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
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 technology (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:

![Figure 1. Research model](source(s): Figure courtesy of Lin et al. (2007))
Optimism about m-learning affects the perceived ease of use.

Optimism about m-learning affects the perceived usefulness.

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

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:

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

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

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

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-Ramírez 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.

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

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

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

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-Ramírez et al., 2019; Iqbal and Bhatti, 2015; Verkijika, 2019). Therefore, the following hypothesis is formulated.

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 0.7, 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.
<table>
<thead>
<tr>
<th>Constructs</th>
<th>Items</th>
<th>Indicators</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimism</td>
<td>OPT1</td>
<td>New technologies contribute to a better quality of life</td>
<td>Parasuraman and Colby (2015), Parasuraman (2000)</td>
</tr>
<tr>
<td></td>
<td>OPT2</td>
<td>Technology gives me more freedom of mobility</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OPT3</td>
<td>Technology makes me more efficient in my occupation</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OPT4</td>
<td>I like the idea of using new technology in education</td>
<td></td>
</tr>
<tr>
<td>Innovativeness</td>
<td>INN1</td>
<td>In general, I am among the first in my circle of friends to acquire new technology when it appears</td>
<td>Parasuraman and Colby (2015), Parasuraman (2000)</td>
</tr>
<tr>
<td></td>
<td>INN2</td>
<td>I can usually figure out new high-tech products and services without help from others</td>
<td></td>
</tr>
<tr>
<td></td>
<td>INN3</td>
<td>I keep up with the latest technological developments in my areas of interest</td>
<td></td>
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<tr>
<td></td>
<td>INN4</td>
<td>I prefer to use the most advanced technology available</td>
<td></td>
</tr>
<tr>
<td>Insecurity</td>
<td>INS1</td>
<td>Excessive use of technology distracts people to a point that is harmful</td>
<td>Parasuraman and Colby (2015), Parasuraman (2000)</td>
</tr>
<tr>
<td></td>
<td>INS2</td>
<td>I worry that information that I make available over the Internet may be misused by others</td>
<td></td>
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<tr>
<td></td>
<td>INS3</td>
<td>I do not feel confident doing any business transaction with a place that can only be reached online</td>
<td></td>
</tr>
<tr>
<td></td>
<td>INS4</td>
<td>I do not consider it safe to provide personal information over the Internet</td>
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<tr>
<td></td>
<td>INS5</td>
<td>Any business transaction I do electronically should be confirmed later with a separate communication</td>
<td></td>
</tr>
<tr>
<td>Discomfort</td>
<td>DIS1</td>
<td>Sometimes, I think that technology systems are not designed for use by ordinary people</td>
<td>Parasuraman and Colby (2015), Parasuraman (2000)</td>
</tr>
<tr>
<td></td>
<td>DIS2</td>
<td>Many new technologies have health or safety risks that are not discovered until after people have used them</td>
<td></td>
</tr>
<tr>
<td></td>
<td>DIS3</td>
<td>There should be caution in replacing important people tasks with technology because new technology can break down or get disconnected</td>
<td></td>
</tr>
<tr>
<td></td>
<td>DIS4</td>
<td>Technology always seems to fail at the worst possible time</td>
<td></td>
</tr>
<tr>
<td>Perceived Usefulness</td>
<td>PU1</td>
<td>M-learning system helps me to learn more efficiently</td>
<td>Davis (1989)</td>
</tr>
<tr>
<td></td>
<td>PU2</td>
<td>M-learning system improves my academic performance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PU3</td>
<td>M-learning system makes my learning more effective</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PU4</td>
<td>M-learning system makes it easier to learn</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PU5</td>
<td>Overall, m-learning system is beneficial for my learning</td>
<td></td>
</tr>
<tr>
<td>Perceived ease of use</td>
<td>PEOU1</td>
<td>Learning to use m-learning system is easy for me</td>
<td>Davis (1989)</td>
</tr>
<tr>
<td></td>
<td>PEOU2</td>
<td>It is easy to get materials from m-learning system</td>
<td></td>
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<tr>
<td></td>
<td>PEOU3</td>
<td>The process of using m-learning system is clear and understandable</td>
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<tr>
<td></td>
<td>PEOU4</td>
<td>It is easy for me to become skillful at using m-learning system</td>
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<td></td>
<td>PEOU5</td>
<td>Overall, I find m-learning system is easy to use</td>
<td></td>
</tr>
</tbody>
</table>

Table 1. Constructs and items adapted to measure technology readiness and acceptance of m-learning (continued)
### Table 1. Constructs, Items, and Indicators

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

**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 (β = 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 (β = 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 (β = 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 (β = 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 (β = 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 (β = 0.885, p > 0.05). Path coefficients estimate proves that it is not significant. Thus, the H6 is not supported.
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 ($\beta = 4.00, p < 0.001$). 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/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


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