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Determinants of mobile learning acceptance for STEM education in rural areas

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ABSTRACT

Science, Technology, Engineering, and Mathematics (STEM) is faced with challenges, resulting in learners' poor performance especially in rural areas. Previous studies have shown that mobile learning can be used to alleviate the challenges faced in STEM education in rural areas. Despite the opportunities that mobile learning can bring to STEM education, very little is known about high school STEM learners', their teachers', and parents' acceptance of mobile learning, particularly in rural settings. This study proposed and used the High School's Acceptance of Mobile Learning Model to investigate the factors that predict rural high school STEM learners', their parents', and teachers' behavioural intention to use mobile learning for STEM learning. The High School's Acceptance of Mobile Learning Model is based on the Technology Acceptance Model (TAM). Stratified random sampling was used to select 550 survey participants. Partial least squares structural equation modeling was used to analyse data from 417 valid questionnaires. The proposed model explained 40.8% of the variance in learners', teachers', and parents' acceptance of mobile learning. The original TAM variables (perceived attitude, perceived usefulness, and perceived ease of use) had direct relationship with behavioural intention, and they also played mediating roles between the external variables and behavioural intention. Multigroup analysis results showed that, for parents and learners, three paths were significantly different. In contrast, all paths were not statistically significant different for learners and teachers. However, all the paths were significant in each group, meaning that High School's Acceptance of Mobile Learning Model can be used to predict acceptance of mobile learning for learners, parents, and teachers.

1. Introduction

Science, Technology, Engineering and Mathematics education was defined by Gonzalez and Kuenzi (2012) as the teaching and learning of Science, Technology, Engineering and Mathematics. On the other hand, the Task Force Report (2014, p. 9) in America, adopts the view that STEM education is "far more than a 'convenient integration' of its four disciplines, rather, it encompasses 'real-world, problem-based learning' that integrates the disciplines through cohesive and active teaching and English learning approaches". What can be learned from this view is that STEM education aims at teaching learners to solve real-world problems, collaborate, integrate these four disciplines, and not to learn them separately, just as they are not separate disciplines in the real world.

During the second world war II, some countries realised the importance of STEM education, as scientist and engineers needed this

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knowledge to build war machines that were used to protect citizens from the military threats posed by other nations (Ritz & Fan, 2014). The STEM knowledge was also important for these countries to build their economies after the war. Educational leaders in these countries began to enrich their STEM education (Ritz & Fan, 2014). In the modern society the critical role of STEM education is frequently putative (Xie, Fang, & Shauman, 2015). The critical role that STEM education plays in promoting technological innovation and sustained economic growth is undisputable. Goldin and Katz (2009) reported that countries that have improved STEM education lead the world both economically and in science.

Important as it is in the development of countries, STEM education is faced with many challenges in rural areas. It is faced with challenges, such as lack of learning materials, science laboratories, learners' motivation, and parental involvement, resulting in learners' poor performance in STEM-related subjects (Bosman & Schulze, 2018; Makgato, 2007; Modisaotsile, 2012; Visser, Juan, & Feza, 2015). Additionally, teachers' use of ineffective pedagogies contribute to poor performance in STEM-related subjects (Bosman & Schulze, 2018). According to Bosman and Schulze (2018), teachers use traditional face-to-face instruction (FTF), which fails to stimulate deep holistic learning experiences. Makgato (2007) stated that the lack of science laboratories and equipment to enhance effective STEM teaching and learning in rural high schools contribute to poor learners' performance. Modisaotsile (2012) attributes learners' poor performance to lack of parental involvement in their children's education. On the other hand, Visser et al. (2015) ascribed this poor performance in STEM-related subjects in rural areas to the lack of learning materials and textbooks. What can be concluded from these studies (Bosman & Schulze, 2018; Makgato, 2007; Modisaotsile, 2012; Visser et al., 2015) is that, many challenges are caused by learners, parents, teachers, and the schooling environment that humper effective STEM teaching and learning in rural areas.

A plethora of studies have shown that m-learning can be used to alleviate the challenges of STEM education (Criollo-C, Luján-Mora, & Jaramillo-Alcázar, 2018; Koehler & Mishra, 2016; Kong, 2018; Pinker, 1997; Yeop, Yaakob, Wong, Don, & Zain, 2019). According to Herring, Koehler, and Mishra (2016), mobile learning (m-learning) changes a teacher-centred approach to learner-centred, which can stimulate deep holistic learning experiences. Additionally, m-learning provides teachers with many different pedagogies such as educational games, quiz and group work which can be utilized to meet learners' diverse learning preferences (Yeop et al., 2019). Mobile learning makes learning and assessment materials available to learners anytime and anywhere (Criollo-C et al., 2018). Mobile learning enables the use of visualised science experiments, which can enhance learners' understanding of science concepts, and enable them to give complete scientific concepts explanations (Pinker, 1997). According to Kong (2018), m-learning improves parental involvement in their children's learning, which in turn improves learners' motivation and performance in STEM-related subjects. Based on these studies one can conclude that, even though STEM education is facing many challenges, m-learning can lessen the impact of challenges in rural high schools (Criollo-C et al., 2018; Herring et al., 2016; Kong, 2018; Pinker, 1997; Yeop et al., 2019).

Notwithstanding the benefits that m-learning can bring to rural STEM education, the rate of its adoption is far below the expected levels (Sánchez-Prietoa, Hernández-Garcíab, García-Peñalvoa, Chaparro-Peláezb, & Olmos-Migueláñeza, 2019). Additionally, researchers have suggested a deficit between what m-learning offers and for what it is used (Sánchez-Prietoa et al., 2019). Padmanathan and Jogulu (2018) stated that the successful implementation and use of m-learning is contingent on the user's acceptance. As a consequence of the assessment of Padmanathan and Jogulu (2018), it could be argued that successful implementation of m-learning in rural high schools for STEM learning is contingent on all stakeholders' acceptance.

Several studies were carried out to find factors that influence users to accept m-learning (Li et al., 2019; Liu, Li, & Carlsson, 2010; Sánchez-Prietoa et al., 2019; Saroia & Gao, 2018; Yeop et al., 2019). However, Bourgonjon, Valcke, Soetaert, Schellens (2011) stated that academics did not adopt an adequately broad approach when investigating the attitudes of the main players in a high school instructional setting. Several m-learning studies focused on teachers (Alshmrany & Wilkinson, 2017; Nikou & Economides, 2018; Sánchez-Prietoa et al., 2019), learners (Li et al., 2019; Park, 2009; Saroia & Gao, 2018), and parents (Bourgonjon, 2011; Tsuei & Hsu, 2019). Even though there are several studies that were carried out to find factors that learners, teachers, and parents consider important when accepting m-learning, their relevance in explaining m-learning acceptance in the context of STEM education, particularly in rural areas, continue to remain limited. Furthermore, the researchers tried to reduce a very complex technology intervention to one of the stakeholders in a high school context instead of considering the complete ecosystem and all stakeholders. Teachers', parents', and learners' perceptions towards m-learning may appear as independent studies, however, this limits comparative analysis among these groups, and the multigroup insights remain absent in the body of knowledge. Multigroup analysis can help to identify significant and meaningful differences in relationships among the determinants of m-learning acceptance across rural STEM learners', their teachers', and parents' results. Understanding these differences help policymaker and m-learning platform developers to develop m-learning platforms that caters for all the needs of all the stakeholders (STEM learners, teachers, and parents), considering the differences among the groups. This increases m-learning acceptance and adoption in rural areas.

Poor performance in STEM-related subjects (DoE, 2017), poor-performing education systems (Kraut, 2013), poor quality of teaching (Bosman & Schulze, 2018), lack of STEM teaching and learning resources (Kraut, 2013; Visser et al., 2015), and lack of science laboratories and equipment (Makgato, 2007) are the main drivers of the emergence of m-learning, due to its potential to open new opportunities for improving the quality of STEM education in rural areas. The growth and widespread of mobile devices access in rural areas enabled m-learning development (Kraut, 2013). Despite the availability of mobile devices and new opportunities that they present to STEM education, there is a poor adoption of m-learning for STEM learning, particularly in rural areas (Kraut, 2013). Consequently, it is important to identify and understand factors that rural high school STEM learners, their teachers and parents consider important when accepting m-learning for it to be successfully implemented. Therefore, the current study investigates factors that predict the acceptance of m-learning by rural high school STEM learners, their parents, and teachers. The current research sought to examine the following research questions.

RQ1. What are the factors that rural high school STEM learners, their parents and teachers consider important when acceptance m-learning?

RQ2. Is there a significant difference between rural high school STEM learners' acceptance of m-learning and their parents'?

RQ3. Is there a significant difference between rural high school STEM learners' acceptance of m-learning and their teachers'?

To answer research question 1, the study proposed and validated the High School's Acceptance of Mobile Learning Model. By answering research questions 2 and 3, the research sought to examine if High School's Acceptance of Mobile Learning Model can be used to predict and understand m-learning acceptance by all the three main stakeholders in rural high schools. The results of the current study may assist the ministry of education officials, policymakers, and other stakeholders in developing countries' education systems on how to successfully implement m-learning in rural areas.

2. Literature review and model development

2.1. Literature review

2.1.1. Factors that predict parents to accept m-learning

Some of the roles that parents play in the integration of m-learning in high schools include decision making (as school governing bodies), financial support (buying devices and data bundles), monitoring and helping children to learn using mobile devices at home, and teacher-parent interaction. Kong (2018) suggested that parental involvement is an effective way of integrating m-learning into the classroom. Tsuei and Hsu (2019) stated that parents consider the effort needed to help their children to learn using m-learning and their attitudes towards m-learning important when adoption m-learning. Parents' attitudes about m-learning predict its use at home. Prior studies have shown that parents have mixed feelings about the integration of m-learning (Fleming Greentree, Cocotti-Muller, Elias & Morrison, 2006; Genc, 2014; Hollingworth, Mansaray, Allen, & Rose, 2011). Hollingworth et al. (2011) reported that parents had a positive attitude towards m-learning, while, Fleming, Greentree, Cocotti-Muller, Elias, and Morrison (2006) found that parents had a negative attitude towards the integration of technology into the classroom. In another study carried out by Genc (2014) on the perception of parents towards m-learning, the results showed that about 46.88% of parents were having negative perceptions, while 26.88% were neutral while 26.56% were having positive perceptions towards m-learning. What can be concluded from these studies (Fleming et al., 2006; Genc, 2014; Hollingworth et al., 2011) is that parents' attitudes towards m-learning are not conclusive.

2.1.2. Factors that teachers consider important when accepting m-learning

Studies show several factors that influence teachers' acceptance of m-learning (Callum, & Kinshuk, 2014; Fathema, Shannon, & Ross, 2015; Osakwe, Dlodlo, & Jere, 2017; Saroia & Gao, 2018). Callum et al. (2014) found that the usefulness and teachers' perceived attitude towards the use had a positive effect on their intention to use m-learning. However, contrary to the results of Saroia and Gao (2018), effort need to learn to use m-learning showed no significant effect on their intention to use it (Callum et al., 2014). Additionally, the study also showed that digital literacy (skills readiness) had a major influence on teachers' behavioural intention, perceived usefulness, and perceived ease of use. Osakwe et al. (2017) reported that all the teachers in their study agreed that the use of m-learning would make them enjoy their teaching. In a study by Fathema et al. (2015), the results revealed a weak positive influence of perceived resources on teachers' perceived ease of use and attitude towards the use of technology. This finding partially supports Teo (2010) who reported that facilitating conditions predicts teachers' perceived ease of use and attitude towards the use of m-learning. However, this finding opposes McGill, Klobas, and Renzi (2011), who stated that the availability of resources does not affect teachers' utilization of learning management systems.

2.1.3. Factors that learners consider important when accepting m-learning

Sánchez-Prietoa et al. (2019) extended TAM by adding subjective norm, perceived enjoyment, and compatibility. Sánchez-Prietoa et al. (2019) reported that learners who enjoy using mobile devices perceive m-learning useful and easy to use for learning. The effort needed to learn to use m-learning influenced learners' intentions to use it. Furthermore, the study also revealed that perceived enjoyment predicts learners' behavioural intention to use m-learning better than their perception that m-learning will improve their academic performance. However, this finding by Sánchez-Prietoa et al. (2019) is inconsistent with some studies (Iqbal & Bhatti, 2017; Mutono & Dagada, 2016; Zhu, Yang, Macleod, Shi, & Wu, 2018), that stressed that learners' attitude towards the use is the best predictor of their intention to use m-learning followed by its usefulness. Sivo, Ku, and Acharya (2018) reported that the availability of resources had a positive effect on learners' perceived usefulness. These findings were consistent with the pre-test results of the study by Ku (2009). However, the results were inconsistent with the post-test results of Ku (2009), who reported that perceived resources had no significant effect on perceived usefulness.

2.1.4. Comparing learners' and parents' attitudes towards m-learning

In China, TAM was expanded by Zhu et al. (2018) and a new model was used to compare the inter-relationships between primary school learners' and their parents' attitudes towards the acceptance of tablets in schools. The findings showed significant differences between learners' and parents' attitudes towards m-learning. The finding suggested that learners hold more positive views regarding m-learning than parents. The findings confirmed the findings of prior research by Salajan, Schonwetter, and Cleghorn (2010), who suggested an inter-generational difference concerning attitudes, perceived usefulness, and perceived ease of use of m-learning. Similar results were also reported by Li, Zhang, Lu, Zhang, and Wang (2013), who cited an increase in internet addicts as the parents' main concern. The study also revealed that both parents and learners perceive the educational benefits (perceived usefulness) as the main predictor of their attitude towards the use of m-learning.

2.1.5. Comparing learners' and teachers' attitudes towards m-learning

In Belgium, Montrieux, Grove, and Schellens (2014) investigated teachers' and learner's perceptions of the acceptance of m-learning. The results showed that for teachers, only the usefulness and the effort needed to learn to use m-learning had a significant effect on their intention to use it. For teachers, the educational benefits (perceived usefulness) was the best predictor of their acceptance of m-learning. This result was later echoed by Odiakaosa, Dlodlo, and Jere (2017), who found that 93,8% of teachers perceived m-learning useful. For learners, even though both educational benefits and perceived enjoyment predicted their intention, perceived enjoyment was the best predictor of their acceptance of m-learning (Montrieux et al., 2014). This finding was also supported by Odiakaosa et al. (2017), who found that 78,6% of learners agreed that m-learning will make their learning enjoyable. The results also revealed that learners had more a positive attitude towards m-learning than their teachers.

2.2. TAM and external variables

Davis, Bagozzi, and Warshaw (1989) proposed the TAM to predict users' intention to adopt new information system. The TAM is considered to be the most used model to predict and explain user's intention to use a new information system (Cheng, 2019). The TAM postulates that the person's behavioural intention to use information system would be jointly determined by perceived usefulness and their attitude towards it (Davis et al., 1989). The individual's attitude towards the information system is conditioned by the usefulness and the effort needed to learn to use the information systems (Davis et al., 1989). The TAM posits that perceived usefulness is influenced by perceived ease of use. Even if users believe that the information system is useful, they may still not use it if they believe that it is too hard and complicated to use (Davis, 1989). The key antecedents of the individual's acceptance of the information system are perceived usefulness and perceived ease of use (Binyamin, Rutter, & Smith, 2019; Cheng, 2019). Perceived usefulness was defined by Davis (1989) as the extent to which an individual believes that using a particular information system would improve his or her job performance. Perceived ease of use was defined as the extent to which an individual believes that using a particular information system would be free of effort (Davis, 1989). Venkatesh, Morris, Davis, and Davis (2003) defined perceived attitude towards in the context of technology acceptance research as a person's overall affective reaction toward the utilization of new technology. Fig. 1 illustrates the TAM.

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). The TAM is also considered to be robust across time (Venkatesh, 2000). In this study, the TAM was selected because it is a well-established technology acceptance theory which was also used by other researchers to study factors that predict the acceptance of m-learning (Iqbal & Bhatti, 2017; Mutono & Dagada, 2016; Sivo et al., 2018; Zhu et al., 2018).

2.2.1. TAM variables

2.2.1.1. Behavioural intention (BI). Behavioural intention was defined by Fang, Kayad, and Misieng (2019) as the cognitive representation of a person's readiness to perform a given behaviour. Behavioural intention predicts system acceptance and thus actual usage (Davis, 1989; Venkatesh et al., 2003). Studies have shown that teachers' or learners' behavioural intention to use m-learning has been shown to correlate strongly with system acceptance and thus usage (Cheng, 2019). This study focused on predicting the acceptance of m-learning in rural areas where it was not in use and as a result there was no actual usage of m-learning. Therefore, the construct actual usage was not part of the model in this study. However, behavioural intention is considered as the best single predictor of information system usage (Davis, 1989; Venkatesh, 2000). Based on the assessment by Davis (1989) and Venkatesh (2000), one can argue that understanding the factors that predict rural high school STEM learners', their teachers' and parents' behavioural intention to use m-learning, lead to understanding the factors that foretell the acceptance and actual usage of m-learning.

2.2.1.2. Perceived attitude towards (ATT). In this study, perceived attitude towards can be defined as a rural high school STEM learner's or teacher's overall affective reaction toward the use of m-learning. Rural high school STEM learners', their teachers', and

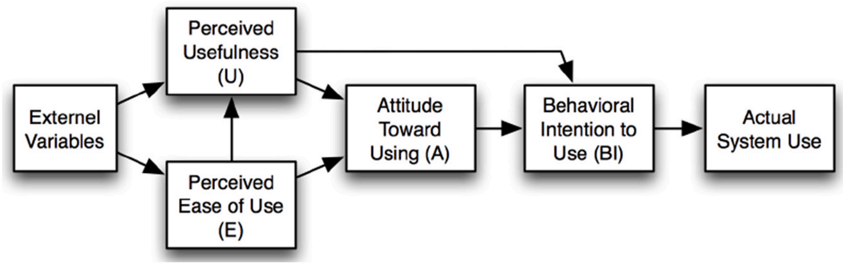

Fig. 1. TAM Model by Davis et al. (1989, p. 985).

parents' attitudes and beliefs play an important role in rejecting or accepting m-learning (Aldheleai et al., 2019). Prior studies have shown that learners' (Odiakaosa et al., 2017), teachers' (Aldheleai et al., 2019) and parents' (Dutota, Bhatiasevib, & Bellallahom, 2019; Tsuei & Hsu, 2019) perceived attitude towards predict their behavioural intention to use m-learning. Rural high school STEM learners', their parents', and teachers' positive or negative feelings about the use of m-learning for STEM learning predict its acceptance. When rural high school STEM learners, their teachers and parents perceive the utility and/or less effort needed to use of m-learning, they will have a positive feeling towards it. These positive feelings enhance their behavioural intention to use it and the actual usage. Therefore, the hypothesis:

H1. Rural high school STEM learners', their teachers', and parents' perceived attitude towards the use predicts their behavioural intention to use m-learning.

2.2.1.3. Perceived usefulness (PU). This study defined perceived usefulness as the perception that using m-learning improves or boosts learners' performance in STEM-related subjects. If perceived usefulness is strong, it creates a positive attitude towards m-learning and as a result, increases rural STEM learners' and teachers' intention to use it. In the original TAM by Davis et al. (1989), perceived usefulness influenced both perceived attitude and behavioural intention to use the information system. In a m-learning context, recent studies (Chen et al., 2019; Liu et al., 2018; Yorganci, 2017) have also found that perceived usefulness is the good predictor of both behavioural intention and perceived attitude towards. The belief that using m-learning will improve rural high school STEM learners' performance in STEM-related subjects will cause teachers, learners, and parents to have a positive attitude towards it and increase their intention to use it. Therefore, the hypotheses:

H2. Rural high school STEM learners', their teachers', and parents' perceived usefulness predicts their behavioural intention to use m-learning.

H3. Rural high school STEM learners', their teachers', and parents' perceived usefulness predicts their perceived attitude towards the use of m-learning.

2.2.1.4. Perceived ease of use (PEOU). In m-learning context, perceived ease of use was defined by Mutambara and Bayaga (2020) as the extent to which users believe that adopting m-learning would be free from effort. The use of m-learning increases workload for teachers (Sánchez-Prietoa et al., 2019), and this increase in workload is even worse if the m-learning platform is not user-friendly. Davis (1998) stated that in the early stages of the adoption of any information system, the belief that the system is difficult to use can be a barrier that may condition user's attitudes, usefulness, and behavioural intention. Rural high school STEM learners, their teachers and parents are acquainted with the use of mobile devices in their daily activities. However, they are not familiar with the use of m-learning for STEM learning, as a result, m-learning is in its early adoption stages. When rural high STEM learners, their teachers and parents perceive that it is easy to use m-learning for STEM learning, they will have a positive attitude towards it, realise its usefulness and accept it. Therefore, the hypotheses:

H4. Rural high school STEM learners', their teachers', and parents' perceived ease of use predicts their behavioural intention to use m-learning.

H5. Rural high school STEM learners', their teachers', and parents' perceived ease of use predicts their perceived attitude towards the use of m-learning.

H6. Rural high school STEM learners', their teachers', and parents' perceived ease of use predicts their perceived usefulness.

2.2.2. Variables added to the original TAM

In m-learning context, the TAM, like any other model, has also been criticized by other researchers (Carlsson, Carlsson, Hyvonen, Puhakainen, & Walden, 2006; Mallat, Matti, Tuunainen, & Oorni, 2008; Venkatesh et al., 2003). Carlsson et al. (2006) criticized 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 personalized and focuses on services offered by the system. Another criticism of the TAM is its low explanatory power of users' attitudes towards the information system (Venkatesh et al., 2003). Furthermore, the TAM is also criticized for assuming that the use of information systems is mandatory (Mallat et al., 2008). Perceived usefulness and perceived ease of use are considered to be extrinsic motivators. The lesson that one can learn from the studies of Carlsson et al. (2006), Mallat et al. (2008), and Venkatesh et al. (2003) is that, the TAM alone is inadequate to predict and explain the acceptance of m-learning in rural areas. Furthermore, Lim (2018a) stated that the TAM provides a conceptual lens that provides the core tenets to user interactions (ease of use and usefulness) that should be extended to develop a fully fledge model that can explain and predict acceptance of technology in different contexts, including the contextualization of technology acceptance constructs (see Lim, Lim, & Phang, 2019). Indeed, theories such as TAM were developed when digital technologies were emerging, and thus, the study herein is deemed to be timely and in line with the call by Lim (2018b) and Mazaheri, Lagzian, and Hemmat (2020) for its (re)investigation in contemporary settings.

In dealing with the TAM's weaknesses, this study followed other researchers (Binyamin et al., 2019; Cheng, 2019; Zhu et al., 2018) who, came up with antecedents of perceived usefulness and perceived ease of use that apply to m-learning. This study added factors that are can predict m-learning acceptance in STEM education in rural context in which the study was conducted in. In dealing the extrinsic nature of the TAM, an intrinsic motivator (perceived enjoyment) were added to the model. Mallat et al. (2008) also emphasized the importance of adding new variables to the traditional adoption models, as research has shown that these newly added variables in some cases posit stronger explanatory capabilities as compared to original variables. In responding to the suggestion by Mallat et al. (2008), this study added perceived enjoyment, perceived resources, perceived social influence, perceived skills readiness, and perceived psychological readiness to the original TAM. The five factors added to the TAM are the factors that STEM learners, their teachers, and parents in rural areas are likely to consider when accepting m-learning.

2.2.2.1. Perceived enjoyment (PEN). People engage in actions because these actions lead to pleasure (Huang, 2014). Perceived enjoyment was defined by Huang (2014) as the degree to which the action of using the technology is perceived to be pleasurable in its own right, apart from any performance consequences that may be anticipated. In this study, perceived enjoyment means the degree to which a rural high school learner or teacher finds the interaction of m-learning intrinsically enjoyable or interesting. Perceived enjoyment is seen as an example of intrinsic motivation, and it has significant effects on perceived ease of use (Huang, 2014). Rural high school STEM learners' and teachers' acceptance and use of m-learning can be promoted by making learning activities more enjoyable. The rationale is that teachers and learners who enjoy using m-learning are psychological ready and are more likely to use it extensively than those who do not (Huang, 2014). Therefore, the hypotheses.

H7. Rural high school STEM learners', their teachers', and parents' perceived enjoyment predicts their perceived ease of use.

H8. Rural high school STEM learners', their teachers', and parents' perceived enjoyment predicts their perceived psychological readiness.

2.2.2.2. Perceived psychological readiness (PPR). Perceived psychological readiness can be described as the feeling that the user feels when faced with the likelihood of having to use an information system. According to Alenezi, Karim, and Veloo (2010), these feelings can range from nervousness to fear. According to Callum et al. (2014), these negative feelings have shown to have a negative effect on teachers' and learners' attitudes, acceptance of m-learning and perception of how easy m-learning will be to use. Perceived psychological readiness has also been shown to influence perceived usefulness (Callum et al., 2014). Rural high school STEM teachers and learners who have used mobile devices for a long time have more confidence in their aptitude to use mobile devices efficiently. The competence of rural high school teachers and learners directly predicts perceived psychological readiness of using m-learning for teaching and learning STEM-related subjects in the classroom. Therefore, the hypothesis.

H9. Rural high school STEM learners', their teachers', and parents' perceived psychological readiness predicts their perceived usefulness.

2.2.2.3. Perceived social influence (PSI). In Theory of Planned Behaviour, perceived social influence is known as a subjective norm, or image in the Innovation Diffusion Theory. Pramana (2018) defined perceived social influence in the m-learning context as, the extent to which a learner or teacher perceives that important persons believe he or she should use a m-learning. Rural high school STEM learners, their parents and teachers are influenced by what they hear about m-learning. This was suggested by Venkatesh and Davis (2000) who stated that people internalize the beliefs of other people and make them a part of their belief system. Pramana (2018) and Huang (2014) found that perceived social influence predicts perceived attitude towards. If rural high school STEM learners, their parents and teachers think that people who are important to them expect them to use m-learning for STEM learning, they would have a positive attitude towards m-learning. Therefore, the hypothesis:

H11. Rural high school STEM learners', their teachers', and parents' perceived social influence predicts their perceived attitude towards the use.

2.2.2.4. Perceived resources (PR). Perceived resources also is known as facilitating conditions in the Unified Technology of Acceptance and Use Theory. Perceived resources is defined as "the degree to which an individual believes that organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003, p. 453). Ku (2009) found that perceived resources predicts perceived ease of use and perceived usefulness but not perceived attitude towards the use of online learning. In the study by Sivo et al. (2018), the results also showed that perceived resources had no significant influence on behavioural intention to use online learning. However, the results are in contradiction to the results found by Mtebe and Raisamo (2014). Mtebe and Raisamo (2014) used the Unified Technology of Acceptance and Use Theory model to study learners' behavioural intention to adopt and use m-learning in tertiary education in East Africa and found that learners' behavioural intention was predicted by the availability of resource.

This study was carried out in a rural area where most families live in poverty and rely on social grants for their survival (Mboweni, 2014). Mobile learning requires money for purchasing devices and data bundles. Basing on the results of Ku (2009), Mtebe and Raisamo (2014) and Mboweni (2014), one can learn that rural high school STEM learners', their teachers' and parents' perceived resources may predict their perceived usefulness, perceived attitude towards, behavioural intention, and perceived ease of use of m-learning. Therefore, the hypotheses.

H12. Rural high school STEM learners', their teachers', and parents' perceived resources predicts their perceived attitude towards the use of m-learning.

H13. Rural high school STEM learners', their teachers', and parents' perceived resources predicts their perceived usefulness.

H14. Rural high school STEM learners', their teachers', and parents' perceived resources predicts their perceived ease of use.

2.2.2.5. Perceived skills readiness (PSR). Perceived skills readiness can be defined as one's perception of his or her capability to use a mobile device in a m-learning environment for the accomplishment of a learning task (Akour, 2009). Young people are technology natives who can operate mobile devices effortlessly and with motivation (Kee & Samsudin, 2014). This was also confirmed by Odi-akaosa et al. (2017), who found that 91.1% of learners can use mobile devices and can explore these devices and their extended features. This means that most learners had the required skills for the implementation of m-learning. Learners with required technical skills will engage better with m-learning than those without the skills (Mutono & Dagada, 2016). Mutono and Dagada (2016) reported that learners with required computer technical skills showed less anxiety and frustration when taking online courses as compared to those without. Rural high school Learners and teachers who possess the required skills for m-learning are most likely to consider m-learning as useful and easy to use. Therefore, the hypothesis.

H15. Rural high school STEM learners', their teachers', and parents' perceived skills readiness predicts their perceived psychological readiness.

Based on the theoretical underpinning, a hypothetical model is shown in Fig. 2.

3. Methods

3.1. Research design

A survey design was employed in this study. A survey design provides a quantitative description of opinions of a population by studying a sample of the population (Creswell, 2015). A survey was used in this study to provide a quantitative description of rural high school STEM learners', their teachers', and parents' attitudes towards m-learning. A survey was chosen as it can collect a large amount of data from rural high school STEM learners, their teachers, and parents in a short time for a fairly low cost. A cross sectional survey was employed in this study, where opinion-related data was collected from rural high school STEM learners, their parents and teachers using a questionnaire. Firstly, descriptive statistics was used to explore the data from rural high school STEM learners, their teachers, and parents. Secondly, partial least squares–structural equation model (PLS-SEM) was used to test the hypothesized model.

3.2. Participants

The stratified sampling was adopted to collect data (Creswell, 2015). All rural high school in King Cetshwayo District in South Africa were grouped using their quintiles. Schools in the same quintile were grouped to form a stratum. Putting schools in the same quintile, in a stratum makes sure that homogenous elements are put in the same stratum, which reduces any error of estimation (Creswell, 2015). Three strata were formed. From each stratum, four schools were selected using simple random sampling. Simple random sampling was also used to select 200 grade 12 STEM learners, from the selected schools. These learners were also given one questionnaire each for their parents, making the sample size for parents to be 200 as well. About 150 STEM teachers were also randomly selected using the same method used to select learners. The total number of participants selected were 550.

The response rate was 80% (444 out of 550 questionnaires were collected). However, 76% (417 responses) were used in this study, while the other 27 responses were removed during data screening. Among the respondents 42% (174) were rural high school grade 12 STEM learners, 31% (129) were their parents, and 27% (114) were their teachers. Of the 417 participants who participated in this study, 221 (53%) were females and the remaining 196 (47%) were males. There were 71 (41%) female STEM learners who took part in the study and the remaining 103 (59%) were males. The range of the age of learners was from 17 to 21.

In this study, 65 (57%) rural STEM teachers who responded to the questionnaires were females while 49 (43%) were males. Of the 114 teachers who participated, 19 (17%) of them were less than 30 years, 31 (27%) were between 30 and 40 years, 44 (39%) were between 40 and 50, and 20 (17%) were above 50 years old. Of the 129 parents who participated in this study, 85 (66%) were females while 44 (34) were males. Out of 129 parents participated, 43 (33%) were between 30 and 40 years, 55 (43) were between 40 and 50

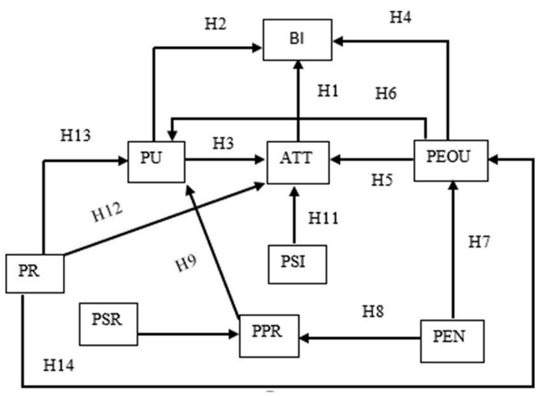

Fig. 2. The high School's acceptance of mobile learning model.

years, and 31 (24%) were above 50 years old.

Perceived usefulness is one of the constructs with most items. Perceived usefulness had five items. Using the recommendation of Hair, Hult, Ringle, and Sarstedt (2017), of 10 times larger than the number of items of the construct with most items, the recommended minimum sample size was 50. The sample size of each group (learners, teachers, and parents) exceeds the recommended 50.

3.3. Procedure

A single cross-sectional field study was used to test the High School's Acceptance of Mobile Learning Model. To ensure ecological validity, the data was collected from research sites that closely mirrored the target situation that the results of this study would generalize to: rural high school where m-learning is about to be introduced. At the time of the study, teachers and learners in King Cetshwayo District were not formally using m-learning. However, learners might be using mobile devices for informal learning. The researchers gave STEM learners, parents, and teachers questionnaires to complete at their own time and there were then collected after two weeks.

3.4. Measures

Firstly, the rural high school STEM learners, their teachers and parents filled in questions about demographical information. Secondly, respondents answered the main part of the questionnaire, which comprised of scales measuring the constructs of the model. The questionnaire was adopted from previous studies (Sivo et al., 2018; Tsuei & Hsu, 2019) and modified to suit the needs of the current study. All the items in this survey questionnaire were directly defined in the context of STEM education. For example, a perceived usefulness item on the learners' questionnaire was "Using mobile learning to learn STEM-related subjects will improve my performance".

The parents, teachers, and learners were required to select an answer from the seven options strongly disagree to strongly agree on a 7-point Likert-type scale. Thus, the higher the score the respondent reported, the higher the value that she or he put on the variable. The measurement instrument consisted of nine constructs making a total of 34 items (see Appendix 1). The questionnaire was developed and translated into IsiZulu and distributed both in English and IsiZulu. The respondents were asked to choose the language they were comfortable with.

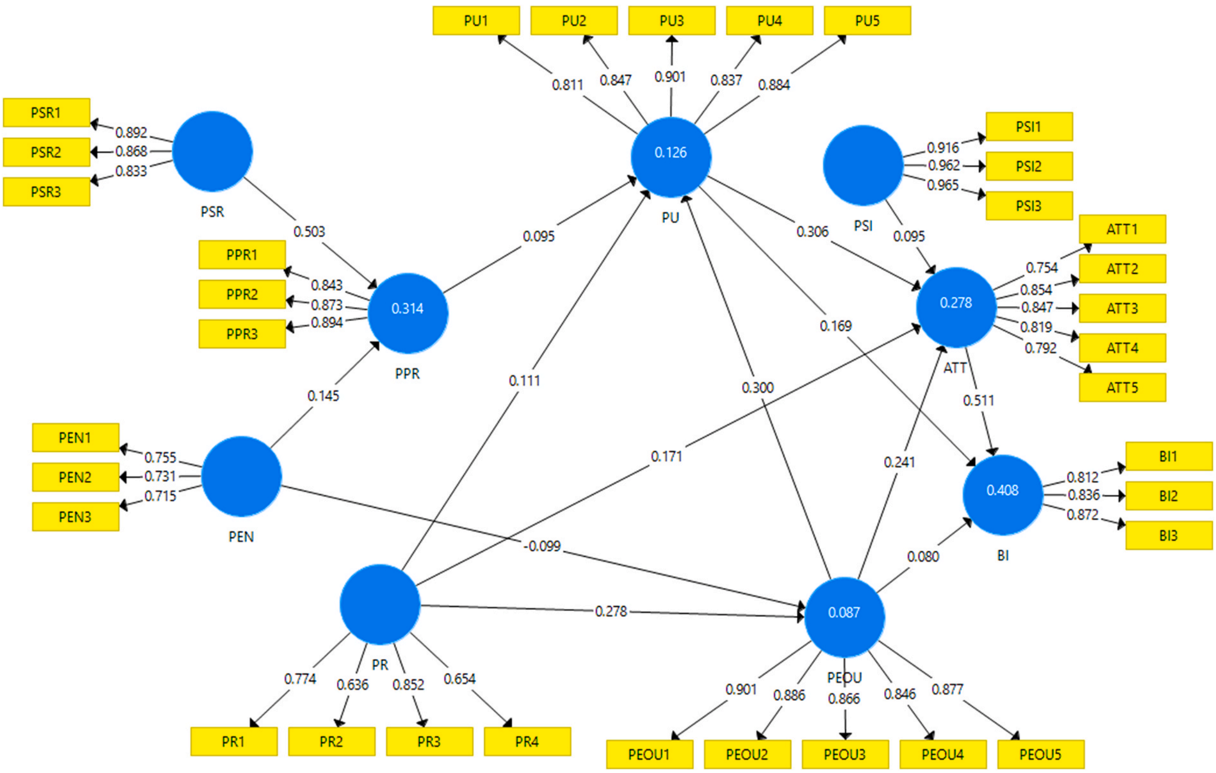

Fig. 3. The High School's Acceptance of Mobile Learning Model 's inner model.

3.5. Analysis technique

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyse data by making use of the software SmartPLS 3.2.8. According to Sánchez-Prietoa et al. (2019), the main function of PLS-SEM is the prediction of the target variable, in our case, rural high school STEM learners', their teachers' and parents' behavioural intention to use m-learning. PLS-SEM was also used to assess the predictive power of antecedent variables, and to assess if there is a significant difference between rural high school learners' and their teachers' and parents' path coefficients. This study followed the suggest of Hair et al. (2017, p. 21) who stated that, "when Covariance-Based Structural Equation Modeling (CB-SEM) assumptions or related methodological anomalies occur in the process of model estimation, PLS-SEM is a good methodological alternative for theory testing". The structural model is considered to be complex (with nine constructs) and the data collected from participants was not normally distributed (see Appendix 2), consequently, the PLS-SEM was preferred to CB-SEM.

The study followed the two-stage approach of model analysis suggested by Hair et al. (2017). First, the reliability and validity of different model variables was assessed to confirm the quality of the outer model. The outer model establishes the relationship between the constructs and their indicators. In the second step, the relationships within the inner model was assessed by testing the significance of the relationships, explained variance of the endogenous variables and predictive power of different variables (Hair et al. (2017).

4. Data analysis results

4.1. Outer model assessment

The outer model describes the association between constructs and their indicators. Convergent validity and discriminant validity of the outer model needs to be assessed (Garson, 2016), in order to ascertain the goodness of fit of the out model. Convergent validity assesses the degree to which there is a high correlation between the latent variables which are theoretically identical, while discriminant validity assesses the degree to which a construct differs from other constructs (Chin, 1998; Hair et al., 2017).

The results (see Fig. 3) show that almost all reflective indicators have loadings higher than 0.7 (Hair et al., 2017) except PR2 (0.636) and PR4 (0.654). These items were returned due to the exploratory nature of the study and removing them did not increase the composite reliability (Garson, 2016). The results confirmed item reliability. The results (Table 1) confirmed convergent validity as well, with composite reliability (CR) above 0.6 and average explained extracted (AVE) values greater than 0.5 (Hair et al., 2017).

4.1.1. Discriminant validity

Following Hair et al. (2017), who suggested that the Heterotrait-Monotrait ratio of correlations (HTMT) gives more accurate results of discriminant validity than the cross-loading and Fornell-Larcker criterion, the study used the HTMT to assess discriminant validity. The results in Table 2 shows that all the HTMT values were under 0.85 (Hair et al., 2017). The results confirmed discriminant validity. The resulted showed that the constructs were truly distinct from each other.

4.2. Inner model assessment

Once the construct measures were confirmed to be reliable and valid, the next step was to assess the High School's Acceptance of Mobile Learning Model's inner model results. Before assessing the inner model, the variance inflation factor values (VIF) were used to assess collinearity issues. Table 3 shows that the VIF values ranged from 1.018 to 1.463. All the VIF values of all the predictors were less than 4 (Hair et al., 2017), indicating that collinearity among the predictors was not an issue in the High School's Acceptance of Mobile Learning Model's inner model. This shows that the precision of the estimated coefficients of the High School's Acceptance of Mobile Learning Model were not affected by multicollinearity. Consequently, the hypothesized relationships depicted in Fig. 2 were analysed. As recommended by Hair et al. (2017), the 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 Fig. 3 summarize the inner model and the hypotheses testing results. The results in Table 3 show that all the hypotheses were accepted.

Fig. 3 shows the R-squared value of the High School's Acceptance of Mobile Learning Model. The results show that the R-squared values of PPR, ATT, PU, PEOU, and BI were 0.314, 0.278, 0.126, 0.087 and 0.408, respectively. The R-squared values of PPR and BI are considered moderate strength, while the R-squared value of ATT, PU and PEOU are considered weak (Chin, 1998). The combined contributions of PEN and PSR on PPR was 31,4%, while the combined contribution of the predictors of ATT the use was 27.8%. The total contribution of the predictors (PPR, PEOU and PR) in the explained variance of PU was 12.6%. An R-squared value of 0.408 means that all the exogenous constructs combined can explain 40.8% of the variance in BI to use m-learning. This means that the combined effect of the factors PEOU, PU, PR, ATT, PEN, PSR, PPR, and PSI in explaining rural high school STEM learners', their

Table 1
Measurement model.

Construct	ATT	BI	PEN	PEOU	PPR	PR	PSI	PSR	PU
CR	0.907	0.878	0.776	0.942	0.904	0.821	0.966	0.899	0.932
AVE	0.663	0.706	0.537	0.766	0.758	0.538	0.904	0.747	0.734

Table 2
HTMT values.

	ATT	BI	PEN	PEOU	PPR	PR	PSI	PSR	PU
ATT									
BI	0.732								
PEN	0.074	0.106							
PEOU	0.421	0.385	0.126						
PPR	0.046	0.053	0.366	0.084					
PR	0.329	0.238	0.080	0.337	0.086				
PSI	0.084	0.167	0.055	0.061	0.077	0.146			
PSR	0.060	0.074	0.357	0.044	0.646	0.054	0.053		
PU	0.470	0.476	0.068	0.353	0.090	0.227	0.051	0.042	

The High School's Acceptance of Mobile Learning Model's measurement model presents satisfactory indicator reliability, convergent validity, and discriminant validity. Therefore, the High School's Acceptance of Mobile Learning Model's outer model demonstrated the ample robustness needed to assess the High School's Acceptance of Mobile Learning Model's inner model.

Table 3
Path coefficients.

Path	Std Beta	Std Error	T Statistics	P Values	Decision	f-squared	VIF
ATT - > BI	0.511	0.052	9.738	0.000	Supported	0.33[b]	1.370
PEN - > PEOU	−0.099	0.038	2.595	0.010	Supported	0.01[c]	1.038
PEN - > PPR	0.145	0.053	2.749	0.006	Supported	0.03[c]	1.080
PEOU - > ATT	0.241	0.053	4.548	0.000	Supported	0.07[c]	1.183
PEOU - > BI	0.080	0.044	1.820	0.069	Supported	0.01[c]	1.256
PEOU - > PU	0.300	0.065	4.577	0.000	Supported	0.09[c]	1.099
PPR - > PU	0.095	0.047	2.002	0.046	Supported	0.02[c]	1.463
PR - > ATT	0.171	0.051	3.338	0.001	Supported	0.04[c]	1.113
PR - > PEOU	0.278	0.052	5.372	0.000	Supported	0.08[c]	1.018
PR - > PU	0.111	0.054	2.063	0.040	Supported	0.02[c]	1.086
PSI - > ATT	0.095	0.048	1.955	0.051	Supported	0.02[c]	1.021
PSR - > PPR	0.503	0.054	9.278	0.000	Supported	0.34[b]	1.080
PU - > ATT	0.306	0.052	5.891	0.000	Supported	0.11[c]	1.140
PU - > BI	0.169	0.061	2.787	0.006	Supported	0.04[c]	1.268

[a] Large effect size.
[b] Medium effect size.
[c] Small effect size.

parents', and teachers' behavioural intention to use m-learning, was 40.8%.

We followed the blindfolding guidelines given by Hair et al. (2017) to assess the predictive relevance of the High School's Acceptance of Mobile Learning Model. The cross-validated redundancy (Q-squared) values of the endogenous variables (BI = 0.267, ATT = 168, PEOU, = 0.059, PPR = 0.220, and PU = 0.084) were all above zero, indicating that the High School's Acceptance of Mobile

Table 4
Learners-parents and learners-teachers multigroup analyses.

Path	Path coefficients-diff (|leaners - parents |)	p-Value (leaners vs parents)	Path	Path Coefficients-diff (learners - teachers)	p-Value (learners vs teachers)
ATT - > BI	0.157	0.164	ATT - > BI	0.003	0.489
PEN - > PPR	0.098	0.367	PEN - > PPR	0.120	0.317
PEN - > PEOU	0.018	0.892	PEN - > PEOU	0.027	0.489
PEOU - > ATT	0.440	0.001*	PEOU - > ATT	0.033	0.437
PEOU - > BI	0.149	0.212	PEOU - > BI	0.155	0.825
PEOU - > PU	0.020	0.888	PEOU - > PU	0.124	0.191
PPR - > PU	0.076	0.487	PPR - > PU	0.114	0.297
PR - > ATT	0.114	0.316	PR - > ATT	0.065	0.639
PR - > PEOU	0.261	0.029*	PR - > PEOU	0.035	0.624
PR - > PU	0.075	0.564	PR - > PU	0.151	0.809
PSI - > ATT	0.278	0.002*	PSI - > ATT	0.106	0.793
PSR - > PPR	0.008	0.942	PSR - > PPR	0.126	0.715
PU - > ATT	0.236	0.061	PU - > ATT	0.222	0.940
PU - > BI	0.137	0.305	PU - > BI	0.208	0.062

*significant at $p < 0.05$.

Learning Model can be used to explain rural high school STEM learners', their parents and teachers' acceptance of mobile learning. Furthermore, Table 3, shows that the only two relations (PSR to PPR and ATT to BI) have a moderate effect size, the rest of the path have small effect sizes (Chin, 1998).

The inner model consists of nine constructs (BI, ATT, PEOU, PU, PR, PEN, PPR, PSI, and PSR). PR predicts PU, PEOU and ATT. The results also show that PEOU predicted BI, ATT, and PU, but itself (PEOU) is affected but PR and PEN. PEN and PSR predicted PPR, which in turn predicted PU. PU and PSI affected ATT. ATT and PU also had a direct effect on BI.

To answer research questions 2 and 3, a non-parametric multigroup analysis (MGA) was used to test if there was a significant difference between learners' and teachers' path coefficients and also learners' and parents' path coefficients. Table 4 shows the results of the MGA.

The results show that for learners and parents three paths (PEOU- > ATT, PR- > PEOU and PSI- > ATT) were significantly different. However, these paths were significant for each group. This implies that even though learners' paths coefficient were higher than their parents', the same model (High School's Acceptance of Mobile Learning Model) can be used to predict m-learning acceptance for both groups since the paths were significant for each group. The results in Table 4 also show that all path coefficient between teachers and learners were not statistically significant across the two groups. This means that the same High School's Acceptance of Mobile Learning Model can be used to explain m-learning for both teachers and learners.

5. Discussions

The results showed that the High School's Acceptance of Mobile Learning Model adequately explains and can predict behavioural intention of rural high school STEM learners', their teachers', and parents' acceptance of m-learning. These results showed that all the Q-squared values were greater than zero, and this supports the model's predictive relevance regarding the endogenous latent variables (Hair et al., 2017). This implies that the High School's Acceptance of Mobile Learning Model can predict rural high school STEM learners', their parents', and teachers' behavioural intention to use m-learning. In other words, the factors perceived ease of use, perceived usefulness, perceived resources, perceived attitude towards, perceived enjoyment, perceived skills readiness, perceived psychological readiness, and perceived social influence are good predictors of rural high school STEM learners', their parents' and teachers' behavioural intention to use m-learning. The combined effect of the factors perceived ease of use, perceived usefulness, perceived resources, perceived attitude towards, perceived enjoyment, perceived skills readiness, perceived psychological readiness, and perceived social influence in explaining rural high school STEM learners', their parents' and teachers' behavioural intention to use m-learning, was 40.8%.

5.1. General discussion

The results show that rural high school STEM learners', their parents', and teachers' perceived attitude towards the use of m-learning predicts their behavioural intention to use it. This finding echoes the sentiments of Montrieux et al. (2014) and Anderson, Schwager, and Kerns (2006), who collectively emphasized the importance of managing users' attitudes towards m-learning. Thus, for m-learning to be successfully adopted for STEM learning in rural areas, it is important to pay attention to factors that improve learners', their teachers, and parents' attitudes towards it.

Rural high school STEM learners', their teachers, and parents' perceived attitude towards the use of m-learning was directly prognosticated by their perceived social influence, perceived resources, perceived usefulness, and perceived ease of use. Contrary to the finding of Ku (200) and Mathieson, Peacock, and Chin (2001), the results showed that rural high school STEM learners', their parents' and teachers' positive feelings about m-learning are enhanced by the availability of the m-learning resources. This implies that for m-learning to be successfully implemented in rural schools, m-learning resources need to be supplied. Rural high school STEM learners', their parents' and teachers' feelings towards m-learning are predicted by perceived social influence. This finding confirms the finding of Venkatesh et al. (2003). This shows that learners, teachers, and parents are not immune to what they hear about m-learning. This indicates the need for m-learning awareness programs for it to be successfully adopted. Perceived ease of use and usefulness projected rural high school STEM learners', their teachers', and parents' attitude towards the use. This shows that rural high STEM learners', their parents' and teachers' belief that using m-learning is easy to use and it can improve learners' performance in STEM-related subjects, forecasts their feeling towards the use of m-learning. Perceived usefulness was the best predictor of perceived attitude towards the use of m-learning. This finding is not surprising because the participants in the study were in an examination class, their positive feelings towards m-learning were linked to their beliefs that it will improve learners' performance. It can be concluded that if awareness of the benefits of m-learning are raised in rural areas and m-learning resources are provided, rural high school learners, teachers and parents would have a positive attitude towards m-learning. Additionally, a user-friendly m-learning platform with as much learning and assessing materials as possible, reinforces rural high school learners', parents', and teachers' feelings towards m-learning.

Perceived ease of use predicted perceived usefulness, and they both prognosticated behavioural intention to use m-learning. These findings were consistent with the findings of Pramana (2018), who reported that behavioural intention was predicted by perceived usefulness and Perceived ease of use. This implies that rural high school STEM learners, their teachers and parents consider the educational benefits and effort needed to learn and to be skilful in using m-learning for STEM learning important when accepting it. However, the results are contrary to the findings of Liu et al. (2010), who found that perceived ease of use does not project behavioural intention. Rural high school STEM learners, their teachers, and parents consider utility more important when accepting m-learning than the effort needed to learn to use it. This was as a result of the environment in which the study was carried out. This study was conducted in rural areas, where there was a lack of learning material, science laboratories, science equipment (Makgato, 2007). The benefits that m-learning brings into the STEM classroom mitigate the challenges that STEM education is currently facing in rural areas and hence, contributes to the acceptance of m-learning.

Perceived skills readiness and perceived enjoyment predicted perceived psychological readiness. This result was in line with the finding of Erlich, Erlich-Philip, and Gal-Ezer (2005), who reported that learners who were not familiar with using computers before registering for an online course reported more frustration and anxiety compared to those who were used to computers. This implies that rural high school STEM learners and teachers who enjoy using mobile devices and have the digital skills needed to perform and complete a task, perceive themselves as psychologically ready for m-learning. Perceived psychological readiness predicted perceived usefulness. This implies that rural high school learners and teachers who enjoy using mobile devices and have the skills needed to use m-learning, are not anxious about using m-learning in class and they perceive it as useful. One can infer that for m-learning to be adopted in rural high schools, teachers and learners need to be trained to use m-learning.

RQ2 and RQ3: For RQ2, the results showed that even though three paths were significantly different between learners and parents, these paths were also statistically significant in each group. This finding partially supports the finding of Zhu et al. (2018), who reported a significant difference learners' and parents' attitudes towards the adoption of tablets in the classroom. These results imply that even though learners' path coefficients were greater than their parents', but the same model (High School's Acceptance of Mobile Learning Model) can be used to explain and predict acceptance of m-learning for both groups. For teachers and learners, there was no statistical difference between teachers' and learners' path coefficients, indicating that the acceptance of m-learning for both groups could be explained by the High School's Acceptance of Mobile Learning Model and there is no different between teachers' and learner's attitudes towards m-learning. The results of RQ2 and RQ3 imply that High School's Acceptance of Mobile Learning Model can be used to predict the acceptance of m-learning for all the three groups. The results also imply that the factors that rural STEM learners, their teachers and parents consider important when accepting m-learning are the same.

5.2. *Theoretical implications*

The current study contributes to the current body of knowledge in three ways. Firstly, the study provides empirical evidence that even though the TAM is general (that is it applies to the acceptance of technology in many different fields (Carlsson et al., 2006)) and was developed when digital technologies were emerging (Lim, 2018b), it can still be used to predict the acceptance of m-learning in developing countries. The study relieved that learners' perceived ease of use predicts perceived usefulness and they both foretell perceived attitude towards the use of m-learning. Based on the results, the usefulness and effort needed to learn to use m-learning are key predictors of learners' attitudes towards it. Perceived attitude towards and perceived usefulness were also found to predict learners' behavioural intention to use m-learning.

Secondly, the study supported the suggestion by Lim (2018a), 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. This study found that perceived enjoyment and perceived skills readiness indirectly predict learners' perceived usefulness through the mediation of perceived psychological readiness. The study also revealed that perceived resources prognosticate both perceived usefulness and perceived ease of use. The predictors that can be added to the TAM's main pillars (usefulness and ease of use) to predict the acceptance of m-learning in in rural areas of developing countries are perceived resources, perceived enjoyment, perceived psychological readiness, and perceived skills readiness.

Finally, the High School's Acceptance of the Mobile Learning model proposes social motivation for increasing the attitude towards using m-learning. The study showed that perceived social influence foretells learners', teachers', and parents' perceived attitude towards the use of m-learning. The results advance our understanding of the relationship between perceived social influence and perceived attitude towards, in the m-learning context. The results highlight that positive social influence of m-learning reinforces learners' attitudes towards it.

5.3. *Managerial implications*

Based on the results of this study and other studies that studied the acceptance of m-learning by learners (Ku, 2009), teachers (Nikou & Economides, 2018) and parents (Tsuei & Hsu, 2019), the following suggestions can be made to the ministry of education, teacher training institutions and mobile developers. Rural high school STEM learners, their parents and teachers consider the effort needed to learn and to be skilful in using m-learning important when accepting it, as a result, m-learning developers should develop m-learning platforms that are user-friendly. The mobile developers should also include as much learning material as possible on m-learning platforms. The learning materials may include question papers and their marking guidelines and textbooks, visualised experiments. This is because rural high school STEM learners, teachers and parents consider the utility of m-learning important when accepting it. The ministry of education should pay attention to rural high school teachers' and learners' attitudes towards m-learning. This can be done through raising awareness on the benefits of m-learning, providing m-learning resources to both teachers and learners, providing training on how to use m-learning, and supplying teaching materials like visualised experiments All these improve learners' and teachers' attitudes towards m-learning which in turn predict its adoption. Teacher training institutions should partner with the ministry of education to provide in-service teachers with the skills needed for m-learning. Teacher training institutions should also equip pre-service teachers with skills needed for m-learning so that when they join schools, they will be able to teach and also help other teachers to teach using m-learning.

5.4. Limitations and future studies

The limitations of this study are that it only focused on rural high schools and it also focused on STEM learners, their teachers, and parents. Therefore, the generalization of the findings of this study to all high school and primary areas should be done with caution. The participants in this study may have exaggerated their answers and this may lead to social desirability bias.

Future studies should also include learners, teachers, and parents of other departments in rural and urban high schools. It will be interesting to evaluate the High School's Acceptance of Mobile Learning Model in urban areas and compare the results. It is in our future plans to add more constructs like content and user interface to the High School's Acceptance of Mobile Learning Model to improve its explanatory power. Perceived attitude towards the use of m-learning plays a pivotal role in its acceptance, therefore future study should focus on the factors that predict users' attitudes towards m-learning.

6. Conclusion

The results of this study confirm the findings of Park (2009), Sánchez-Prietoa et al. (2019) and Teo (2009) that the TAM can be used to explain the acceptance of m-learning. All the TAM hypotheses were also confirmed in this study. Additionally, the results support the suggestion by Venkatesh and Davis (2000)), who proposed that more variables that are context-related can be added to the TAM to study the acceptance of an information system. In this study, perceived resources, perceived psychological readiness, perceived enjoyment, perceived social influence, and perceived skills readiness were added to the TAM. The results showed that perceived social influence indirectly predicted behavioural intention through perceived attitude towards. Perceived skills readiness, perceived psychological readiness, and perceived enjoyment indirectly forecasted behavioural intention through the mediation of perceived usefulness and perceived attitude towards the use. Perceived resources was found to be a prognosticator of all the TAM predictors of behavioural intention (perceived usefulness, perceived attitude towards, and perceived ease of use). This means that for m-learning to be successfully adopted in rural areas, resources need to be provided. The results also show that the High School's Acceptance of Mobile Learning Model can be used to explain and predict the acceptance of m-learning for learners, teachers, and parents. This study had the following major contributions:

- This study investigates m-learning acceptance in rural high schools' context, a setting that has not been sufficiently studied (Ng & Nicholas, 2013; Nikou & Economides, 2017). Elementary school, college, and university learners are the most frequently m-learning research population (Nikou & Economides, 2017).
- The study extends the m-learning acceptance literature by investigating variables, such as perceived enjoyment, perceived social influence, perceived resources perceived skills readiness, and perceived psychological readiness that have not been extensively studied so far.
- To the best of the researchers' knowledge, this study is one of the first to study the factors affecting acceptance of m-learning for high school STEM education.
- To the best of our knowledge, this study is one of the first to study the factors predict the acceptance of m-learning by all the stakeholders (learners, teachers, and parents) in high school context.
- The study is also one of the first to study the multi-group analysis that compare the factors that teachers, learners, and parents consider important when accepting m-learning.

Appendix 1. The instrument

Construct	Measure	Source
Behavioural Intention (BI)	BI1: Assuming I have access to mobile learning, I intend to use it to learn STEM	Alrajawy et al. (2018)
	BI2: I am planning to use mobile learning in learning STEM	
	BI3: I would like to use many different mobile applications for learning STEM in the future	
Perceived attitude towards (ATT)	ATT1: I believe it is beneficial to use mobile learning to learn STEM.	Mathieson et al. (2001)
	ATT2: I feel positive about using mobile learning for learning STEM.	Siegel (2008)
	ATT3: My experience with mobile learning to learn STEM will be good.	
	ATT4: I like my STEM-related subjects more when I use mobile learning.	
	ATT5: Using m-learning to learn STEM-related subjects will be a pleasant experience	
Perceived ease of use (PEOU)	PEOU1: It will be easy to learn how to use mobile learning to learn STEM	Alrajawy et al. (2018)
	PEOU2: I will find it easy to use mobile learning to learn STEM.	
	PEOU3: I will find mobile learning easy to use in STEM classes	
	PEOU4: I would find mobile learning to be flexible to interact with my teacher.	
	PEOU5: It will be easy for me to become skilful in learning STEM using mobile learning	
Perceived skills readiness	PSR1 I have the skills I would need to learn STEM using mobile learning	Newly created
	PSR2 I can use a mobile phone to download applications from the Internet	
	PSR3 I can use a mobile phone to access information/services on the internet	
Perceived social influence	PSI1 My friends think that I should use mobile learning for learning STEM	(Zalah, 2018)
	PSI2 Learners' parents think that I should use mobile learning for learning STEM	
	PSI3 My learners think that I should use mobile learning for learning STEM	

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(*continued*)

Construct	Measure	Source
Perceived psychological readiness	PPR1 Mobile devices (like a phone) are difficult to use PPR2 Mobile devices (like a phone) frustrate me PPR3 I feel insecure about my ability to use learn STEM using a mobile device (like a phone)	Newly created
Perceived enjoyment	PEN1 learning STEM using mobile learning would be enjoyable PEN2 I would find it fun to learn STEM using mobile learning PEN3 I would find using mobile learning interesting	Al-Adwan et al., 2018
Perceived usefulness	PU1: Using mobile learning in class will improve my work efficiency in learning STEM PU2: Using mobile learning to learn STEM will improve my performance in STEM-related subjects. PU3: Using mobile learning would make it easier for me to learn STEM PU4: I would find mobile learning useful in learning STEM. PU5: Using mobile learning would enhance my effectiveness in learning STEM	Alrajawy et al. (2018)

Appendix 2. Descriptive data of the constructs

Construct	Indicator	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
							Statistic	Std. Error	Statistic	Std. Error
Perceived usefulness	PU1	417	2	7	6,66	0,727	−2575	0,120	7775	0,238
	PU2	417	3	7	6,60	0,740	−2141	0,120	4960	0,238
	PU3	417	2	7	6,55	0,819	−2100	0,120	4766	0,238
	PU4	417	1	7	6,47	0,869	−2167	0,120	6411	0,238
	PU5	417	2	7	6,54	0,771	−2108	0,120	5735	0,238
Perceived attitude towards	ATT1	417	1	7	6,12	1185	−1521	0,120	2204	0,238
	ATT2	417	1	7	5,67	1314	−1326	0,120	2154	0,238
	ATT3	417	2	7	5,97	1088	−0,903	0120	0,351	0238
	ATT4	417	1	7	6,02	1087	−1232	0,120	1860	0,238
	ATT5	417	1	7	5,96	1190	−1352	0,120	2201	0,238
Behavioural intention	BI1	417	1	7	6,36	0,951	−1727	0,120	3592	0,238
	BI2	417	1	7	5,59	1483	−1221	0,120	1242	0,238
	BI3	417	1	7	6,11	1138	−1446	0,120	2166	0,238
Perceived ease of use	PEOU1	417	1	7	6,27	1047	−2023	0,120	5162	0,238
	PEOU2	417	2	7	6,14	1030	−1417	0,120	2038	0,238
	PEOU3	417	1	7	6,11	1044	−1639	0,120	3848	0,238
	PEOU4	417	1	7	6,45	0,989	−2560	0,120	7814	0,238
	PEOU5	417	1	7	6,41	1005	−2405	0,120	7031	0,238
Perceived resources	PR1	417	1	7	5,31	1140	−1683	0,120	2077	0,238
	PR2	417	2	6	5,79	0,641	−3692	0,120	14,848	0,238
	PR3	417	1	5	3,83	1267	−0,727	0120	−0,596	0238
	PR4	417	1	7	3,80	1900	0,026	0120	−1156	0,238
Perceived psychological readiness	PPR1	417	1	7	6,15	1217	−1808	0,120	3647	0,238
	PPR2	417	1	7	5,55	1506	−1119	0,120	0966	0,238
	PPR3	417	1	7	5,81	1446	−1399	0,120	1650	0,238
Perceived skills readiness	PSR1	417	1	7	5,86	1215	−1033	0,120	0839	0,238
	PSR2	417	1	7	5,81	1218	−1114	0,120	1201	0,238
	PSR3	417	1	7	5,90	1250	−1330	0,120	1898	0,238
Perceived enjoyment	PEN1	417	1	7	6,30	0,980	−1827	0,120	4064	0,238
	PEN2	417	1	7	4,93	1431	−1228	0,120	0532	0,238
	PEN3	417	1	6	5,46	1096	−2459	0,120	5979	0,238
Perceived social influence	PSI1	417	1	7	5,61	1551	−1030	0,120	0575	0,238
	PSI2	417	1	7	5,64	1558	−0,949	0120	0,071	0238
	PSI3	417	1	7	5,64	1491	−0,890	0120	−0,004	0238

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