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PREDICTING RURAL STEM TEACHERS' ACCEPTANCE OF MOBILE LEARNING IN THE FOURTH INDUSTRIAL REVOLUTION

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ABSTRACT
In South Africa, high schools' Science, Technology, Engineering, and Mathematics (STEM) education is faced with many challenges. However, previous studies have shown that mobile learning (m-learning) can be used to lessen the challenges faced in STEM education. Despite the benefits that m-learning can bring into STEM classrooms, its adoption is still below the expected rate. The acceptance of m-learning depends on the attitude of its users. Most studies focused on learners' acceptance of m-learning. However, very little is known about rural high school STEM teachers' acceptance of m-learning in the Fourth industrial revolution (4IR) era. This study proposes a model, which extends the Technology Acceptance Model by introducing perceived social influence and perceived resources. Stratified random sampling was used to select 150 teachers to participate in the survey. A total of 114 valid questionnaires were collected, and data were analysed using partial least squares structural equation modelling. The proposed model explained 37.9 % of the variance in teachers' behavioural intention to use m-learning in the 4IR era. Perceived attitude towards the use was found to be the best predictor of teachers' behavioural intention, followed by perceived ease of use, perceived resources, perceived social influence, and lastly perceived usefulness.

Keywords: Acceptance, Fourth industrial revolution, Mobile learning, STEM, Technology Acceptance Model

1. INTRODUCTION
The increased advancement in technological developments is transforming the way we live, communicate, socialise, travel, and work. Schwab (2016) observes that "in its scale, scope, and complexity, the transformation will be unlike anything humankind has experienced before," and we are finding ourselves in yet another revolution called the Fourth Industrial Revolution (4IR). The 4IR started in the early 2000s (Yusuf, Walters and Sailin, 2020). The 4IR often is described as "the compounding product and multiple integrating effects of "exponential technologies," like artificial intelligence, computer networking technology, biotechnologies, and nanomaterials" (Yusuf et al. 2020, p.94). The 4IR is powered by 'Internet of Things'(IoT), Robotics, Nanotechnology, Genomics, Artificial Intelligence, Virtual Reality (VR), Cloud, Edge, Fog computing, and other technologies (Yusuf et al. 2020). The 4IR can improve the quality of life of all the people around the world and raise global income levels. Shortly, countries that will lead in this revolution will benefit a lot as the cost of transportation will drop, the global supply chain will become effective, the cost of trade will decrease, and this will drive economic growth. Additionally, this technological advancement

will allow these countries to produce services and products more cheaply than low wage workers (Sekiyama 2020).

Makgato (2019) reported that 4IR is creating new forms of jobs. It is estimated that 65% of children entering primary school will work in jobs that are currently not existing (Yusuf et al. 2020). To prepare these children for 4IR jobs, schools should equip them with cognitive abilities, basic skills, and cross-functional skills. Cognitive abilities require a child to have a flexible mindset, be creative, think logically, and to reason mathematically (Yusuf et al. 2020). Yusuf et al. (2020) differentiated basic skills into content and process skills. M-learning can help learners to acquire these skills through the use of educational games. Content skills require active learning, information and communication technology literacy, written and oral expression. Through the use of m-learning learners will be able to use digital technology, communications tools, and/or networks to access, manage, integrate, evaluate, and create information in order to function in a knowledge society (Tomei, 2008). Critical thinking, active listening, and collaboration form process skills. Yusuf et al. (2020) stated that cross-functional skillset cuts across other skillsets dimensions, like complex problem-solving skills, social skills, and technical skills. Most of these skills that the 4IR require are part of Science, Technology, Engineering, and Mathematics (STEM) education. Makgato (2019) reported that 75% of the fastest-growing occupations require STEM skills and knowledge. However, there is no interest and poor performance in STEM-related subjects in South Africa (Makgato, 2019).

In South Africa, high schools' STEM education is faced with many challenges, especially in rural areas (Bosman and Schulze 2018; Makgato 2007; Mashaba and Maile 2018; Mboweni 2014). Coupled with local assessments, international assessments in Mathematics and Science, like the Trends in International Mathematics and Science Studies, show that, compared to other developing countries, the performance of South African learners in Mathematics and Science is very poor, especially for African learners in rural areas (Mupira and Ramnarain 2018). According to Bosman and Schulze (2018), teachers use traditional face-to-face instruction (FTF) which fail to stimulate deep holistic STEM learning experiences. Bosman and Schulze (2018) added that this poor performance in STEM-related subjects in rural areas is caused by prolonged mismatches between the teaching styles and learners' learning preferences in the classroom. Lack of learning materials, science laboratories, and equipment to enhance effective STEM teaching and learning in rural high schools contribute to poor learners' performance (Mboweni 2014). Mashaba and Maile (2018) attribute learners' poor performance in mathematics and science in rural areas to a high rate of teacher absenteeism. The high rate of teacher absenteeism is caused by teachers getting into the classroom late or leaving the classroom early before time, teachers attending union meetings, workshops, transport problems, and violence in high schools. The conclusion that can be drawn from these studies (Bosman and Schulze 2018; Makgato 2007; Mashaba and Maile 2018; Mboweni 2014) is that in rural high schools there is no effective STEM teaching and learning. This leads to learners not acquiring the skills needed in the 4IR.

A plethora of studies has shown that m-learning can be used to mitigate the challenges in STEM education (Almaiah et al. 2016; Alrajawy et al. 2017; DoE 2017; Koehler and Mishra 2016; Pinker 1997). With the coming in of the 4IR to Africa, m-learning will be improved even in rural areas, as mobile broadband and fast, and reliable internet access will be made available. Data bundles will also be made cheaper, making m-learning affordable in rural areas. According to Koehler and Mishra (2016), m-learning changes a teacher-centred approach to learner-centred, which can stimulate deep holistic learning experiences. M-learning also provides teachers with many different teaching methods such as the use of audio recording features, live polling tools, chat, online discussion forums, and group work (Yeap et al. 2016), which can be used to meet learners' different learning preferences. M-learning enables learners to visualise science experiments, which can improve learners' knowledge of science, and enable them to give complete explanations of scientific concepts

(Pinker 1997).

Al-Emran and Salloum (2017) stated that m-learning provides learning material anywhere and anytime. M-learning increases contact time between teachers and learners (Almaiah et al. 2016), thereby minimising time loss. Mobile devices are affordable, can be used as a cognitive tool in learning tasks to solve realistic problems and encourage reflection and collaboration during learning (Grimus and Ebner, 2016). Grimus and Ebner (2016), carried out a study to assess the effects of m-learning on learners' performance in STEM-related subjects, and the results showed that it improves learners' performance. What can be learnt from these studies (Almaiah et al. 2016; Alrajawy et al. 2017; DoE 2017; Grimus and Ebner, 2016; Koehler and Mishra 2016; Pinker 1997), is that even though rural high school STEM education is faced with many challenges, m-learning can be used to alleviate these challenges and to help rural high school learners to acquire STEM skills which can prepare them for jobs in the 4IR era.

Mobile Learning denotes learning involving the use of a mobile device such as smartphone, tablets, Ipad, and laptops (Almaiah et al., 2016). M-learning provides unique opportunities for addressing many of the STEM education needs (Krishnamurthi and Richter, 2013). For effective STEM learning, m-learning can make content more engaging, and this motivates learners to spend time on learning. This can be achieved by implanting videos and problem-solving steps in their mobile STEM notes (Krishnamurthi and Richter, 2013). Lessons can also be recorded and delivered asynchronously, which allows STEM learners to watch them repeatedly until they understand the content. Furthermore, m-learning should enable learners to visualise experiments or to be able to interfere with the experimental setup online (Krishnamurthi and Richter, 2013).

Despite the benefits that m-learning can bring in a rural STEM classroom, Odiakaosa et al. (2017) stated that the potentials of m-learning are roundly overlooked, and cannot be tapped in if the attitudes of educators are not put into consideration. There is a big gap between the availability of technology and how it is being used by teachers for instructional purposes. Learners can informally support their learning using mobile devices; however, it will remain informal until teachers support its integration into a more formal way (Callum et al. 2014). Teachers select the instructional method they see fit to teach in their classes; they consider the type of technology to be used by learners, its quality, and the frequency (Sánchez-Prietoa et al. 2019). Learners' acceptance of m-learning can easily be influenced by their teachers. Consequently, teachers' intention to adopt m-learning in the 4IR era is vital for the successful implementation of m-learning in rural areas. Davis (1989) also stated that the acceptance of an information system (IS) depends on the user's attitudes. Because of the assessments of Callum et al. (2014) and Davis (1989), it could be argued that for m-learning to be successfully implemented in the 4IR era in rural in high schools, it depends on teachers' attitudes. Thus, it is necessary to investigate high school STEM teachers' attitudes towards m-learning in the 4IR era.

Several studies have been conducted in tertiary institutions on the acceptance of m-learning (Alasmari and Zhang 2019; Aldheleai et al. 2019; Al-Emran et al. 2016; Callum et al. 2014; Waheed and Jam 2010), hence its successful implementation. It is reasonable to state that, for m-learning to be successfully accepted in the 4IR era in rural high schools of developing countries, more teacher-acceptance studies are needed. Few studies have focused on high school teachers' (Siyam 2019; Alshmrany and Wilkinson 2017; Nikou and Economides 2018), and learners' (Estrieganaa et al. 2019; Ford and Botha 2010) acceptance of m-learning. Nikou and Economides (2018) investigated the acceptance of mobile assessment in 32 European countries, Siyam (2019) focused on the acceptance of m-learning by special education teachers, and Alshmrany and Wilkinson (2017) focused on the acceptance of m-learning by primary school teachers. Additionally, studies that explain m-learning acceptance in the 4IR era in the context of STEM, particularly in rural areas, continue to remain limited.

According to Ford and Botha (2010), for m-learning to be successfully implemented in South Africa, more studies on the acceptance of m-learning need to be conducted, especially on teachers' acceptance and not to blindly follow examples in developed countries. Based on the suggestion of Ford and Botha (2010), this study sought to examine the factors that rural high school STEM teachers consider important when accepting m-learning in the 4IR era. This is primarily because, (Siyam 2019; Alshmrany and Wilkinson 2017; Nikou and Economides 2018), did not look at the perceptions of rural high school STEM teachers towards m-learning in the 4IR era.

For m-learning to be successfully implemented in rural areas in the 4IR era, it is important to identify and understand the factors that rural high school STEM teachers consider important when accepting it. Thus, this study explores the variables that predict the rural high school STEM teachers' behavioural intention to use m-learning in the 4IR era. Specifically, the study aims to give answers to the following research questions:

> RQ1. What are the effects of perceived attitude towards the use, perceived resources, perceived social influence, perceived usefulness, and perceived ease of use on rural high school STEM teachers' behavioural intention to use m-learning in the 4IR era?
>
> RQ2. What is the relative importance of each of these factors in explaining rural high school STEM teachers' behavioural intention to use m-learning in the 4IR era?

By providing answers to these study questions, this study aims to gain insights into the relative importance of the factors that rural high school STEM teachers consider important when adopting m-learning in the 4IR era. The study proposes the development and validation of a model. The proposed model is an extension of the Technology Acceptance Model (TAM).

2. LITERATURE REVIEW

To encourage the use of an information system (IS), the IS needs to be made known to the potential users, and they should accept it. Getting more insight into the factors that potential users of IS consider is at the heart of adoption research (Hoi 2019) and helps relevant decision-makers to form informed decisions. Several models have been developed to explain user acceptance. In the context of m-learning, the TAM (Davis 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003) are the commonly used models. UTAUT is criticised for failing to predict behaviours that are not totally within an individual's control. M-learning can be implemented, and users can be forced to use it. Since UTAUT fails to predict the behaviours that an individual cannot decide on, it cannot be used in the current study.

Prior research has been carried out to understand teachers' acceptance of m-learning (Callum et al. 2014; Nikou and Economides 2019; Siyam 2019). Siyam (2019) extended the TAM to study the factors that special education high school teachers consider important when adopting the technology, like the study by Davis (1989), Siyam (2019) found that teachers' behavioural intention (BI) is influenced by both perceived usefulness (PU) and perceived attitudes towards (ATT) the use. These results were in line with the findings of Callum et al. (2014), who reported that the teachers' intentions to use m-learning were conditioned by their attitudes and the usefulness of m-learning. Congruent to the findings of Nikou and Economides (2019), both PU and perceived ease of use (PEOU) had a significant effect on ATT. Confirming the results of Callum et al. (2014), PEOU was found to influence teachers' PU (Siyam 2019).

Nikou and Economides (2019) extended the TAM by adding facilitating conditions (perceived resources (PR)). Nikou and Economides (2019) found that PR influences teachers' PEOU. Teo (2010) also extended the TAM by adding perceived social influence (PSI). The results showed that PSI influences teachers' PU, PEOU, and ATT.

3. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

Davis, Bagozzi, and Warshaw (1989) developed the TAM to predict the intention to adopt a new IS. Technology acceptance is defined as a person's thoughts regarding his or her planned use of technology (Siyam, 2019). Cheng (2019) reported that TAM is the most used model in predicting and explaining the intention of users to use a new IS. The TAM is built upon two pillars: perceived ease of use (PEOU) and perceived usefulness (PU). PU is influenced by PEOU. The TAM posits that perceived ease of use and perceived usefulness (PU) predicts perceived attitude towards the use (ATT). PU and ATT determine the user's behavioural intention to use (BI), which in turn influences the actual usage.

The TAM has received empirical support in academia for being robust in explaining and predicting m-learning acceptance (Park 2009; Sánchez-Prietoa et al. 2019; Teo 2009). However, the TAM has been criticised by other researchers (Carlsson, Carlsson, Hyvonen, Puhakainen, and Walden 2006; Venkatesh et al. 2003). Carlsson et al. (2006) criticised the TAM for being more general and applicable to the acceptance of technology in many different fields. Carlsson et al. (2006) stressed that m-learning is more individual, more personalised and focuses on services offered by the system. Another criticism of the TAM is its low explanatory power of users' attitudes towards the IS (Venkatesh et al. 2003). Based on the criticism by Carlsson et al. (2006) and Venkatesh et al. (2003), the TAM alone is not enough in predicting and explaining STEM teachers' acceptance of m-learning in the 4IR era. Consequently, this paper extended the TAM by adding two external variables: perceived resources and perceived social influence. These two factors are the factors that rural high school STEM teachers are more likely to consider important when accepting m-learning in the 4IR era.

3.1 Behavioural intention (BI)

Davis (1989) defined BI as the degree of strength of a user's intention to carry out a specified behaviour. Many studies have confirmed that the user's BI has a high correlation with the actual usage (Davis 1989; Teo 2010; Venkatesh and Davis 2000; Venkate et al. 2003). BI is considered the single best predictor of actual usage (Davis 1989; Venkatesh 2000). Based on the finding of Davis (1989) and Venkatesh (2000), one can conclude that understanding factors that influence BI is the same as understanding factors that influence the actual usage of m-learning by rural high school STEM teachers in the 4IR era.

3.2 Perceived attitude toward the use (ATT)

In the current study, ATT can be defined as a rural high school STEM teachers' overall affection reaction towards the use of m-learning. Teachers' attitudes and beliefs toward m-learning are the key factors for its successful adoption (Aldheleai et al. 2019). Siyam (2019) and Aldheleai et al. (2019) found that teachers' ATT positively influences their BI to use m-learning. If rural high school STEM teachers develop a positive attitude towards m-learning, they will use it in their STEM classrooms. Therefore, the hypothesis:

H1: Rural high school STEM teachers' ATT influences their BI to use m-learning in the 4IR.

3.3 Perceived ease of use (PEOU)

Sánchez-Prietoa et al. (2019) investigated the acceptance of m-learning by pre-service teachers. Their results confirmed the findings of Davis (1989) that PEOU had a direct positive effect on PU and ATT and an indirect effect on BI through PU and ATT. If rural

high school STEM teachers could experience m-learning and find it to require less effort to master, they will find m-learning useful and develop a positive attitude towards it. Therefore, the hypotheses:
H2: Rural high school STEM teachers' PEOU influences their PU.
H3: Rural high school STEM teachers' PEOU influences their ATT the use of m-learning in the 4IR era.
H4: Rural high school STEM teachers' PEOU influences their BI to use m-learning in the 4IR era.

3.4 Perceived usefulness (PU)

In the m-learning context, PU can be defined as the extent to which a learner or teacher believes that the use of m-learning will improve learners' performance. Prior studies revealed that teachers' PU has a significant positive effect on their BI to use m-learning (Hoi 2020, Aldheleai et al. 2019). Rural high school STEM teachers' feelings towards m-learning are influenced by their belief that it will improve learners' performance in STEM-related subjects. Therefore, the hypotheses:
H5: Rural high school STEM teachers' PU influences their ATT the use of m-learning in the 4IR era.
H6: Rural high school STEM teachers' PU influences their BI to use m-learning in the 4IR era.

3.5 Perceived social Influence (PSI)

PSI was defined by Venkatesh et al. (2003) as the degree to which a person thinks that people who are important to him or her believe that he or she should use an IS. For rural high school STEM teachers, the influence could come from learners, parents of learners, the Department of Education officials, and colleagues. Teachers are influenced by the messages they hear about m-learning. This was suggested by Venkatesh (2000), who stated that people internalise the beliefs of other people and make them part of their belief system. A person's intention to use m-learning is highly influenced by their perception that other people important to them expect that they should use m-learning (Teo 2010). If the influence on rural STEM teachers to accept m-learning in the 4IR era is coming from their learners, the influence is most likely to positively affect their PU and PEOU. In the study by Venkatesh and Davis (2000), PSI was found to have an indirect effect on BI through PU and PEOU. Therefore, the hypotheses:
H7: Rural high school STEM teachers' PSI influences their ATT the use in the 4IR era.
H8: Rural high school STEM teachers' PSI influences their PU.

3.6 Perceived resources (PR)

PR in m-learning can be defined as a person's belief that the availability of resources can facilitate the use of m-learning. The resources that are needed to facilitate m-learning are access to a wireless network, computer technical assistance, and availability of mobile devices and data bundles. Studies have shown that PR influences PU, PEOU, and ATT (Lim and Khine, 2006; Sivo et al., 2018; Teo, 2010). Contrary to the finding of Lim and Khine (2006), Alshmrany and Wilkinson (2017) found that the availability of resources did not influence primary school teachers' adoption of information and communication technology into the classroom. For m-learning to be successfully implemented, both the teachers and learners should have devices. This study is being carried out in rural areas. In rural areas, most families have financial problems, and they rely on social grants for survival (Mboweni 2014). Based on the results of Lim and Khine (2006) and Mboweni (2014), one can learn that rural high school STEM teachers' perceived resources will influence their PU, ATT, and PEOU towards the use of m-learning in the 4IR. Therefore, the hypotheses:

H9: Rural high school STEM teachers' PR influences their PU.
H10: Rural high school STEM teachers' PR influences their PEOU.
H11: Rural high school STEM teachers' perceived PR influences their ATT the use in the 4IR era.

Based on the theoretical underpinning and what prior studies have established, a hypothetical model is shown in Figure 1.

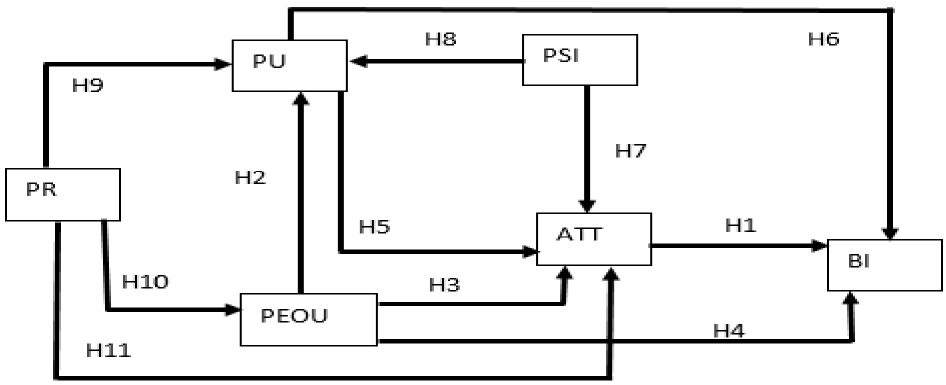

Figure 1. Hypothetical model

4. METHODS

4.1 Research Design

This study follows a quantitative methodology that collects demographic and opinion-related data by employing a survey. A survey method is considered the most appropriate for theory testing. According to Creswell (2014), survey designs are cost-effective and fast. Hypotheses were tested using the partial least squares structural equation model (PLS-SEM).

4.2 Participants

Participants of this study were rural high school STEM teachers in King Cetshwayo District in KwaZulu Natal. To collect data, the study used stratified sampling (Creswell 2014). All rural high schools in the district were grouped using their quintiles. Three strata were formed. Schools in the same quintiles were grouped to ensure that homogenous elements formed a stratum. Simple random sampling was then used to select 50 teachers from each stratum. A total of 150 teachers were selected and were given questionnaires. Of the 150 questionnaires given out, 114 (76 %) valid questionnaires were collected. Of the 114 who responded to the questionnaire, 65 (57%) were female, and the remaining 49 (43%) were males. Teachers who were 50 years and above were 20 (17%), while 44 (39%) were between 40 and 50, 31 (27%) were between 30 and 40, and 19 (17%) were less than 30.

Hair, Hult, Ringle, and Sarstedt (2017) and Chin (1998) recommended using a minimum sample size of 10 times larger than the number of indicators of the latent variable with the most items. In this study, perceived usefulness (with five indicators) was the constructs with most items, meaning that the minimum sample size should be 50. The study sample size is greater than the recommended minimum sample size of 50.

4.3 Measures

The questionnaire was divided into two sections. In the first section, rural high school STEM teachers were required to provide their demographical information. The second section comprised of the questions that were adopted from Sivo et al. (2018), Alrajawy et al. (2018), and Venkatesh et al. (2003) and modified to suit the needs of the current study. The items to measure teachers' BI, PEOU, and PU were adopted from Alrajawy et al. (2018). The items to measure ATT and PR were adopted from Sivo et al. (2018). The items used in this study to measure PSI were adopted from Venkatesh et al. (2003). This section comprised of scales measuring the latent variables of the model. The instrument consisted of six latent variables, with a total of 25 indicators. All items were measured on a 7-point Likert-type scale with 1 corresponding to "strongly disagree" and 7 to "strongly agree."

4.4 Structural Equation Modelling Analysis

To ascertain whether PU, PR, ATT, PSI, and PEOU are good predictors of rural high school STEM teachers' BI to use m-learning in the 4IR era. SmartPLS 3.2.8's PLS-SEM was employed to analyse the data. The PLS-SEM is a regression-based technique that minimises the residual variances of the independent variables (Hair et al. 2017). PLS-SEM deals with two path models: the outer model and the inner model. According to Henseler et al. (2016), the outer model establishes the relationship between the construct and its indicators while the inner model establishes the relationships among the constructs. In evaluating the outer model, reliability and validity tests were conducted on the latent variables to determine their suitability for inclusion in the inner model analysis.

4.4.1 Reliability and validity of latent variables

To ascertain the degree of consistency of various items of each latent variable, the reliability was conducted. The composite reliability (CR) was used to assess the internal consistency of each construct. Table 1 shows that all the CR scores were all above the 0.70 recommended threshold (Nunnally 1978), indicating that all the items used had satisfactory internal consistency reliability. Furthermore, convergent validity test was conducted using the average variance extracted (AVE) values of the constructs. Convergent validity assesses the degree to which a measure of the same constructs positively correlates with each other (Hair et al. 2017). According to Hair et al. (2017), at least 50% of the total variance should be explained by the indicators within the construct.

Table 1 shows that all the AVE values were above 0.50, indicating that convergent validity was assured. The indicator reliability was assessed using indicator outer loadings. Figure 3 shows that all the outer loadings were higher than the threshold value of 0.70, indicating indicator reliability. PU4 and ATT1 were removed from the model because they were having outer loadings lower than 0.70 and removing them increased the CR and AVE scores of their respective constructs (Hair et al. 2017).

Table 1: The CR and AVE values

Construct	ATT	BI	PEOU	PR	PSI	PU
Composite Reliability (CR)	0.918	0.898	0.941	0.860	0.956	0.941
Average Variance Extracted (AVE)	0.692	0.746	0.762	0.754	0.881	0.761

Lastly, Heterotrait – Monotrait Ratio (HTMT) discriminant validity tests were carried to ascertain how uncorrelated and distinct constructs are from each other. Figure 2 shows that all the HTMT values < 0.85, indicating that discriminant validity had been established.

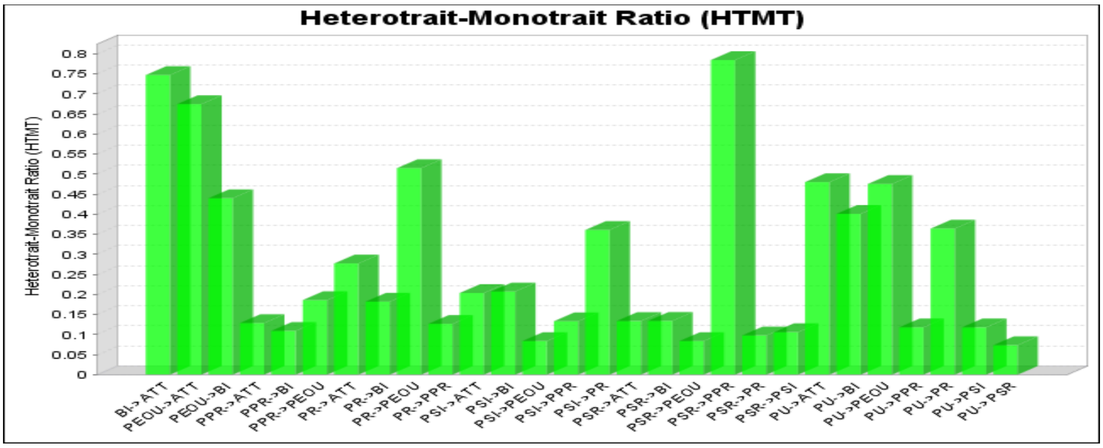

Figure 2. Heterotrait – Monotrait Ratio

The measurement model has demonstrated satisfactory reliability and validity. Therefore, it demonstrates the ample robustness needed to assess the inner model. However, before this analysis, the measurement model was tested for collinearity issues. The variance inflation factor (VIF) values were used to test for multicollinearity. This was done to assess whether the path coefficient to be estimated would be biased because of multicollinearity problems. Table 2 shows that the VIF values ranged from 1.088 to 1.899. All the VIF values of all predictors were less than 4, indicating that collinearity among the predictors was not an issue in the structural model (Hair et al. 2017). After ascertaining the suitability of the outer model, the inner model was examined, and the hypotheses were tested. As recommended by Hair et al. (2017), a bootstrapping procedure using 5000 subsamples was used to test the hypotheses. Due to the exploratory nature of the study, the study followed Hair et al. (2017), who stated that the significant level should be 0.1 (10%). Table 3 and Figure 3 summarise the inner model and the hypotheses testing results. The teachers' m-learning acceptance inner model consists of six constructs. Only ATT has a direct effect on BI. PEOU, PU, and PSI had a direct effect on ATT. PR, PSI, and PEOU are predictors of PU. PEOU is only predicted by PR.

Table 2: Path coefficient

Hypotheses	Path	Standard Beta	T-statistics	P-values	Results	VIF	f-squared
H1	ATT -> BI	0.616	11.785	0.000	Accepted	1.772	0.303
H3	PEOU -> ATT	0.524	4.476	0.000	Accepted	1.395	0.361
H4	PEOU -> BI	0.019	0.189	0.850	Rejected	1.899	0.000
H2	PEOU -> PU	0.388	3.984	0.000	Accepted	1.235	0.132
H10	PR -> PEOU	0.426	4.764	0.000	Accepted	1.088	0.226
H9	PR -> PU	0.177	1.859	0.064	Accepted	1.334	0.050
H7	PSI -> ATT	0.197	2.784	0.006	Accepted	1.140	0.065
H8	PSI -> PU	0.188	3.364	0.001	Accepted	1.105	0.046
H5	PU -> ATT	0.174	1.974	0.049	Accepted	1.324	0.041
H6	PU -> BI	0.105	0.934	0.351	Rejected	1.379	0.014
H11	PR -> ATT	0.013	0.985	0.240	Rejected	1.396	0.000

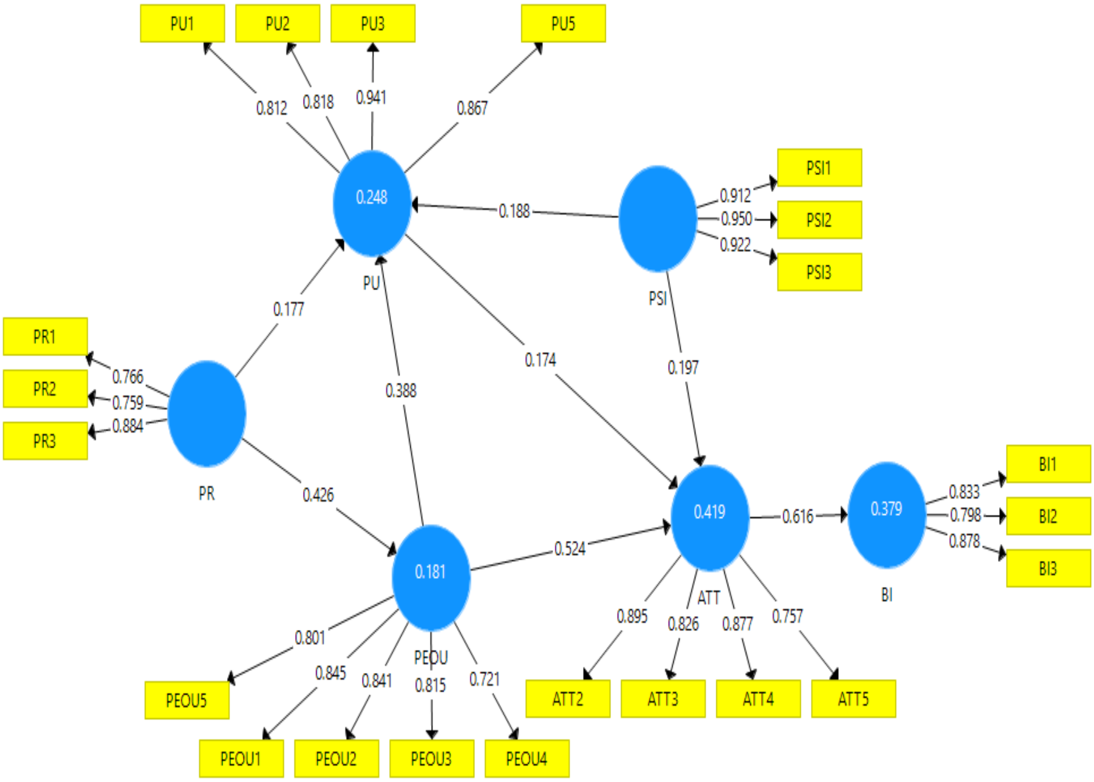

Figure 3. The structural model.

Figure 3 shows the R-squared of the model. According to Chin (1998), the model explained a moderate variance in teachers' BI and ATT the use of m-learning in the 4IR era of 37,9% and 41.9% respectively. The model also explained weak variance in teachers' perceived usefulness and ease of use of 24.8 % and 18.1 % respectively. Figure 3 also shows the standardised path coefficients. Table 2 shows the results of the bootstrapping procedure, which was used to answer the research question (RQ1). The results show that out of the eleven hypotheses that were tested only 3 (H6, H11, and H4) were not significant. The significant hypotheses were H10, H2, H1, H3, H5, H7, H9, and H8. Furthermore, the table also shows the effect size (f-squared). The f-squared shows the contribution of an exogenous latent variable on the R-squared value of the endogenous variable (Hair et al. 2017). The f-squared of PEOU on ATT was considered large, while the effect size of ATT on BI was considered medium (Cohen 1988). The f-squared of all other exogenous variables on their respective endogenous variables were considered small (Cohen 1988). This implies that teachers' ATT contributes a substantial amount to the variance of their BI to use m-learning in the 4IR era. The construct cross-validated redundancy (Q-squared) values ranged from 0.099 to 0.255. All the Q-squared values were greater than zero, supporting the predictive relevance of the model. To answer the research question (RQ2), the observation of total effects (Table 3) was used. The results show the ordinal strength of predictors of rural high school STEM teachers' BI to use m-learning in the 4IR era; perceived attitude towards (β .616, $p < .05$), perceived ease of use (β .364, $p < .05$), perceived resources (β .174, $p < .05$), perceived social influence (β .141, $p < .05$), and perceived usefulness (β .107, $p < .10$).

Table 3: Total effects

Path	Std Beta	Std Error	T Statistics	P Values
ATT -> BI	0.616	0.052	11.785	0.000
PEOU -> ATT	0.591	0.101	5.884	0.000
PEOU -> BI	0.364	0.076	4.796	0.000
PEOU -> PU	0.388	0.097	3.984	0.000
PR -> ATT	0.283	0.058	4.874	0.000
PR -> BI	0.174	0.045	3.872	0.000
PR -> PEOU	0.426	0.089	4.764	0.000
PR -> PU	0.342	0.083	4.132	0.000
PSI -> ATT	0.23	0.069	3.338	0.001
PSI -> BI	0.141	0.045	3.159	0.002
PSI -> PU	0.188	0.056	3.364	0.001
PU -> ATT	0.174	0.088	1.974	0.049
PU -> BI	0.107	0.058	1.859	0.064

5. DISCUSSION

Research question (RQ1). The study sought to examine how rural high school STEM teachers' BI to use m-learning in the 4IR era is influenced by their PU, ATT, PR, PEOU, and PSI. The results showed that the model was appropriate for determining rural high school STEM teachers' acceptance of m-learning in the 4IR era as it explained 37.9% of the variance in BI, which is considered moderate (Chin 1998). It is interesting to note that unlike in the study by Siyam (2019) and the original TAM, only teachers' perceived attitude towards the use directly influenced their behavioural intention to use m-learning in the 4IR era. This finding confirmed the findings of studies by Montrieux et al. (2014) and Anderson et al. (2006), who collectively emphasised the importance of managing teachers' attitudes towards m-learning. What can be learnt from this finding is that, for m-learning to be successfully implemented in rural areas, teachers should be positive about it. Teachers' ATT mediates the effect of their PU, PR, PSI, and PEOU on their BI to use m-learning in the 4IR era.

Congruent to the results of a study by Montrieux et al. (2014) and Siyam (2019), PEOU and PU were found to influence ATT. The results also confirmed the original TAM hypotheses (Davis et al., 1989). These results mean that rural high school STEM teachers' feelings towards m-learning are influenced by both the effort needed to learn and being skilful in using m-learning in the 4IR era and their belief that it will improve learners' performance. The finding is due to participants belonging to "digital immigrants" generation who struggle to use mobile devices to carry out specific tasks. The teachers in this study are under pressure to improve learners' performance in STEM-related subjects; as a result, any tool that has the potential to improve learners' performance positively influences their attitude towards it.

Perceived resources positively influence both PEOU and ATT. This finding echoes the findings of Hamzah and Muchlis (2018), who studied the acceptance of e-learning in Saudi Arabia. These results are not surprising considering the rural setting of the study. According to Mboweni (2014), most families in rural areas are living in poverty and rely on social grants. These results mean that for rural high school STEM teachers, the availability of resources influences their feelings towards m-learning, and the effort needed to learn to use it. One can conclude that for m-learning to be successfully implemented in rural high schools, resources need to be provided.

PSI influences PU and ATT. This finding is in line with the findings of Toe (2010), who reported that teachers are not immune from what people around them say about m-learning. These results imply that if DBE officials, parents, and learners say good things about m-learning to teachers, teachers will realise its usefulness and they will have positive feelings about the use of m-learning in the 4IR era.

Research question RQ2. ATT was found to be the best predictor of teachers' BI to use m-learning in the 4IR, followed by PR, PEOU, PSI, and then PU. These results mean that rural high school STEM teachers' behavioural intention to use m-learning in the 4IR era is mainly influenced by their attitudes and the availability of resources. This finding is contradictory to the findings of Siyam (2019), who found that perceived usefulness is the best predictor of behavioural intention to use the system. It is interesting but not surprising to find that perceived resources predicts behavioural intention better than perceived usefulness. This result implies that in rural areas where resources are a constraint like in rural areas, the availability of resources influences users' intention to m-learning. It can be argued that for m-learning to be successfully implemented for STEM learning in rural areas in the 4IR era, teachers need to be supplied with the m-learning resources.

5.1 Theoretical implications

The current study contributes to the current body of knowledge in two ways. Firstly, the study provides empirical evidence that even though the TAM is robust and well-established theory, it still needs to be extended to develop a fully-fledged model that can explain and predict acceptance of technology in different contexts. The study showed that unlike in the original TAM, teachers' perceived usefulness does not influence their behavioural intention to use m-learning. Perceived attitude towards mediate the relationship between behavioural intention and the exogenous variables (perceived usefulness, perceived ease of use, perceived social influence, and perceived resources). Secondly, the study supported the suggestion by Lim (2018), who recommended that the TAM should be extended by providing context-related antecedents of perceived ease of use and perceived usefulness to explain the acceptance of technology in a different context. In this study, perceived social influence and perceived resources were added. The results showed that perceived resources influenced perceived usefulness and perceived ease of use, while perceived social influence affected perceived attitude towards and perceived usefulness.

5.2 Managerial implications

Based on these findings, the following suggestions can be made to the DBE. M-learning resources need to be supplied in rural areas for m-learning to be successfully implemented. The DBE should form a partnership with cellular network service providers to provide boosters to improve network connectivity and to allow some educational platforms and websites to be accessed free of charge. Additionally, teachers need thorough training on how to use m-learning for STEM teaching in the 4IR era. The DBE should provide m-learning platforms that are user-friendly and should contain as many learning materials as possible.

One limitation of this study is that it has focused on rural high school STEM teachers only; consequently, the generalisation of the findings of this study to all high school teachers both in rural areas and urban should be done with caution. It will be interesting to replicate the same study using other teachers from other departments, namely, Languages, Commerce, and Humanities and compare the results. Based on the results, the perceived attitude was the only factor that has a direct effect on behavioural intention to use m-learning in the 4IR era, and as a result, future studies should focus on how to improve teachers' attitudes towards m-learning.

6. CONCLUSION

The research was conducted to identify the determinants of rural high school STEM teachers' behavioural intention to use m-learning in the 4IR era. The study also sought to find the ordinal strength of the predictors of rural high school STEM teachers' behavioural intention to use m-learning in the 4IR era. The structural model explained 37.9% of rural high school STEM teachers' behavioural intention to accept m-learning in the 4IR era. Teachers' attitudes towards the use of m-learning in the 4IR era influence their intentions to use it. Additionally, their attitude mediates the effects of perceived resources, perceived usefulness, perceived ease of use, and perceived social influence on their behavioural intention to use m-learning in the 4IR era. The ordinal strength of rural high school STEM predictors of acceptance of m-learning in the 4IR era is as follows; perceived attitude towards the use, perceived ease of use, perceived resources, perceived social influence, and perceived usefulness. The effect of perceived resources cannot go unnoticed, even though it was not having a direct effect on behavioural intention, but it has a strong indirect effect on BI. The predictive relevant (Q-squared) of PSI and PR were all greater than zero, meaning that the added constructs are important in predicting rural high school STEM teachers' adoption of m-learning in the 4IR era in rural areas. The lessons that can be learnt from this study are:

- For m-learning to be successfully implemented in rural areas, resources need to be provided.
- Teachers' attitudes towards m-learning in the 4IR era play a very important role in its acceptance.
- The effort needed to learn to use m-learning platforms play a more important role in its adoption than its usefulness.
- M-learning awareness programmes are needed to improve teachers' attitudes towards which in turn influence their behavioural intention to use them in the 4IR era.

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