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Combining technology readiness and acceptance model for investigating the acceptance of m-learning in higher education in India

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Abstract

Purpose – The study aims to validate a mobile learning readiness scale through the technology readiness and acceptance model (TRAM), thereby assessing students' readiness to adopt m-learning in teaching and learning, including its acceptance.

Design/methodology/approach – A structured questionnaire was administered to open and distance learning (ODL) students in Odisha, India, to assess their readiness and acceptance of m-learning. 665 valid responses were collected, and collected data was analysed using statistical packages for social sciences (SPSS) and SmartPLS.

Findings – The findings of the study reveal that optimism contributes positively to perceived ease of use (PEOU) and perceived usefulness (PU) of m-learning ($\beta = 7.921$, $p < 0.001$; $\beta = 2.123$, $p < 0.05$), whereas innovativeness positively contributes to PEOU of m-learning ($\beta = 2.227$, $p < 0.05$), but not PU of m-learning. ODL student's optimism improves his/her PEOU and PU of m-learning, but innovativeness improves only his/her PEOU. Further, the impact of innovativeness is higher than that of optimism in the TRAM and innovativeness is the strong predictor to adopt m-learning. It also shows that the PU of m-learning positively influences behavioural intention to use m-learning ($\beta = 4.757$, $p < 0.001$). Integrating technology readiness (TR) with technology acceptance model (TAM) to predict students' acceptance of m-learning is very useful.

Practical implications – The paper will help decision-makers to adopt and use m-learning in higher educational institutions.

Originality/value – This paper is the first to explore the readiness and acceptance of m-learning in higher education in India.

Keywords M-learning, Technology acceptance model, Technology readiness and acceptance model, Distance education, Acceptance of m-learning

Paper type Research paper

Introduction

Of late, the educational sector has witnessed digital disruption. With its intrinsic potential to provide educational resources to learners more instantaneously, Internet coupled with mobile technology, is the principal driver of disruption in higher education. Mobile technology is not a panacea for education but a powerful tool supporting education phenomenally. Mobile-based learning system or m-learning allows aggregation and dissemination of educational

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resources to larger groups of students, which was impossible through previous delivery forms. M-learning can seamlessly support students in their pursuit of education and facilitate synchronous learning experiences (Rudestam and Schoenholtz-Read, 2009). With smartphones, tablets and laptops, users can access rich multimedia teaching materials and gain knowledge without restrictions on time and geographical boundaries (Ho Cheong and Park, 2005). Recently, smartphone ownership has increased phenomenally with affordable mobile data. Corollary m-learning has become a valuable supplement for formal and informal education (Huang and Chiu, 2015), and it is more effective than face-to-face learning (Shih *et al.*, 2010).

Owing to this, most higher education institutions (HEIs) have started leveraging m-learning in teaching and learning. However, m-learning is inadequately used in open and distance learning (ODL) environments (Krull and Duart, 2017). There is an increasing gap between the teaching and learning of regular students and ODL students. Plausibly, it can be bridged with the use of m-learning in ODL system. Since most of the students are avid users of mobile phones, m-learning may be useful to ODL students, and it would be possible to leverage m-learning into ODL. However, no empirical evidence demonstrates the extent to which ODL students are ready to adopt and use m-learning in their teaching and learning. In view of the above, the present study tries to validate a mobile learning readiness scale through the technology readiness and acceptance model (TRAM), thereby assessing students' readiness to adopt m-learning in teaching and learning, including its acceptance. The study explores the readiness and acceptance of m-learning in higher education in general and ODL in particular in India. The findings of the study would be helpful for the decision-makers to make an informed decision while implementing m-learning in ODL environment.

Relevant studies

Acceptance of M-learning

Recently, there has been immense interest in adopting and using m-learning in teaching and learning in HEIs because it offers collaborative and ubiquitous learning. Various research studies have been conducted in education and computer science to understand the problems and prospects of adopting m-learning in HEIs, including its acceptance by students and teachers. Verkijika (2019) examined the factors influencing entrepreneurs' acceptance of m-learning apps. The results showed that "perceived enjoyment", "perceived usefulness", and "social influence" have a positive influence on the intention to adopt and use m-learning apps. Wang *et al.* (2019) developed and validated a multidimensional model for evaluating the success of the proprietary m-learning app. The results revealed that users' satisfaction and "intention to reuse" affect learning effectiveness. In addition, system quality, information quality, perceived enjoyment and perceived fee affect satisfaction and behavioural intention to reuse m-learning apps. Shuja *et al.* (2019) examined how m-learning pedagogy affects the learning outcome and educational performance of students in Pakistan. The study results showed that mobile phone use is on a rising trend for providing flexible and discussion-oriented learning to students, thereby enhancing their academic performance. Sánchez-Prieto *et al.* (2019) analysed the behavioural intention of first-year pre-service teachers to use mobile devices in their future teaching practice. The results revealed that compatibility and enjoyment strongly influence the intention to use mobile devices rather than perceived ease of use (PEOU) and perceived usefulness (PU). Li *et al.* (2019) studied the relationships between nursing students' learning motivation, m-learning practice and study performance. The results showed that using mobile devices strongly affects the student's performance in their study.

Jeno *et al.* (2019) investigated the novelty effect of various learning tools. The results showed that "m-learning tools and ebooks are perceived as more novel than a traditional textbook". M-learning distinctively improves satisfaction, autonomous motivation and internalisation of the students. Arain *et al.* (2019) revealed that performance expectancy, hedonic motivation, habit, ubiquity and satisfaction strongly influence behavioural intention (BI). Further, the information quality and system quality strongly influence satisfaction toward m-learning. Chavoshi and Hamidi (2019) revealed that PU is a strong determinant in m-learning acceptance. Fagan (2019) showed that enjoyment and performance expectations strongly influence the acceptance of m-learning. Gómez-Ramirez *et al.* (2019) indicated in their study that PU and attitude have a statistically significant influence on the acceptance of m-learning by the students. Aloqaily *et al.* (2019) revealed that performance expectancy, effort expectancy and social influence are determinants of m-learning adoption in higher education. Skills and psychological readiness of the students strongly influence their PEOU and PU of m-learning. PU and PEOU positively influenced BI to use m-learning (Iqbal and Bhatti, 2015).

Technology readiness and acceptance model

Numerous models and theories have been developed in various disciplines to accept and adopt new technologies, products, and services. During the last couple of decades, several research studies have been carried out using the technology acceptance model (TAM) to predict the acceptance of new technology (Adams *et al.*, 1992; Chau and Hu, 2002; Davis *et al.*, 1989; Szajna, 1994; Venkatesh *et al.*, 2003). Several studies have been conducted to investigate the acceptance of educational technology with strong and positive results (Davis, 1993; Escobar-Rodriguez and Monge-Lozano, 2012; Padilla-Meléndez *et al.*, 2008; Sánchez and Hueros, 2010; Szajna, 1994).

Of late, technology readiness (TR) and TAM have been integrated to have an improved technology readiness and acceptance model (TRAM), wherein TR is the strong predictor of PU and PEOU of TAM. Lin *et al.* (2007) integrate TR with TAM in the context of e-service systems adoption by users and theorise that PU and PEOU entirely mediate the influence of TR on the intention to use. The authors review TAM and constructs of TR, and propose and empirically test an integrated TRAM to expand TAM by taking the constructs of TR into the realm of users' adoption of innovations. The results indicate that TRAM extensively expands prior TAM's applicability and explanatory power. The integrated model may be a better way to measure technology adoption and use in a situation where adoption of new technology is not compulsorily done by organisational objectives.

Buyle *et al.* (2018) identified the criteria for implementing data standards in the public sector by analysing the factors that affect the adoption of data governance using TRAM. Results show that respondents, who scored high on innovativeness, have a higher intention to use data standards. Moreover, it reveals that personality characteristics are not a strong predictor of PU and PEOU of data standards. Chen and Lin (2018) extended TRAM to consider individual health consciousness (HC) to predict their attitude and intention to download and use dietary and fitness apps. The HC-TRAM and the TRAM results indicate that in addition to TR, HC significantly and positively affects PEOU and PU of dietary and fitness apps. A person's readiness to adopt modern technology plays a major role when predicting their intention to download and use dietary and fitness apps. Chung *et al.* (2015) revealed that TR is a strong predictor of PU. Visual appeal and facilitating conditions of new technology strongly influence PEOU, and PEOU affects PU. PEOU and PU influence BI to use augmented reality (AR) and, in turn, to visit a destination via AR. Huang *et al.* (2015) investigated the behavioural intention of golfers to use global positioning system (GPS) navigation using TRAM. The results reveal that TR has a statistically strong effect on PU and PEOU. PEOU significantly influences PU, whereas PU has no major influence on the golfer's attitude. PEOU has a significant influence on the golfer's attitude, and the golfer's attitude has no significant influence on BI, but PU has a significant influence on BI.

Jin (2013) investigated the factors that influence users' acceptance of Facebook using TRAM and the role of a revised TRAM on social capital building. Results of the study reveal that positive and negative TR significantly affect PEOU, PU, perceived playfulness (PP) and behavioural intention to use Facebook and social capital building. However, negative readiness does not influence PP significantly. PEOU, PU and PP strongly affect the intention to continue using Facebook. Jin (2020) explored factors that influenced the acceptance of brand apps using TRAM and explained users' mobile application preferences. The results reveal that positive and negative TR significantly affect PU, PEOU, satisfaction with brand apps and the behavioural intention to continue using them. The study found that negative TR did not considerably affect PEOU.

Kim and Chiu (2019) investigate consumers' acceptance and use of sports and fitness wearable devices using TRAM. The results found that positive TR significantly and positively influences PEOU and PU, whereas negative TR negatively influences PEOU and PU. PEOU strongly affects PU. Both PEOU and PU significantly affect the intention to use it. Further, a significant correlation exists between TR and PEOU in case of male users. Marhefka *et al.* (2019) examined theoretical applications of the TRAM to predict the willingness of women living with HIV (WLH) to participate in an e-health videoconferencing group program. The results revealed that the constructs of the TRAM were evident; however, additional mediating factors specific to WLH emerged, including group readiness and HIV-related privacy concerns. Martens *et al.* (2017) investigated the determinants of mobile payment adoption. They examined the relationships between the personality trait dimensions of TRI 2.0 and the system-specific dimensions of the TAM in Germany and South Africa. Results reveal that some, but not all, of the TRI 2.0 variables significantly influence the dimensions of the TAM. PU is the strongest predictor of the intention to use mobile payments.

Sivathanu (2019) examined the behavioural intention of using open banking technology using TRAM in India. The results show that TR is a significant predictor of PEOU and PU of open banking technology, and discomfort negatively contributes to PEOU and PU; however, it significantly influences PEOU and has no significant influence on PU. Insecurity is negatively significant to PU and has no significant influence on PEOU. PEOU positively contributes to PU. PEOU and PU are strong predictors of perceived customer value (PCV). PCVs strongly influence the intention to use open banking technology.

Conceptual framework and hypothesis development

As information communication technolohy (ICT) continues to grow at an unprecedented rate and digital disruption happens in education, health care and commerce, researchers are intrigued by the factors that influence users' acceptance of a particular technology, including their readiness to use it. To address these issues, the experts have developed tools and methods to measure the readiness and acceptance of new technology. Parasuraman (2000) developed the technology readiness index (TRI), a 36-item scale to measure TR. TRI is defined as "people's propensity to embrace and use new technologies for accomplishing goals in home life and at work." TR affects the acceptance of new technology. TR embodies a "gestalt of mental motivators and inhibitors that collectively determine a person's predisposition to use new technologies." It is comprised four dimensions, firstly, optimism- "a positive view of technology and a belief that it offers people increased control, flexibility, and efficiency in their lives," secondly, innovativeness – "a tendency to be a technology pioneer and thought leader"; thirdly discomfort – "a perceived lack of control over technology and a feeling of being overwhelmed by it" and fourthly, insecurity "distrust of technology, stemming from skepticism about its ability to work properly and concerns about its potentially harmful consequences".

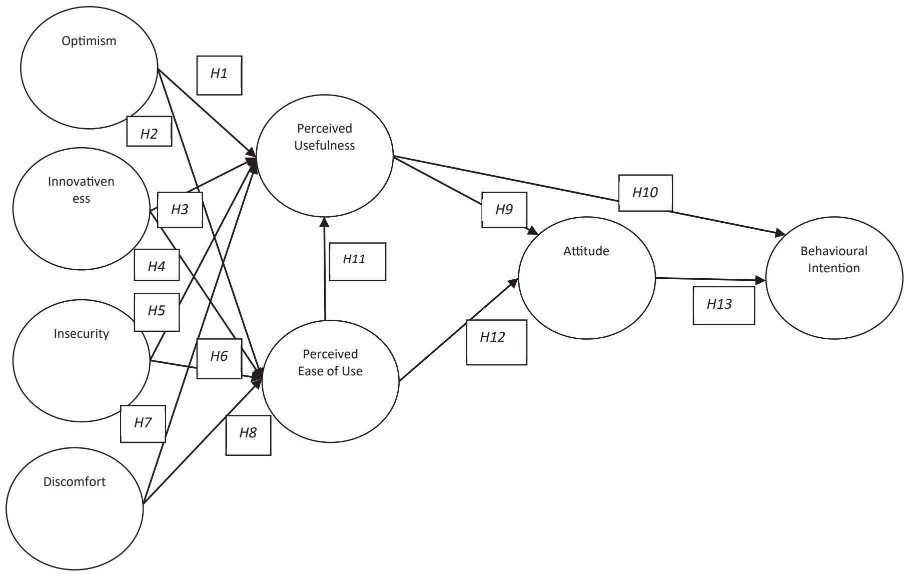
The TAM, which is a theoretical extension of the theory of reasoned action (TRA) (Ajzen and Fishbein, 1980), delineates how users accept and use new technology. Developed by Fred

Davis in 1989, TAM proposes that when the user is offered a new technology, primarily PU and PEOU are determinants to appraise what makes the user of new technology to accept or reject it. PU is "the degree to which a person believes that using a particular system would enhance his or her job performance." On the other hand, PEOU is defined as "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989). TAM stipulates the causal relationships between PU, PEOU, attitude, and user's actual behaviour (Davis, 1993).

The TRAM is an improved model coupling the TAM and TR, wherein TR is the predictor of PU and PEOU of TAM. Kuo *et al.* (2013) postulated three reasons for integrating TAM and TRI into TRAM. Firstly, both TAM and TRI can be used to explain peoples' acceptance of new technologies (Davis, 1989; Parasuraman, 2000); secondly, the TAM uses system-specific perceptions to explain technology acceptance, whereas the TRI explains acceptance through individuals' general inclinations (Yi *et al.*, 2003). Thirdly individual differences are mediated by cognitive dimensions (i.e. PEOU and PU) in predicting people's acceptance of new technologies (Agarwal and Prasad, 1999). The independent variables for the study are optimism, innovativeness, discomfort, insecurity, PU and PEOU, whereas attitude and BI are dependent variables. A graphical representation of the proposed research model and hypothesis is illustrated in Figure 1.

Optimism and innovativeness

Optimism and innovativeness of the users, which are positive readiness, are strong predictors of TR. It encourages users to adopt new technology and have a positive attitude towards technology (Yen, 2005). Individuals, who are optimistic and have an innovative attitude towards new technology, are generally likely to perceive new technology as easier to use and useful. Further, they have a positive attitude toward using new technology (Buyle *et al.*, 2018; Chen and Lin, 2018; Chung *et al.*, 2015; Jin, 2013; Kim and Chiu, 2019; Kuo *et al.*, 2013). So, the following hypotheses are formulated:



Source(s): Figure courtesy of Lin *et al.* (2007)

Figure 1.
Research model

H1. Optimism about m-learning affects the perceived ease of use.

H2. Optimism about m-learning affects the perceived usefulness.

H3. Innovativeness about m-learning affects the perceived ease of use.

H4. Innovativeness about m-learning affects the perceived usefulness.

Discomfort and insecurity

Discomfort and insecurity are negative readiness having negative attitudes toward new technology; they dissuade them from adopting new technology (Yen, 2005). Insecurity about using technology affects attitude negatively (Lin *et al.*, 2007; Sivathanu, 2019). So, the following hypotheses are formulated:

H5. Discomfort with regard to m-learning leads to lower perceived ease of use.

H6. Discomfort with regard to m-learning leads to lower perceived usefulness.

H7. Insecurity with regard to m-learning leads to lower perceived ease of use.

H8. Insecurity with regard to m-learning leads to lower perceived usefulness.

Perceived usefulness and perceived ease of use

PU is "the degree to which a person believes that using a particular system would enhance his or her job performance". In contrast, PEOU is "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989). PEOU is a strong predictor of PU in new technology adoption. Both PU and PEOU are the strongest predictors of positive attitude to use it (Adams *et al.*, 1992; Chau and Hu, 2002; Davis, 1989; Davis *et al.*, 1989; Szajna, 1994; Venkatesh *et al.*, 2003). PU and attitude towards new technology affect BI to use and adopt it (Gómez-Ramirez *et al.*, 2019; Park *et al.*, 2012; Roca *et al.*, 2006; Smith *et al.*, 2013; Verkijika, 2019). Obviously, once individuals perceive technology as easy to use and have PU, in turn, both influence attitude and BI. So, the present study formulated the following hypotheses based on the findings of earlier studies.

H9. Perceived usefulness of m-learning affects attitude to use it.

H10. Perceived usefulness of using m-learning affects behavioural intention to use it.

H11. Perceived ease of use of m-learning affects perceived usefulness of it.

H12. Perceived ease of use of m-learning affects attitude to use it.

Attitude and behavioural intention

Attitude influences the intention to use new technology (Davis, 1993; Venkatesh, 2000). Once individuals have a positive attitude about the new technology, they use and adopt it. Earlier studies indicated that PU and attitude significantly influence students' acceptance of m-learning (Gómez-Ramirez *et al.*, 2019; Iqbal and Bhatti, 2015; Verkijika, 2019). Therefore, the following hypothesis is formulated.

H13. Attitude towards m-learning affects behavioural intention to use it.

Research design and methodology

Extant literature on the TRI and TAM is used to formulate the research instrument to validate the ODL students' readiness and behavioural intention to m-learning. The measurement scale is developed using the existing literature on TR and acceptance (Davis, 1989; Parasuraman, 2000;

Parasuraman and Colby, 2015). The researcher used online and offline survey methods to conduct the study, as the study population was geographically distributed in Odisha. The questionnaire has four sections. Section 1 gathered demographic information of the respondents, namely name, gender, age, education and occupation. Section 2 gathered information about ownership of digital devices, i.e. smartphones, Ipad and laptops/desktops. Section 3 gathered information about the online activities of the respondents. Section 4 consists of five points Likert scale questions to measure the TR, PU, PEOU, attitude and behavioural intention of ODL students towards using m-learning. Table 1 presents constructs and items adapted to measure the TR and acceptance of m-learning.

Since the study subjects were ODL students of Odisha, the survey questionnaire was distributed by email and by hand to them. Current students and passed-out students were administered a structured questionnaire. A pilot test was conducted to examine the validity and reliability of the research instrument. 30 face-to-face and telephonic interview with the help of a scheduled questionnaire was conducted to pre-test the instrument among the target respondents. After satisfactory results were obtained from the pilot study, the first call to participate in the main survey was made in August 2020, and subsequently, calls were made every month until November 2020. The respondents were contacted over the phone/email and reminded to fill out the survey questionnaire. Collected data was analysed using statistical packages for social sciences (SPSS), and SmartPLS, a software for partial least squares structural equation modeling (PLS-SEM).

Results

Demographic profile of the respondents

665 ODL students, who are pursuing/passed out from different open and distance universities, and Odisha State Open University participated in the study. Of 665 participants, 72% (n = 479) were male and 28% (n = 186) were female. 63% of the respondents were either pursuing or passed out post-graduation, 32.2% were graduate students, and only 4.7% were intermediate students.

Reliability and validity analysis of the items

In order to test the internal validity and consistency of the items of each construct, a reliability analysis was conducted. Cronbach's α provides the measurement of internal consistency of test or scale. Internal consistency depicts the extent to which all the items in the test measure the same concept or construct; hence, it is connected to the interrelatedness of the items within the test.

Cronbach's α of all the items was tenable as it is above 0 0.7, which is recommended in social science research (Nunnally, 1978). Like Cronbach's alpha, composite reliability, called construct reliability, is a measure of internal consistency in scale items (Netemeyer *et al.*, 2003). It is an "indicator of the shared variance among the observed variables used as an indicator of a latent construct" (Fornell and Larcker, 1981). The composite reliability of each construct is greater than 0.7, confirming the internal consistency reliability (Hair *et al.*, 2014). Since the average variance extracted (AVE) for each construct is greater than the accepted threshold of 0.5, the convergent validity is confirmed (Table 2).

The Fornell-Larcker criterion was used to evaluate the discriminant validity of the constructs. Table 3 shows the correlation between the latent constructs and the existence of discriminant validity (Fornell and Larcker, 1981).

Testing of hypothesis

After determining the appropriateness of the measurement model, the outcome of the structural model is analysed. The results of the testing of the hypothesis are shown in Table 4.

Constructs	Items	Indicators	Source
Optimism	OPT1	New technologies contribute to a better quality of life	Parasuraman and Colby (2015), Parasuraman (2000)
	OPT2	Technology gives me more freedom of mobility	
	OPT3	Technology makes me more efficient in my occupation	
	OPT4	I like the idea of using new technology in education	
Innovativeness	INN1	In general, I am among the first in my circle of friends to acquire new technology when it appears	Parasuraman and Colby (2015), Parasuraman (2000)
	INN2	I can usually figure out new high-tech products and services without help from others	
	INN3	I keep up with the latest technological developments in my areas of interest	
	INN4	I prefer to use the most advanced technology available	
Insecurity	INS1	Excessive use of technology distracts people to a point that is harmful	Parasuraman and Colby (2015) Parasuraman (2000)
	INS2	I worry that information that I make available over the Internet may be misused by others	
	INS3	I do not feel confident doing any business transaction with a place that can only be reached online	
	INS4	I do not consider it safe to provide personal information over the Internet	
	INS5	Any business transaction I do electronically should be confirmed later with a separate communication	
Discomfort	DIS1	Sometimes, I think that technology systems are not designed for use by ordinary people	Parasuraman and Colby (2015) Parasuraman (2000)
	DIS2	Many new technologies have health or safety risks that are not discovered until after people have used them	
	DIS3	There should be caution in replacing important people tasks with technology because new technology can break down or get disconnected	
	DIS4	Technology always seems to fail at the worst possible time	
Perceived Usefulness	PU1	M-learning system helps me to learn more efficiently	Davis (1989)
	PU2	M-learning system improves my academic performance	
	PU3	M-learning system makes my learning more effective	
	PU4	M-learning system makes it easier to learn	
	PU5	Overall, m-learning system is beneficial for my learning	
Perceived ease of use	PEOU1	Learning to use m-learning system is easy for me	Davis (1989)
	PEOU2	It is easy to get materials from m-learning system	
	PEOU3	The process of using m-learning system is clear and understandable	
	PEOU4	It is easy for me to become skilful at using m-learning system	
	PEOU5	Overall, I find m-learning system is easy to use	

(continued)

Table 1.
Constructs and items adapted to measure technology readiness and acceptance of m-learning

Constructs	Items	Indicators	Source
Attitude	ATT1	Learning on m-learning system platform is fun	Davis (1989)
	ATT2	Using m-learning system is a good idea	
	ATT3	M-learning system is smart way of learning	
	ATT4	Overall, I like using m-learning system	
Behavioural intention	BI1	I will use m-learning system on a regular basis in the future	Davis (1989)
	BI2	I will frequently use m-learning system in the future	
	BI3	I intend to use m-learning system to assist my learning	
	BI4	Assuming I had access to the m-learning system, I would use it	

Source(s): Table by author

Table 1.

Constructs	Items	Outer loading	Cronbach's alpha	Composite reliability	AVE
Attitude	ATT1	0.733	0.912	0.939	0.796
	ATT2	0.95			
	ATT3	0.933			
	ATT4	0.935			
Behavioural intention	BI1	0.929	0.95	0.964	0.869
	BI2	0.926			
	BI3	0.938			
	BI4	0.936			
Discomfort	DIS1	0.746	0.855	0.901	0.696
	DIS2	0.884			
	DIS3	0.882			
	DIS4	0.817			
Innovativeness	INN1	0.84	0.911	0.937	0.79
	INN2	0.881			
	INN3	0.914			
	INN4	0.917			
Insecurity	INS1	0.854	0.885	0.915	0.684
	INS2	0.86			
	INS3	0.78			
	INS4	0.825			
	INS5	0.813			
Optimism	OPT1	0.941	0.951	0.964	0.872
	OPT2	0.922			
	OPT3	0.928			
	OPT4	0.943			
Perceived ease of use	PEOU1	0.927	0.964	0.972	0.874
	PEOU2	0.927			
	PEOU3	0.938			
	PEOU4	0.935			
	PEOU5	0.948			
Perceived Usefulness	PU1	0.936	0.969	0.976	0.891
	PU2	0.953			
	PU3	0.95			
	PU4	0.944			
	PU5	0.937			

Source(s): Table by author

Table 2.
Constructs reliability and validity

Table 3.
Discriminant validity

	ATT	BI	DIS	INN	INS	OPT	PEOU	PU
ATT	0.892							
BI	0.884	0.932						
Discomfort	0.375	0.352	0.834					
Innovativeness	0.54	0.523	0.468	0.889				
Insecurity	0.376	0.299	0.775	0.53	0.827			
Optimism	0.576	0.538	0.464	0.861	0.543	0.934		
PEOU	0.759	0.728	0.457	0.625	0.482	0.674	0.935	
PU	0.773	0.74	0.428	0.615	0.438	0.664	0.925	0.944

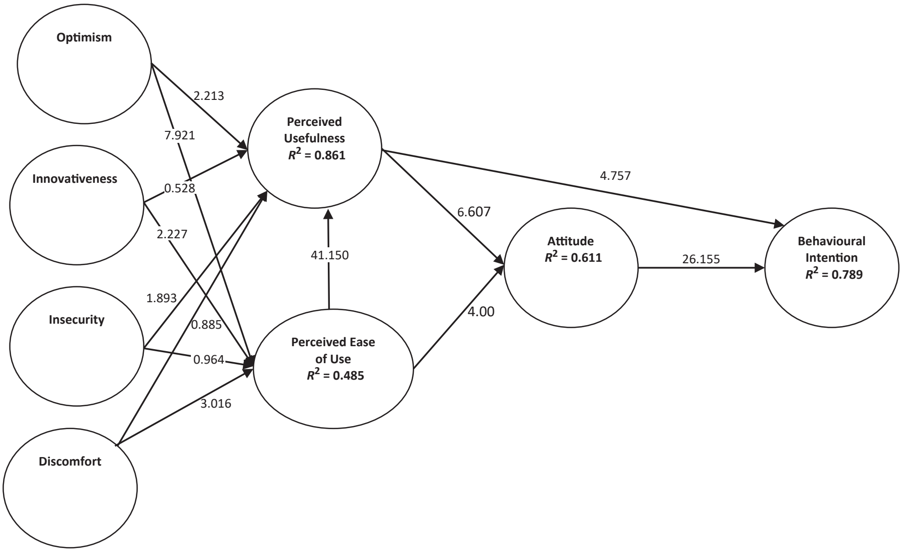
Source(s): Table by author

Table 4.
Results of testing of hypothesis

Hypothesis	Path	Mean	SD	t	Supported
H1	Optimism → PEOU	0.469	0.06	7.921*	Supported
H2	Optimism → PU	0.074	0.035	2.123**	Supported
H3	Innovativeness → PEOU	0.128	0.056	2.227**	Supported
H4	Innovativeness → PU	0.019	0.036	0.528***	Not Supported
H5	Discomfort → PEOU	0.139	0.046	3.016**	Supported
H6	Discomfort → PU	0.027	0.03	0.885***	Not Supported
H7	Insecurity → PEOU	0.05	0.051	0.964***	Not Supported
H8	Insecurity → PU	−0.057	0.029	1.893***	Not Supported
H9	PU → ATT	0.491	0.074	6.607*	Supported
H10	PU → BI	0.141	0.03	4.757*	Supported
H11	PEOU → PU	0.878	0.021	41.15*	Supported
H12	PEOU → ATT	0.303	0.076	4.006*	Supported
H13	ATT → BI	0.774	0.03	26.155*	Supported

Note(s): * $p < 0.001$ ** $p < 0.05$ *** $p > 0.05$
Source(s): Table by author

The structural model in SmartPLS supports the given hypotheses, as shown in Figure 2, by the standardised coefficients and significance levels for each path. The results obtained in the study supported that optimism about m-learning positively affects PEOU ($\beta = 7.921$, $p < 0.001$). OPT (optimism) → PEOU is significant, thus supporting H1. ODL students were optimistic about new technology vis-a-vis m-learning, which positively influences PEOU. The study results show that optimism about m-learning positively affects PU ($\beta = 2.123$, $p < 0.05$). OPT → PU is significant, thus, supporting *H2*. ODL students are optimistic about new technology, which positively influences PU. Innovativeness is a significant predictor of PEOU. Innovativeness about m-learning positively affects PEOU ($\beta = 2.227$, $p < 0.05$), and the path coefficient estimate is significant. Thus, *H3* is supported. Nowadays, ODL students are ready to accept innovative technologies like e-learning and m-learning in teaching and learning, so it positively influences PEOU. Unlike H3, the results of the present study show that innovativeness does not affect PU ($\beta = 0.525$, $p > 0.05$), and the path estimate is not significant. Thus, the *H4* is not supported. It is assumed that negative readiness for new technology, like discomfort, negatively affects PEOU. The results show that discomfort about m-learning led to lower PEOU ($\beta = 3.016$, $p < 0.05$). Path coefficients estimate proves that it is significant, thus supporting H5. Unlike hypothesis H5, the study results show that discomfort with regards to m-learning did not lead to lower PU ($\beta = 0.885$, $p > 0.05$). Path coefficients estimate proves that it is not significant. Thus, the H6 is not supported.



Source(s): Figure by author

Figure 2.
Results of PLS-SEM model

The results obtained in the study did not support that insecurity with regard to m-learning leads to lower PEOU ($\beta = 0.964$, $p > 0.05$), and the path estimate is not significant. Thus, H7 is not supported. The study's findings did not support that insecurity regarding m-learning leads to lower PU ($\beta = 1.893$, $p > 0.05$). There is no statistically significant relationship between insecurity and PU. Thus, H8 is not supported. The results obtained in the study supported the TAM theory that PU affects the attitude toward m-learning ($\beta = 6.607$, $p < 0.001$). It reveals that the path is statistically significant. Thus, H9 is supported. M-learning is very useful in teaching and learning of ODL students. Consequently, it affects their attitude towards m-learning. The results obtained in the study supported the perception that the PU of m-learning positively affects BI to use it ($\beta = 4.757$, $p < 0.001$). It reveals that the path estimate is significant. Thus, H10 is supported. It may be concluded that the usefulness of m-learning is a strong predictor of BI of ODL students to use or continue their use of m-learning for their studies.

PEOU is considered one of the main predictors that positively influence their PU of m-learning. The findings of the study support the hypothesis with survey data. Table 4 shows that all the items of the construct PEOU strongly correlate with that PU ($\beta = 41.15$ $p < 0.001$). Thus, H11 is supported. Once ODL students perceive that m-learning is easy to use, its usefulness increases. The results obtained in the study support that PEOU positively affects attitude ($\beta = 4.006$, $p < 0.001$). It reveals that the path estimate is significant. Thus, H12 is supported. ODL students reported to have used m-learning with ease; therefore, it affected their attitude towards m-learning. The results obtained in the study supported the hypothesis that attitude towards m-learning positively affects behavioural intention to use it ($\beta = 26.155$, $p < 0.001$). The path estimate is significant, and H13 is supported. It can be concluded here that attitude is a strong predictor of BI to use m-learning.

Discussion

M-learning is a form of distance education wherein m-learners use mobile educational technology conveniently (Crescente and Lee, 2011). Due to its intrinsic benefits, particularly the mobility of learning, the use of m-learning is growing manifold by millennial students irrespective of their academic discipline. The present study validated a m-learning readiness scale through TRAM and assessed ODL students' readiness to adopt m-learning in teaching and learning, including its acceptance. Optimism and innovativeness are the two key drivers of TR. The results obtained from the TRAM shows that optimism contributes positively to PEOU and PU of m-learning (H1, $p < 0.001$, H2, $p < 0.05$), which is in line with the earlier studies (Buyle *et al.*, 2018; Chen and Lin, 2018; Chung *et al.*, 2015; Kim and Chiu, 2019), whereas innovativeness positively contributes to the PEOU of m-learning (H3, $p < 0.05$), but not the PU of m-learning. Interestingly, the results show that the ODL student's optimism improves his/her PEOU and PU of m-learning, but innovativeness improves only his/her PEOU. That is to say, ODL students' innovativeness can encourage him/her to use m-learning, but whether m-learning is useful in his/her pursuit of academic activities depends on the structure, design and contents of m-learning. Plausibly, the impact of innovativeness is higher than that of optimism in the TRAM. In line with the earlier research studies (Chen and Lin, 2018), innovativeness is a strong predictor of adopting and adapting to new services and features like m-learning. Discomfort and insecurity are the two negative TR. The results obtained from TRAM showed that discomfort has a negative impact on PEOU of m-learning (H5, $p < 0.05$). This indicates that when an ODL student perceives a lack of control over m-learning and a feeling of being overwhelmed by it, he/she is less likely to perceive m-learning as easy to use.

PEOU and PU of m-learning positively influence ODL students' attitudes toward using m-learning (H9, $p < 0.001$; H12, $p < 0.001$). That is to say, if a student perceives m-learning as easy to use and having learning benefits, his/her attitude is more positive. PU is a strong predictor of BI. The present study shows that the PU of m-learning by the ODL student positively influences his/her intention to use m-learning for teaching and learning (H10, $p < 0.001$). That means the more the usefulness of m-learning, the stronger the students' behavioural intention to use m-learning. Conforming to existing literature (Davis, 1993; Gómez-Ramirez *et al.*, 2019; Iqbal and Bhatti, 2015; Venkatesh, 2000; Verkijika, 2019) results indicate that the attitude of ODL students has a significant influence on behaviour intention to use m-learning (H13, $p < 0.001$). The findings of the study are in conformation with earlier research studies (Lin *et al.*, 2007), and it is proved that the integration of TR with TAM to predict students' acceptance of m-learning is very useful.

Conclusions

The findings of the study have methodological, theoretical and practical contributions. From the methodological and theoretical point of view, earlier studies using TRAM have only focussed on health care, tourism, sports, banking and e-services (Chen and Lin, 2018; Chung *et al.*, 2015; Huang *et al.*, 2015; Jin, 2020; Kim and Chiu, 2019; Marhefka *et al.*, 2019; Sivathanu, 2019) and the acceptance of m-learning (Shuja *et al.*, 2019; Verkijika, 2019; Wang *et al.*, 2019) have been researched. However, m-learning readiness and its acceptance by students using TRAM have not been investigated. This study has attempted to empirically explore the readiness and acceptance of m-learning by higher education students, particularly ODL students. The findings of this study reveal that eight constructs, namely optimism, innovativeness, insecurity, discomfort, PEOU, PU, attitude and BI, extracted from the TRI and TAM, have contributed most to the readiness and acceptance of m-learning by the ODL students. Structural equation model (SEM) results show that these eight constructs reveal 78% of m-learning acceptance among ODL students. Therefore, this study academically suggests that the potential of m-learning may be leveraged in ODL environment. The present study offers some practical contributions to higher education in general, and open and distance education in particular. The results show that TR has a positive and significant effect on PU of m-learning, and the ODL student's PU of m-learning affects his/or her intention to utilise m-learning for teaching and learning. Despite some contributions of the study, it has a few limitations too. The study findings are specific to ODL students in Odisha, India and cannot be generalised to higher educational institutions. Thus, future research should focus on other higher educational institutions with larger samples.

References

Adams, D.A., Nelson, R.R. and Todd, P.A. (1992), "Perceived usefulness, ease of use, and usage of information technology: a replication", *MIS Quarterly*, Vol. 16 No. 2, p. 227, doi: 10.2307/249577.

Agarwal, R. and Prasad, J. (1999), "Are individual differences germane to the acceptance of new information technologies?", *Decision Sciences*, Vol. 30 No. 2, pp. 361-391, doi: 10.1111/j.1540-5915.1999.tb01614.x.

Ajzen, I. and Fishbein, M. (1980), *Understanding Attitudes and Predictiing Social Behavior*, Prentice-Hall, NJ.

Aloqaily, A., Al-Nawayseh, M.K., Baarah, A.H., Salah, Z., Al-Hassan, M. and Al-Ghuwairi, A.-R. (2019), "A neural network analytical model for predicting determinants of mobile learning acceptance", *International Journal of Computer Applications in Technology*, Vol. 60 No. 1, pp. 73-85, doi: 10.1504/IJCAT.2019.099502.

Arain, A.A., Hussain, Z., Rizvi, W.H. and Vighio, M.S. (2019), "Extending UTAUT2 toward acceptance of mobile learning in the context of higher education", *Universal Access in the Information Society*, Vol. 18 No. 3, pp. 659-673, doi: 10.1007/s10209-019-00685-8.

Buyle, R., Van Compernolle, M., Vlassenroot, E., Vanlishout, Z., Mechant, P. and Mannens, E. (2018), "'Technology readiness and acceptance model' as a predictor for the use intention of data standards in Smart cities", *Media and Communication*, Vol. 6 No. 4, pp. 127-139, doi: 10.17645/mac.v6i4.1679.

Chau, P.Y.K. and Hu, P.J.-H. (2002), "Investigating healthcare professionals' decisions to accept telemedicine technology: an empirical test of competing theories", *Information and Management*, Vol. 39 No. 4, pp. 297-311, doi: 10.1016/S0378-7206(01)00098-2.

Chavoshi, A. and Hamidi, H. (2019), "Social, individual, technological and pedagogical factors influencing mobile learning acceptance in higher education: a case from Iran", *Telematics and Informatics*, Vol. 38, pp. 133-165, doi: 10.1016/j.tele.2018.09.007.

Chen, M.-F. and Lin, N.-P. (2018), "Incorporation of health consciousness into the technology readiness and acceptance model to predict app download and usage intentions", *Internet Research*, Vol. 28 No. 2, pp. 351-373, doi: 10.1108/IntR-03-2017-0099.

Chung, N., Han, H. and Joun, Y. (2015), "Tourists' intention to visit a destination: the role of augmented reality (AR) application for a heritage site", *Computers in Human Behavior*, Vol. 50, pp. 588-599, doi: 10.1016/j.chb.2015.02.068.

Crescente, M.L. and Lee, D. (2011), "Critical issues of m-learning: design models, adoption processes, and future trends", *Journal of the Chinese Institute of Industrial Engineers*, Vol. 28 No. 2, pp. 111-123, doi: 10.1080/10170669.2010.548856.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, p. 319, doi: 10.2307/249008.

Davis, F.D. (1993), "User acceptance of information technology: system characteristics, user perceptions and behavioral impacts", *International Journal of Man-Machine Studies*, Vol. 38 No. 3, pp. 475-487, doi: 10.1006/imms.1993.1022.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989), "User acceptance of computer technology: a comparison of two theoretical models", *Management Science*, Vol. 35 No. 8, pp. 982-1003, doi: 10.1287/mnsc.35.8.982.

Escobar-Rodriguez, T. and Monge-Lozano, P. (2012), "The acceptance of Moodle technology by business administration students", *Computers and Education*, Vol. 58 No. 4, pp. 1085-1093.

Fagan, M.H. (2019), "Factors influencing student acceptance of mobile learning in higher education", *Computers in the Schools*, Vol. 36 No. 2, pp. 105-121, doi: 10.1080/07380569.2019.1603051.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50.

Gómez-Ramirez, I., Valencia-Arias, A. and Duque, L. (2019), "Approach to M-learning acceptance among university students: an integrated model of TPB and TAM", *International Review of Research in Open and Distance Learning*, Vol. 20 No. 3, pp. 141-164.

Hair, F.J., Jr, Sarstedt, M., Hopkins, L. and Kuppelwieser, V.G. (2014), "Partial least squares structural equation modeling (PLS-SEM)", *European Business Review*, Vol. 26 No. 2, pp. 106-121, doi: 10.1108/EBR-10-2013-0128.

Ho Cheong, J. and Park, M. (2005), "Mobile internet acceptance in Korea", *Internet Research*, Vol. 15 No. 2, pp. 125-140, doi: 10.1108/10662240510590324.

Huang, Y.-M. and Chiu, P.-S. (2015), "The effectiveness of a meaningful learning-based evaluation model for context-aware mobile learning", *British Journal of Educational Technology*, Vol. 46 No. 2, pp. 437-447, doi: 10.1111/bjet.12147.

Huang, J.-M., Ho, T.-K., Liu, Y.-C. and Lin, Y.-H. (2015), "A discussion on the user intention of golfers toward golf GPS navigation", *Journal of Hospitality and Tourism Technology*, Vol. 6 No. 1, pp. 26-39, doi: 10.1108/JHTT-02-2015-0013.

Iqbal, S. and Bhatti, Z.A. (2015), "An investigation of university student readiness towards M-learning using technology acceptance model", *International Review of Research in Open and Distance Learning*, Vol. 16 No. 4, pp. 83-103.

Jeno, L.M., Vandvik, V., Eliassen, S. and Grytnes, J.-A. (2019), "Testing the novelty effect of an m-learning tool on internalization and achievement: a Self-Determination Theory approach", *Computers and Education*, Vol. 128, pp. 398-413, doi: 10.1016/j.compedu.2018.10.008.

Jin, C. (2013), "The perspective of a revised TRAM on social capital building: the case of Facebook usage", *Information and Management*, Vol. 50 No. 4, pp. 162-168, doi: 10.1016/j.im.2013.03.002.

Jin, C.H. (2020), "Predicting the use of brand application based on a TRAM", *International Journal of Human-Computer Interaction*, Vol. 36 No. 2, pp. 156-171, doi: 10.1080/10447318.2019.1609227.

Kim, T. and Chiu, W. (2019), "Consumer acceptance of sports wearable technology: the role of technology readiness", *International Journal of Sports Marketing and Sponsorship*, Vol. 20 No. 1, pp. 109-126, doi: 10.1108/IJSMS-06-2017-0050.

Krull, G. and Duart, J.M. (2017), "Research trends in mobile learning in higher education: a systematic review of articles (2011-2015)", *International Review of Research in Open and Distance Learning*, Vol. 18 No. 7, pp. 1-23, doi: 10.19173/irrodl.v18i7.2893.

Kuo, Y.-C., Walker, A.E., Belland, B.R. and Schroder, K.E.E. (2013), "A predictive study of student satisfaction in online education programs", *The International Review of Research in Open and Distributed Learning*, Vol. 14 No. 1, p. 16, doi: 10.19173/irrodl.v14i1.1338.

Li, K.C., Lee, L.Y.K., Wong, S.L., Yau, I.S.Y. and Wong, B.T.M. (2019), "The effects of mobile learning for nursing students: an integrative evaluation of learning process, learning motivation, and study performance", *International Journal of Mobile Learning and Organisation*, Vol. 13 No. 1, p. 51, doi: 10.1504/IJMLO.2019.096471.

Lin, C.-H., Shih, H.-Y. and Sher, P.J. (2007), "Integrating technology readiness into technology acceptance: the TRAM model", *Psychology and Marketing*, Vol. 24 No. 7, pp. 641-657, doi: 10.1002/mar.20177.

Marhefka, S.L., Turner, D. and Lockhart, E. (2019), "Understanding women's willingness to use e-health for HIV-related services: a novel application of the technology readiness and acceptance model to a highly stigmatized medical condition", *Telemedicine and E-Health*, Vol. 25 No. 6, pp. 511-518, doi: 10.1089/tmj.2018.0066.

Martens, M., Roll, O. and Elliott, R. (2017), "Testing the technology readiness and acceptance model for mobile payments across Germany and South Africa", *International Journal of Innovation and Technology Management*, Vol. 14, p. 6, doi: 10.1142/S021987701750033X.

Netemeyer, R.G., Bearden, W.O. and Sharma, S. (2003), *Scaling Procedures: Issues and Applications*, Sage, New York.

Nunnally, J.C. (1978), *Psychometric Theory, Educational Researcher*, McGraw-Hill, New York.

Padilla-Meléndez, A., Garrido-Moreno, A. and Del Aguila-Obra, A.R. (2008), "Factors affecting e-collaboration technology use among management students", *Computers and Education*, Vol. 51 No. 2, pp. 609-623, doi: 10.1016/j.compedu.2007.06.013.

Parasuraman, A. (2000), "Technology readiness index (Tri): a multiple-item scale to measure readiness to embrace new technologies", *Journal of Service Research*, Vol. 2 No. 4, pp. 307-320, doi: 10.1177/109467050024001.

Parasuraman, A. and Colby, C.L. (2015), "An updated and streamlined technology readiness index", *Journal of Service Research*, Vol. 18 No. 1, pp. 59-74, doi: 10.1177/1094670514539730.

Park, S.Y., Nam, M. and Cha, S. (2012), "University students' behavioral intention to use mobile learning: evaluating the technology acceptance model", *British Journal of Educational Technology*, Vol. 43 No. 4, pp. 592-605.

Roca, J.C., Chiu, C.-M. and Martínez, F.J. (2006), "Understanding e-learning continuance intention: an extension of the Technology Acceptance Model", *International Journal of Human Computer Studies*, Vol. 64 No. 8, pp. 683-696, doi: 10.1016/j.ijhcs.2006.01.003.

Rudestam, K.E. and Schoenholtz-Read, J. (2009), *Handbook of Online Learning*, Sage Publications, CA.

Sánchez, R.A. and Hueros, A.D. (2010), "Motivational factors that influence the acceptance of Moodle using TAM", *Computers in Human Behavior*, Vol. 26 No. 6, pp. 1632-1640, doi: 10.1016/j.chb.2010.06.011.

Sánchez-Prieto, J.C., Hernández-García, Á., García-Peñalvo, F.J., Chaparro-Peláez, J. and Olmos-Migueláñez, S. (2019), "Break the walls! Second-Order barriers and the acceptance of mLearning by first-year pre-service teachers", *Computers in Human Behavior*, Vol. 95, pp. 158-167, doi: 10.1016/j.chb.2019.01.019.

Shih, J.-L., Chuang, C.-W. and Hwang, G.-J. (2010), "An inquiry-based mobile learning approach to enhancing social science learning effectiveness", *Journal of Educational Technology and Society*, Vol. 13 No. 4, pp. 50-62.

Shuja, A., Qureshi, I.A., Schaeffer, D.M. and Zareen, M. (2019), "Effect of m-learning on students' academic performance mediated by facilitation discourse and flexibility", *Knowledge Management and E-Learning*, Vol. 11 No. 2, pp. 158-200, doi: 10.34105/j.kmel.2019.11.009.

Sivathanu, B. (2019), "An empirical study on the intention to use open banking in India", *Information Resources Management Journal*, Vol. 32 No. 3, pp. 27-47, doi: 10.4018/IRMJ.2019070102.

Smith, R., Deitz, G., Royne, M.B., Hansen, J.D., Grünhagen, M. and Witte, C. (2013), "Cross-cultural examination of online shopping behavior: a comparison of Norway, Germany, and the United States", *Journal of Business Research*, Vol. 66 No. 3, pp. 328-335, doi: 10.1016/j.jbusres.2011.08.013.

Szajna, B. (1994), "Software evaluation and choice: predictive validation of the technology acceptance instrument", *MIS Quarterly*, Vol. 18 No. 3, p. 319, doi: 10.2307/249621.

Venkatesh, V. (2000), "Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the technology acceptance model", *Information Systems Research*, Vol. 11 No. 4, pp. 342-365, doi: 10.1287/isre.11.4.342.11872.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27, pp. 425-478.

Verkijika, S.F. (2019), "Understanding the acceptance and use of m-learning apps by entrepreneurs: an application of the social-cognitive and motivational theories", *Information Resources Management Journal*, Vol. 32 No. 4, pp. 42-55, doi: 10.4018/IRMJ.2019100103.

Wang, Y.-Y., Wang, Y.-S., Lin, H.-H. and Tsai, T.-H. (2019), "Developing and validating a model for assessing paid mobile learning app success", *Interactive Learning Environments*, Vol. 27 No. 4, pp. 458-477, doi: 10.1080/10494820.2018.1484773.

Yen, H.R. (2005), "An attribute-based model of quality satisfaction for internet self-service technology", *The Service Industries Journal*, Vol. 25 No. 5, pp. 641-659.

Yi, Y., Lai Tung, L., Wu, Z. and Lai, L. (2003), "Incorporating technology readiness (TR) into TAM: are individual traits important to understand technology acceptance?", *Digit 2003 Proceedings*.

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