU and PU for technology-based learning such as e-learning are valuable predictors (Pires et al., 2011) among doctoral students.

We evaluated the TRI 2.0 with TAM by way of integration to form the TRAM model using hypotheses H4a+ to H7b–. These hypotheses attempted to verify the four TRI dimensions – OPT, INN (motivators), DIS, and INS (inhibitors) – relationships with TAM variables. The analysis revealed that OPT and INN dimensions of TRI had a significant impact on "perceived ease of use (PEU)," a similar outcome matching to Walczuch et al.'s (2007) study related to technology acceptance among service employees and Rahman et al.'s (2017) work on the adoption of technology by micro-entrepreneurs in Bangladesh. This led to the acceptance of hypotheses H4a+, and H5a+. Regarding perceived usefulness (PU), we found that both optimism ($\beta=0.575$ and $p<0.01$) and innovativeness ($\beta=0.207$ and $p<0.01$) had a significant impact on PU, leading to the acceptance of H4b+ and H5b+. Rahman et al. (2017) in Bangladesh also reported a similar finding. Both optimism and innovativeness are influencing PEU and PU of doctoral students. This suggests that doctoral students who are optimistic will welcome learning from online platforms and innovative scholars will be eager to experience it and be among the first ones to comprehend the advantages. Therefore, optimistic, and innovative scholars are more likely to adopt e-learning platforms during their research journey.

In addition, it was discovered that insecurity and PEU had a positive association ($\beta=0.571$ and $p<0.01$). Based on the p-value, the result is significant, but the path coefficient turned out to be positive which is a deviation from the proposed theory. The theory states that the lower the level of insecurity, the higher will be the PEU. Therefore, the result does not support hypothesis H6a–. A possible explanation could be the contextual perception of doctoral students and the platform used for online learning. It may be because of the user-friendliness of the online platform used; the ease of use outweighs the sense of insecurity among doctoral scholars. This discovery is consistent with earlier studies done by Rahman et al. (2017). Thus, insecurity is an inhibitive personality trait exhibited by an individual which prevents/limits acceptance of technology. All individuals who exhibit high levels of insecurity logically cannot have a positive perception of the ease of use of technology. Hence hypothesis H6a– is not supported. Moreover, insecurity was found to be unrelated to PU too ($\beta=0.036$ and $p>0.05$), hence H6b– is also not supported. The outcome is found to be similar to the previous study of Galaige et al. (2018) on respondents learning analytics using a distance-based system.

In the hypotheses H7a– and H7b–, it was stated that dimension discomfort has a negative effect on PEU and PU, respectively. The outcome reveals that discomfort had a negative and significant impact on PEU ($\beta= -0.478$ and $p<0.05$) that led to the acceptance of H7a–. The doctoral students surveyed expressed discomfort towards user-friendliness. This means if scholars are unable to navigate the online platforms in any way, resulting in a loss of control over their learning process (Galaige et al., 2018), they will perceive online platforms as not easy to use. The perceived ease of use is likely to be lower in the absence of technical support or when technical support hotlines are not helpful, and when manual instruction is not provided (Rahman et al., 2017) to the users. However, the discomfort had no significant impact on PU ($\beta=0.196$ and $p>0.05$), hence H7b– was not supported among doctoral students, which is identical to past studies (Galaige et al., 2018; Rahman et al., 2017). This means that doctoral students are not skeptical about the usefulness of online learning platforms, i.e., discomfort and usefulness of online platforms are unrelated. According to Walczuch et al. (2007), if there is a high level of discomfort while using a technology it lowers PEU, but it does not increase or decrease the perceived usefulness of a particular technology. This complete outcome of discomfort in PEU and PU is similar to a previous study by Bessadok (2017) conducted among participants of the learning management system training program. When accessing digital resources, 46.42% of professors and doctorate students experienced discomfort (Thanuskodi & Ravi, 2011) due to a lack of IT understanding. Again, Kaushik and Agrawal (2021) presented a considerable amount of discomfort among learners to adopt digital learning. In addition, a survey at a well-known B-School in Hyderabad, India, revealed a significant gap in digital literacy and ICT literacy requirements (Makhachashvili & Semenist, 2021). The current study found that adopting digital learning causes significant anxiety and unease even for optimistic and creative learners.

IMPLICATIONS

This study has contributed to IS theory and provided information to practitioners involved in the development of online platforms. TRAM evolved in developed nations but lacked research in developing nations. The results depict that, like in many other developed nations, the TRAM model is relevant in the Indian online learning environment. The constructs of TAM explain adoption intention well, and TR as a personality trait plays an important role. Based on the results, practitioners and researchers can develop better strategies to increase the intention for e-learning. The results not only reimposed the reliability of the TAM constructs but also highlighted the importance of TRI dimensions. Thus, validation of the TRAM model in Indian settings highlights the applicability and relevance of the model beyond developed countries and provides adoption intention in diverse educational settings.

Higher educational institutes (HEI) involved in research and universities offering research programs should encourage digital learning. They should focus on developing an infrastructure for smooth implementation and uptake of e-learning among doctoral students. The TRAM model validated PEU and PU as predictors of adoption intention for e-learning, developers should design an easy-to-use system. The study emphasizes the role of personality traits in shaping doctoral students' perception of online learning. Positive traits such as OPT and INN were found to have a favorable impact, while discomfort was identified as an inhibitory trait both in the past and the present study. This suggests that e-learning providers should provide support to address discomfort. In the Indian context, a similar suggestion was made by Paliwal and Singh (2021) for online education enterprises to provide user-friendly tools for online teaching and learning. We reiterate the same. The learning material designed should be interactive, with the learner feeling involved in the delivery and learning process. All the interfaces added should be easy to use and support the intention to learn from e-learning platforms.

CONCLUSION

E-learning helps to increase subject knowledge and to collect additional information on a specific topic. The online platform for learning can be chosen based on one's willingness and comfort. The TRAM model, which is a combination of TAM and TRI scales, was used to perform the current study. The model, which examined doctoral students' adoption intention to learn from e-learning platforms, proved its potential to identify the predictors. The system's characteristics, i.e., PU and PEU, have again been found to be effective predictors among doctoral students. Similarly, the personality traits optimism, innovativeness (positive traits), and discomfort (inhibitory traits) were found to have an influence on PU and PEU in the study. However, the effect of the insecurity dimension was not found significant as proposed in the theory. The present findings can be used as a base that serves as a reference for the identification of individual personality traits and information systems characteristics, for e-learning adoption intention. The research was significant because, firstly, it used the TRAM model in e-learning and, secondly, it was validated in a developing country. To the extent of the availability of literature with the authors, studies based on TRAM in the Indian context were not carried out.

LIMITATIONS AND FUTURE DIRECTIONS

Although the authors followed the research process rigorously, there are still some limitations that may potentially be taken up in upcoming studies. Firstly, the study was undertaken in the Delhi NCR region, hence, the findings are derived from the particular geographical boundary. Therefore, the generalizability of the results requires some care. Second, since the research was cross-sectional the intents measured may alter over time. Finally, the study was limited to finding the intentions of doctoral students for online learning, not incorporating the construct's actual use. Since past and present quantitative studies have already reported the presence of discomfort among users while using online platforms for learning, future studies should consider conducting a qualitative study to analyze what issues learners face while using online platforms for learning.

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AMERICAN INNOVATION INDEX

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