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An exploration of STEM students' and educators' behavioural intention to use mobile learning

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Abstract

This study sought to find factors that Science, Technology, Engineering, and Mathematics (STEM) students and educators in a developing country consider important when accepting mobile learning. The study developed a new model by extending the Technology Acceptance Model (TAM) using the construct perceived resources. Using stratified random sampling, a total of 160 STEM students and 100 educators were selected to participate in this study. The study employed a quantitative design where partial least squares structural equation modeling was used to examine STEM students' and educators' behavioural intention to use mobile learning. The developed model explained 74.1% of the variance in STEM students' and educators' behavioural intention to use mobile learning. Perceived resources, perceived ease of use, and perceived usefulness variables explained 54.8% of the variance in attitudes of STEM students' and educators' behavioural intention to use mobile learning. Attitude was the strongest indicator of STEM students' and educators' behavioural intention to use m-learning. The results indicated that both educators and students have a positive attitude towards mobile learning, given how important online learning is becoming nowadays. Additionally, there is no statistically significant difference between educators' and students' attitudes towards mobile learning. The implication is that developers of mobile learning systems should make their platforms easy to use and have more resources available for both teachers and learners to increase the overall acceptance of mobile learning in STEM subjects.

KEYWORDS: Mobile Learning, Educators, Students, Attitude, Acceptance, TAM, STEM.

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1. Introduction

STEM education refers to the teaching and learning of science, technology, engineering, and mathematics (STEM) in both formal and informal classroom settings (Gonzalez, & Kuenzi, 2012). STEM education has evolved into a meta-discipline, a holistic endeavour that focuses on creativity and the process of producing answers to complex contextual circumstances using existing methods and technologies, rather than traditional topic boundaries. STEM education has been a hot topic on a global scale in the last decade. This is motivated by the changing global economy and labour requirements that indicate that there will be a shortage of staff and educators trained for STEM around the world (Kennedy & Odell, 2014).

Since STEM education is still in its inception in developing-country secondary schools, it faces many challenges that result in poor performance of students at the matriculation level (Makgato, 2007; Modisaotsile, 2012; Visser, Juan, & Feza, 2015). This dissatisfactory achievement in STEM-related subjects was attributed by Makgato (2007) to the scarcity of learning resources, science laboratories, and tools to facilitate successful teaching and learning. Modisaotsile (2012) blames the low performance of students in STEM-related subjects on to absence of parental participation in the education of their children. Visser et al. (2015), on the other hand, attributed the shortage of learning materials and textbooks to these poor results in STEM-related

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subjects. Based on the findings of these studies, (Visser, Juan, & Feza, 2015; Modisaotsile, 2012; Makgato, 2007), it can be concluded that in developing countries, many obstacles negatively influence effective STEM teaching and learning.

Mobile learning (m-learning) can be utilized to address the issues of STEM education (Criollo-C et al., 2018; Pinker, 1997; Wong et al., 2019). Odiakaosa, Dlodlo, and Jere (2017) described m-learning as learning that incorporates the use of a mobile device like a smartphone, PDA, iPod, palmtop, or tablet computer, laptops, or even digital cameras and USB keys. Major education and content providers, like Blackboard and Coursera, offer free apps for accessing course materials (Hao, Dennen & Mei, 2017). What can be learned from Hao et al, (2017)'s concept and evaluation is that the introduction of mobile gadgets into the classroom has the ability to impact educators' and students' academic performance and experiences (Callum, Jeffrey & Kinshuk, 2014).

Mobile learning helps students to access materials for learning at anywhere and anytime (Criollo-C et al., 2018). M-learning allows visualized science experiments to be used to strengthen the comprehension of science concepts by students and to provide complete explanations of scientific concepts (Pinker, 1997). In addition, m-learning enhances parental interest in the learning of their children, which in turn enhances the motivation and success of students in STEM-related subjects (Wong et al., 2019). The takeaway from these researches is that, while STEM education faces numerous problems, m-learning can mitigate the effects of these obstacles in secondary schools (Criollo-C et al., 2018; Pinker, 1997).

In spite of the advantages, Davis et al., 1989, claimed that the effective implementation of any information system (IS) be determined by the acceptance of the users. It can be claimed, based on the evaluation by Davis et al. (1989), that the acceptance of m-learning for STEM learning is dependent on its acceptance by educators and students. As a corollary, it may be claimed that effective deployment of m-learning in developing-country secondary schools needs research on its reception by both educators and students (Kim et al., 2013). For example, a plethora of studies in tertiary institutions based on the acceptance of m-learning by lecturers and students, hence its successful adoption (Alrajawy, Isaac, Ghosh, Nusari, Al-Shibami, & Ameen, 2018; Akinbode, Agboola, Senanu & Adeniji, 2020; Sánchez-Prietoa et al., 2019). However, the views of secondary school STEM educators and students of m-learning remains dearth in the body of knowledge.

A few studies in secondary schools in developing countries have focused on m-learning (Mutambara & Bayaga, 2021; Osakwe et al., 2017). Osakwe et al. (2017) assessed the real use of m-learning by secondary school educators and students in Namibia. Mutambara and Bayaga (2021) emphasized the importance of developing nations doing studies on educators' and students' attitudes toward m-learning rather than mindlessly following models from developed countries. The current study sought to assess the views of the attitudes of secondary school STEM educators and students towards m-learning. This study is inspired by the work of Kim et al. (2013), who indicated that more studies must be carried out, especially in STEM, on the views of educators and students towards m-learning. This is principal because researchers (Osakwe et al., 2017; Odiakaosa et al., 2017) did not concentrate on students' and educators' attitudes towards m-learning, nor did they compare whether there was a noticeable difference between STEM educators' and students' attitudes towards m-learning, necessitating the current study.

The following research questions were posed in an attempt to explore the factors that affect secondary school STEM students and educators to embrace m-learning, as well as the interrelationships between students' and educators' attitudes toward m-learning acceptance:

1. What factors do STEM students and educators think are significant when it comes to accepting m-learning?
2. Is there a substantial difference in the attitudes of STEM students and educators about m-learning?

2. Literature review

2.1 Mobile learning in developing countries

Many developing countries encourage the utilisation of m-learning. For example, the South African Department of Basic Education (DoE) encouraged educators and students to utilise m-learning for STEM learning (DoE, 2020a). The DoE argued that students and educators should take advantage of the ubiquitous presence of mobile devices in our daily lives. The DoE had been gradually introducing digital technologies in schools (Mhlanga & Moloi, 2020). However, during the nationwide lockdown caused by the Covid-19 outbreak, the DoE developed a STEM lockdown digital school in collaboration with Africa Teen Geeks, a non-profit coding organization (DoE, 2020a). Additionally, the DoE partnered with network providers (Vodacom, MTN, Telkom, and Cell C) to make students access mobile learning platforms for free (Mhlanga & Moloi, 2020). According to the DoE, Siyavula Maths and Science assistance was also available to students for free, which was offered in collaboration with MTN (DoE, 2020b).

Despite all these interventions, the DoE noted with concern that the rate of m-learning usage was below the expected levels (Mhlanga & Moloi, 2020). As a result, research was conducted to determine the variables that educators and learners deem crucial when accepting m-learning (Akinbode et al., 2020; Lin et al., 2020). The key characteristics that consistently influence students' and educators' adoption and use of m-learning are perceived usefulness (PU) and perceived ease of use (PEOU) (Lin et al., 2020). Educators' and students' perceived attitude was also found to influence their intention to utilise m-learning (Lin et al., 2020). Lin et al. (2020) also noted that the students' and educators' intentions to utilisation m-learning is influenced by their availability of resource, perceived enjoyment, and perceived social influence.

2.2 Comparing secondary school students' and educators' acceptance of m-Learning

Montrieux et al. (2014) explored the acceptance of m-learning by educators and students. A computerized questionnaire was developed to gather data from 83 educators and 694 pupils on three occasions. The data was analysed using multiple regression. For educators, the models explained variance in behavioural intention (BI) of 60% in the first phase and 71% in the second and third phases. For students, the models explained 60%, 59%, and 61%, of variance in their BI to utilise m-learning. Only PU, perceived attitude toward (ATT), and PEOU had a significant impact on their BI in the first wave, according to the educators' findings, although status and perceived enjoyment (PEN) had no effect. These findings corroborate the research outcomes of Kim and Lee (2020), who indicated that when educators accept m-learning, they assess the benefits as well as the effort involved to learn how to use m-learning. Contrary to educators' findings, PEN had the strongest influence on students' BI. All five determinants (status, ATT, PU, PEN, and PEOU) had a noticeable influence on BI in the first wave.

The second wave of results revealed that educators' PU, PEN, and PEOU had a significant impact on their BI to use m-learning, whereas BI, on the other hand, was unaffected by status (Montrieux et al., 2014). Only ATT, PU, and PEN, on the other hand, proved to have a substantial effect on students' BI. Only the PEOU of students had a negligible effect in the third wave, whereas the other four factors had a large impact on their BI for adopting m-learning. These findings are in agreement with those of Osakwe et al. (2017), who found that students have a good attitude toward m-learning and believe it is beneficial. All five determinants (status, PEN, PEOU, ATT, and PU) had a substantial impact on educators' willingness to employ m-learning. These findings, however, contrast those of Callum et al. (2014), who found that educators' PEOU does not influence their BI while adopting. The students' results reveal a mix of enjoyment and utility, which influenced their adoption of m-learning. The researchers came to a conclusion that educator and student models reasonably mimicked one another (Montrieux et al., 2014). However, the findings of the study did not reveal whether there was a notable difference in the attitudes of students and educators towards m-learning.

2.3 Theoretical Frameworks and Hypotheses Development

A variety of models have been proposed to promote understanding of the aspects that influence the acceptance of a new information system (IS) (Lin et al., 2020). The Technology Acceptance Model (TAM) and Unified Technology of Acceptance and Use Theory (UTAUT) are the most commonly used models to describe the acceptance of m-learning. UTAUT, however, has been chastised for its inability to forecast actions that are not entirely under the control of a person (Estrieganaa et al., 2019). It is possible to incorporate m-learning, and users are compelled to use it. STEM students and educators, for example, were forced to use m-learning in this study due to the sudden closing of schools due to the spread of the Covid-19 virus. UTAUT can't be used in this study since it can't predict behaviours that are completely under a person's control.

This research utilised TAM to examine the intention of STEM educators and students to use m-learning. The TAM was chosen as it is thought to be accurate in explaining user adoption of technology in a variety of scenarios (Estrieganaa et al., 2019). "TAM is a well-regarded and widely validated theory of technology acceptance and use" Estrieganaa et al. (2019, p.4) added. TAM was also effectively used in education to forecast the adoption of m-learning (Mohammadi & Mahmoodi 2019; Mutambara & Bayaga, 2021).

In educational contexts, some scholars criticized the TAM (Carlsson et al., 2006; Venkatesh et al., 2003). The TAM is accused of the poor explanatory capacity of the users' perspectives on the IS (Venkatesh et al., 2003). Carlsson et al. (2006) criticized the TAM for being too generic and applicable to technology adoption in a variety of fields. Based on these studies (Carlsson et al., 2006; Venkatesh et al., 2003), it can be inferred that TAM alone is insufficient to explain and clarify m-learning adoption. In addition, Lim (2018) proposed that the TAM offers the two foundations of the acceptance of the IS (PEOU) and PU)), from which a fully fledge model can be established to clarify and forecast the technology acceptance in various circumstances, including the contextualization of acceptance constructs. Centred on the Lim (2018) proposal, this study expanded the TAM by adding perceived resources (R) to clarify the adoption of m-learning by STEM students and educators in developing countries.

2.4 The TAM

Davis, Bagozzi, and Warshaw (1989) developed the TAM to determine users' intentions to accept new technologies. IS. The TAM postulates that PEOU and PU are the two key pillars of a new IS adoption (Davis, et al., 1989). PEOU predicts PU. PEOU and PU predict the attitude of users towards the new IS. The PU and ATT predict their BI to use the system, which, in turn predicts the actual usage of the user. PU was defined by Davis et al. (1989) as an individual's belief that using a specific IS will improve his or her job performance. The

PEOU is defined as the degree to which a person believes that using a given IS would be simple (Davis et al., 1989). Venkatesh et al. (2003) defined ATT as an individual's total emotive reaction to the use of new technology in technology acceptance studies. Figure 1 illustrates the TAM.

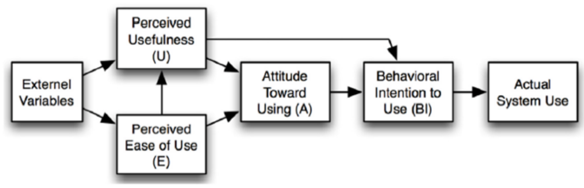

Figure 1 - The TAM Model by Davis et al. (1989, p. 985).

2.4.1. Behavioural Intention (BI)

The BI was described as the cognitive representation of the willingness of an individual to conduct a particular action (Kim & Lee, 2020). The BI is considered the most important determinant of the actual behaviour of the person and has a major and direct impact on the use of technology (Kim & Lee, 2020). Zarafshani et al. (2020) stated that the BI of users to use ICTs in education affects their actual use. The current study posits, based on the results of Kim and Lee (2020) and Zarafshani et al. (2020), that understanding the determinants of BI of STEM educators and students to use m-learning is to understand the determinants of their acceptance of m-learning for STEM learning.

2.4.2. Perceived Usefulness (PU)

The PU was described as "capable of being used advantageously" (Estrieganaa et al., 2019, p.5). PU is described as the belief of an individual that utilising m-learning would enhance his or her performance, in the field of m-learning (Lin et al., 2020). According to Alrajawy et al. (2018), utility value is a key factor of students' inclinations to use m-learning. Alrajawy et al. (2018) agree with the findings of Alrajawy et al. (2017), who discovered that PU has a beneficial influence on BI. PU was also found to be a major determinant of ATT of educators towards m-learning (Zarafshani et al., 2020). If educators and students understand the advantages of mobile learning, their attitudes toward using these technologies will improve.

As a result, the hypotheses are:

H1: STEM students' and educators' PU predicts their ATT toward m-learning.

H2: The PU of STEM students and educators predicts their BI to use m-learning.

2.4.3. Perceived Ease of Use (PEOU)

Perceived ease of use refers to the extent to which users believe that the use of a given information technology would be free from effort (Mutambara & Bayaga, 2021). Ease of use does not only refer to m-learning platforms. M-learning faces many difficulties, such as networking, restricted processing capacity and decreased input capabilities (Ford & Botha, 2010). Kukulska-Hulme (2007) argued that on devices that are not intended for educational use, m-learning activities continue to take place and that usability problems are commonly mentioned. However, it is claimed that educators' PEOU has no substantial impact on their BI to utilise m-learning (Callum et al., 2014). Saroia and Gao (2018) and Sánchez-Prietoa et al. (2019) subsequently concluded that BI is not specifically influenced by PEOU. In comparison, other studies have shown that PEOU had a major direct impact on BI (Kukulska-Hulme, 2007; Sivo et al., 2018). PEOU has a clear favorable influence on the utilization of m-learning through PU, BI, and ATT, according to Estrieganaa et al. (2019). As a result, the three hypotheses were posited:

H3: STEM students' and educators' PEOU predicts their PU toward m-learning.

H4: STEM students' and educators' PEOU predicts their BI to adopt m-learning.

H5: STEM students' and educators' PEOU predicts their ATT toward m-learning.

2.4.4. Perceived Attitude Towards (ATT)

In this research, the ATT can be described as the overall affective reaction of a secondary school STEM student or educator to the use of m-learning. The values and attitudes of students and educators are stated to play a significant influence in either resisting or embracing m-learning (Dutota et al., 2019). For example, if educators think that m-learning is inadequate to meet their own requirements or the needs of their students, they would refuse using it (Dutota et al., 2019). ATT has long been proven to be an important factor of intention to use m-learning in the literature (Saroia & Gao, 2018). As a result, the following hypothesis is proposed:

H6: STEM students' and educators' ATT predicts their BI to utilise m-learning.

2.4.5. Resources perceived (R)

The R is defined as an individual's belief in the existence of an organizational and technological infrastructure that will make it easier to use the system (Venkatesh et al., 2003). Resources availability influences the attitude of users towards m-learning (Sivo et al., 2018). The availability of resources for m-learning helps to boost the attitudes of students and educators towards it. Perceived resources predict actual use (Kim & Lee, 2020). They are more likely to use m-learning if STEM students and educators perceive that they have the resources required for it. Perceived resources was found to affect both PU and PEOU in another study by Zarafshani et al. (2020). Therefore, the hypotheses:

H7: STEM students' and educators' perceived resources predicts their ATT.

H8: STEM students' and educators' perceived resources predicts their PU.

H9: STEM students' and educators' perceived resources predicts their PEOU.

H10: STEM students' and educators' perceived resources predicts their BI.

Based on the theoretical underpinnings, a conceptual model is shown in Figure 2. This is a combination of all the hypotheses and their associated latent variables, as conceptualised by the authors.

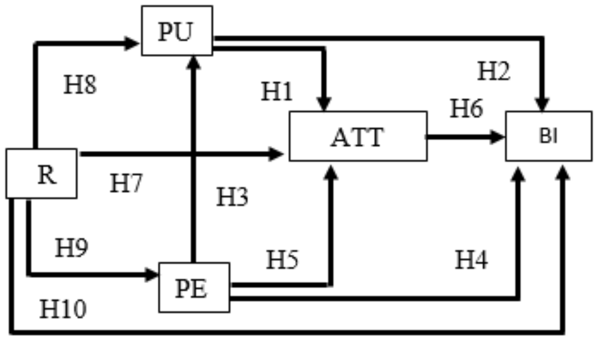

Figure 2 - Conceptual model of the study.

3. Methodology

3.1 Research Design

A questionnaire was utilized to collect survey demographic and opinion-related data from STEM students and educators, and the study used a quantitative method. The educators' and students' perspectives were first discussed using descriptive statistics. Second, the model was evaluated using partial least squares structural equation modelling (PLS-SEM).

3.2 Participants

Stratified random sampling was utilised to acquire data (Creswell, 2017). The quintiles were used to categorize all secondary schools in South Africa's Imifolozi Districts. A stratum was formed by schools from the same quintile. This ensured that a stratum was generated by homogeneous element. The schools formed five strata. Schools were grouped in alphabetical order in a stratum, and a number was allocated to each school. To get two schools in each stratum, computer-generated random numbers were used. This approach was used to provide an equal opportunity for each school in the district to be chosen, thereby providing an impartial the population's representation (Creswell, 2017). Five schools were chosen, and 40 grade 12 students from each were chosen using a simple random sample approach. A total of 200 grade 12 students were handed questionnaires, with 160 (80%) being valid responses of the survey. Around 65 (41 %) of the students who took part in this study were from urban, 53 (33 %) from suburban, and 42 (26 %) from rural areas. Students ranged in age from 17 to 21. The survey included 69 (43 %) female students and 91 (57 %) male students.

The district's STEM educators were then chosen using simple random sampling. A total of 128 educators took part in the study, with 100 (78%) valid surveys collected. Of the 100 educators that took part, 63 (63 %) were male, while 37 (37 %) were female. Of the 100 educators who took part, 13 (13%) were under the age of 30, 33 (33%) were among the ages of 30 and 40, 28 (28%) were between the ages of 40 and 50, and 26 (26%) were above the age of 50.

3.3 Procedure

To evaluate the conceptual model, a cross-sectional field study was conducted. Data was collected from research sites that closely reflected the target environment that the study's findings would generalize to in order to ensure ecological validity: Secondary schools in rural, semi-urban, and urban areas where m-learning is about to be fully implemented. The data was collected soon after schools were reopened following abrupt closure due to the national lockdown which aimed at combatting the spread of the Covid-19. In a bid to alleviate the impact of the Covid-19 pandemic on education during the lockdown, the DoE and Ministry of Communication and Digital Technologies collaborated to ensure virtual learning took place, especially for the examination class (grade 12) (Mhlanga & Moloi, 2020). South Africa's government collaborated with network providers to create zero-rated applications and instructional websites (Mhlanga & Moloi, 2020). This meant that STEM students and educators could make use of these learning platforms free of charge. However, the government did not supply devices to STEM students and educators. The STEM educators and students were not trained to utilise m-learning for STEM learning. Grade 12 students were chosen because these were the students who continually attended classes throughout the lockdown period using m-learning. The researchers distributed questionnaires to STEM students and educators and allow them two weeks to complete on their own time.

3.4 Instrument

The research sought to explore factors deemed significant by high school STEM students and educators when embracing m-learning. To gather data, a questionnaire was used. The questionnaire's first section inquired about the demographics of STEM students and educators. Section two used a seven-point Likert scale to collect data on five latent variables (BI, ATT, R, PU, and PEOU), with options ranging from strongly disagreeing to strongly agreeing. The BI, R, PEOU, and PU items were taken from thoroughly affirmed and precise instruments (Alrajawy et al., 2018). The questionnaire contained 19 indicators.

3.5 Analysis technique

The SmartPLS3 software was used to do data analysis employing the PLS-SEM approach. The PLS-SEM methodology was utilized to evaluate the effects of PU, R, ATT and PEOU on BI. It was also utilized to see if there was a noticeable difference in the acceptance of m-learning by STEM educators and students. Hair et al. (2017) proposed a two-step approach for evaluating the research model, which was employed in this study. First, the measurement model's validity and reliability were assessed (Garson, 2016). The structural model was then assessed in the second step. This was done to see if the model met the quality standards for empirical work (Garson, 2016).

4. Data Analysis

4.1 Measurement Model

The reflective measurement model was validated using convergent validity, internal consistency, indicator reliability, and discriminant validity (Hair et al., 2017).

Indicator reliability

A construct ought to explain a significant portion of the variance in each indicator, typically more than 50% (Chin, 1998). Hair et al. (2017) proposed a threshold value for the outer loadings of 0.7. All of the indicators had outer loadings greater than the threshold value of 0.7, as shown in Table 1 (Hair et al., 2017), suggesting that the constructs explained all their indicators well. The findings also indicate that less than 50% of the variance of all indicators was due to error.

Internal Consistency Reliability

The composite reliability (CR) and Cronbach's alpha (CA) tests were employed to determine internal consistency reliability. Cronbach's alpha (CA) is favoured over CR because it provides more precise results (Hair et al., 2017). Table 1 shows that all of the latent variables employed had sufficient internal consistency reliability, since their CR and CA values were all greater than the 0.7 threshold value (Hair et al., 2017).

Convergent validity

Convergent validity refers to the degree to which "a measure positively correlates with alternative measures of the same construct" (Hair et al., 2014, p.102). The convergent validity was tested using the outer loadings and average variance extracted (AVE). Table 1 shows that all of the outer loadings were greater than the 0.70 threshold value. Hair et al. (2017) found that all of the AVE values were greater than 0.50, indicating that the assessments of each latent variable were significantly correlated. The findings show that convergent validity is acceptable.

Construct	Indicator	Convergent validity		Internal consistency reliability		Discriminant validity
		Loadings	AVE	CA	**CR**	
		>0.7	**>0.5**	**>0.7**	**>0.7**	**HTMT confidence interval does not include 1**
ATT	ATT1	0.917	0.803	0.918	0.942	Yes
	ATT2	0.915				
	ATT3	0.884				
	ATT4	0.867				
BI	BI1	0.927	0.792	0.950	0.950	Yes
	BI2	0.755				
	BI3	0.930				
	BI4	0.895				
	BI5	0.930				
PU	PU1	0.843	0.676	0.840	0.893	Yes
	PU2	0.855				
	PU3	0.824				
	PU4	0.763				
PEOU	PEOU1	0.758	0.693	0.852	0.900	Yes
	PEOU2	0.794				
	PEOU3	0.889				
	PEOU4	0.880				
R	R1	0.916	0.840	0.810	0.913	Yes
	R2	0.917				

Table 1 - Measurement model.

Discriminant validity

The amount to which "a construct is actually distinct from other constructs by empirical standards" was defined as discriminant validity (Hair et al., 2014, p. 104). To establish discriminant validity, the Heterotrait-Monotrait ratio of correlations (HTMT) values were utilized (Garson, 2016). The values of HTMT were less than 0.90 (Garson, 2016). Discriminant validity was verified by the results.

The indicator reliability, internal consistency reliability, convergent validity, and discriminant validity tests of the measurement model were all successful. As a result, the measurement model gives the structural model the essential robustness to evaluate it.

4.2 Structural model

After confirming the measurement model's adequacy, the structural model was evaluated. Collinearity was assessed using the variance inflation factor (VIF). Table 1 shows that the VIF values of all latent variables were all less than four (Garson, 2016), indicating that predictor collinearity was not an issue in the structural model. As a result, the path coefficients can be calculated.

To test the statistical significance of each path coefficient, we performed bootstrapping (with 5000 subsamples) as recommended by Chin (1998), and the results are given in Table 2. Only two path coefficients were not significant, as shown in Table 2. PEOU to BI (= -0.016, $p > 0.05$) and PU to ATT ($\beta = 0.082$, $p > 0.05$) were not significant.

Using the f-squared, the contribution of each latent variable to the explained variance of its endogenous concept was assessed. The results are shown in Table 2. According to Cohen (1988), the acceptable f-squared values of 0.02, 0.15, and 0.35 are regarded as a small, medium, and significant effect sizes, respectively. Following the guideline provided by Cohen (1988), the effect size of ATT to BI (0.766), was considered significant. The following paths had medium effect size PEOU to ATT (0.225), R to ATT (0.285), and R to PEOU (0.313). PEOU to PU (0.032), PU to BI (0.054), R to BI (0.073), and R to PU (0.135) had a small effect size.

Path	Std Beta	Std error	T Statistics	P Values	Decision	VIF	f-squared
ATT -> BI	0.663	0.047	14.230	0.000	Accepted	2.214	0.766
PEOU -> ATT	0.371	0.063	5.853	0.000	Accepted	1.355	0.225
PEOU -> BI	-0.016	0.043	0.364	0.716	Rejected	1.659	0.001
PEOU -> PU	0.179	0.072	2.475	0.014	Accepted	1.313	0.032
PU -> ATT	0.082	0.064	1.275	0.203	Rejected	1.303	0.011
PU -> BI	0.135	0.052	2.584	0.010	Accepted	1.318	0.054
R -> ATT	0.438	0.057	7.640	0.000	Accepted	1.491	0.285
R -> BI	0.191	0.043	4.393	0.000	Accepted	1.922	0.073
R -> PEOU	0.488	0.059	8.296	0.000	Accepted	1.000	0.313
R -> PU	0.369	0.072	5.148	0.000	Accepted	1.313	0.135

Table 2 - Bootstrapping Results.

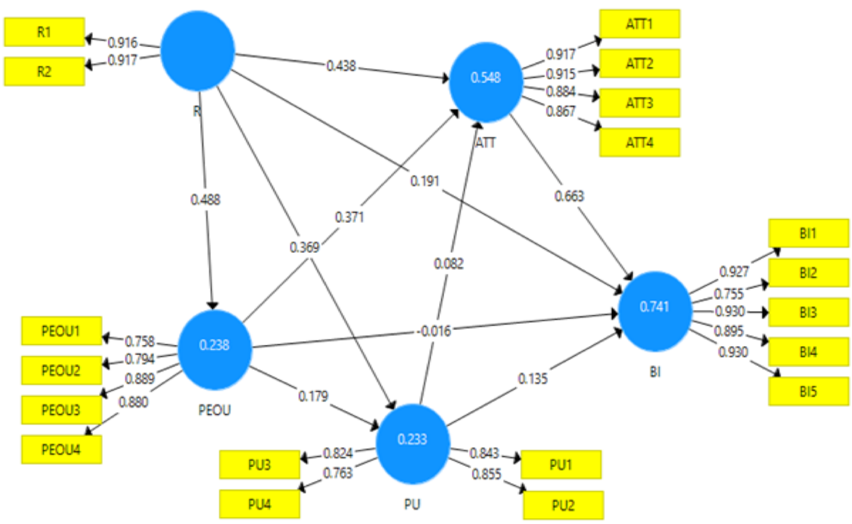

Figure 3 - Structural model.

Figure 3 depicts the model's explanatory value (R-squared). The R-squared value represents the variance explained by the exogenous factors in the endogenous variables (Hair et al., 2017). The model explained 74.1% of the variance in BI. R, PEOU, and PU explained 54.8% of the variance in ATT. R also explains 23.8% of the variance in PEOU. The combined contribution of R and PEOU to PU's explained variance was 23.3 %. Following the guideline by Cohen (1988), the variance explained in BI and ATT was considered substantial, while PU and PEOU were considered moderate.

Q-squares were used to assess the model's predictive relevance. All of the Q-squares were greater than zero, indicating that the model can be used to predict whether or not m-learning will be accepted by STEM students and educators.

The standardized path coefficients are also shown in Figure 3. The structural model is made up of five structures (ATT, BI, R, PEOU, and PU). PU, ATT, and PEOU all predict BI. PU and PEOU are antecedents of ATT.

4.3 Multigroup analysis

The multigroup analysis (MGA) was employed to determine whether there was a noticeable difference in the path coefficients of STEM students and educators. The findings of the MGA are shown in Table 3.

Table 3 summarizes the results for all hypotheses and shows that there are no significant differences in path estimates for educator and student groups, as evidenced by an insignificant difference ($P > 0.05$). The findings suggest that there was no difference between the adoption of m-learning by STEM students and educators.

Path	Path Coefficients-diff (EDUCATORS - STUDENTS)	p-Value new (EDUCATORS vs STUDENTS)
ATT -> BI	-0.037	0.707
PEOU -> ATT	-0.174	0.142
PEOU -> BI	0.052	0.562
PEOU -> PU	-0.078	0.625
PU -> ATT	-0.061	0.640
PU -> BI	0.053	0.629
R -> ATT	0.255	0.051
R -> BI	-0.046	0.639
R -> PEOU	0.045	0.698
R -> PU	0.057	0.695

Table 3 - MGA results.

5. Discussion

Objective 1: The findings reveal that the structural model appropriately explains and predicts the BI of high school STEM students and educators to adopt m-learning. All Q-squared values were greater than zero, indicating that the model's predictive validity for endogenous constructs was confirmed (Hair et al., 2017). In other words, R, PEOU, PU, and ATT are strong predictors of students' and educators' willingness to adopt m-learning for STEM learning. The total effect of the factors PEOU, PU, R, and ATT in describing STEM students' and educators' BI to use m-learning for STEM learning was 74.1 %.

In line with the findings of Alrajawy et al. (2017), STEM students' and educators' PU influence their BI. The results supported H2 ($\beta = 0.135$, $p < 0.05$). The results imply that STEM students' and educators' belief that m-learning can increase students' performance in STEM-related subjects influence their BI to use m-learning. There are several reasons for these findings. In this research, most STEM educators and students come from under-resourced schools, so their BI to use m-learning is affected by its ability to provide learning materials anywhere and at any time. Additionally, the ability of m-learning to enable students to visualize experiments influenced their BI to use it. This is specifically because most of the respondents in this study were coming from rural and semi-urban areas where most schools do not have science laboratories and equipment (Makgato, 2007). Furthermore, the ability of m-learning to supply learning materials at anytime and anywhere assists STEM students and educators in improving learning productivity by repurposing time that was previously unproductive, such as travel and commuting time.

The findings suggested that, contrary to widespread perception in the m-learning literature, educators and students regard utilizing m-learning to be difficult. The findings also indicated that the effort required to learn to use m-learning has no bearing on their BI. This can primarily be due to the efforts of both developers of m-learning sites and content creators for learning. Learning content designers are designing materials in a way that allows them to be used handheld. On the other hand, developers of m-learning systems are designing easy to learn platforms. As a result, educators and students think of m-learning as simple to use, which showed in this study as an insignificant antecedent of their behavioural intention.

Inconsistent with the findings of Sivo et al. (2018), the results revealed that R influences STEM students' and educators' BI to use m-learning. The findings imply that the availability of resources influences STEM students and educators to utilise m-learning. A possible reason for this finding is that, even though educators and students have smartphones that can support m-learning, they are facing difficulties such as connectivity, restricted computing capacity, small screen size, and reduced input capabilities. This is because smartphones have not been designed for learning purposes explicitly. Consequently, providing STEM students and educators with data packages and mobile devices that are specifically designed for learning will boost their acceptance and intentions to use m-learning.

It's encouraging to see that STEM students' and educators' attitudes are the strongest indicator of their BI. As a result, it's critical to consider the elements that influence STEM students' and educators' attitudes toward mobile learning. This study's findings contradict those of Padayachee (2017), who discovered that educators have a negative attitude toward mobile learning. Educator training and user-friendly m-learning systems may help to improve educators' attitudes regarding m-learning. This is because the findings suggest that STEM students' and educators' PEOU ($\beta = 0.371$, $p < 0.05$) explains their attitude toward m-learning better than PU ($\beta = 0.082$, $p < 0.05$). Giving STEM educators and students mobile devices that are specifically built for m-learning purposes will reinforce their favourable attitude toward m-learning.

Objective 2: Table 3 demonstrates that there was no substantial difference in the path coefficients of all STEM students and educators. This contrasts with the findings of Odiakaosa et al. (2017), who discovered that students are more enthusiastic about m-learning than educators. This research demonstrates that STEM students believe m-learning can increase their performance just as much as their educators do. STEM educators and students see m-learning as a tool designed to satisfy the diverse learning preferences of students.

Furthermore, the study's respondents were STEM students and educators who saw the benefits of m-learning. Students can visualize experiments and simulations of science concepts via m-learning, which helps them understand the concepts better. Furthermore, the participants of this study acknowledged that even though the schools were closed due to Covid-19, they could still teach and learn STEM related-subjects using m-learning. This utility of m-learning motivates both STEM students and educators to have favourable perceptions of it. These findings show that the same model may be utilised to predict m-learning adoption by both populations (students and educators).

Based on the findings of this study, the following recommendations can be made to mobile application developers, teacher training colleges, education administrators, and faculties of education in universities. Education administrators can collaborate with private companies to provide educators and students with mobile devices such as laptops and tablets that are specifically built for education purposes. Difficulty navigating, downloading, searching, and sharing a mobile device from a small screen can affect the interest of STEM students and educators in using m-learning. The R affect STEM educators' and students' attitude towards m-learning and their intent to use it. Mobile developers should continue to improve m-learning platforms to make them more user-friendly. Instructional designers should continue to improve m-learning learning material to make it more suitable for handheld usage.

They should also make additional m-learning and evaluation materials available to STEM students and educators. This is due to the fact that the PU of both STEM students and educators determines their behavioural intention to use m-learning. The provision of assessment materials on a user-friendly platform encourages STEM students to use m-learning because it makes it easier for them to practice and prepare for exams. The availability of learning and evaluation content on a user-friendly platform reduces the amount of time STEM educators spend preparing lessons. Teacher education institutes can work with the Department of Basic Education to train STEM educators on how to effectively employ m-learning to fulfil the different learning needs of STEM students. This is because the PEOU of STEM educators predicts their ATT usage.

6. Contribution of the study

• When embracing m-learning, both STEM students and educators consider the availability of m-learning resources important. Smart devices that are specifically designed for learning must be supplied to all STEM students and educators.

• ATT is the strongest indicator of STEM students' and educators' BI to use m-learning. For m-learning to be adopted for STEM learning, students and educators required to have a positive attitude toward it. STEM students' and educators' attitudes toward m-learning could be enhanced by using user-friendly platforms, providing them with mobile devices specifically designed for learning, uploading quite enough learning and assessment material on m-learning platforms, and training STEM students and educators on using m-learning platforms.

• When it comes to m-learning, STEM students and instructors appreciate the same things. The time and effort required to learn how to use m-learning platforms, the accessibility of m-learning resources, the utility of m-learning, and their attitudes toward m-learning are all issues to consider.

One drawback of the current research is that it focused only on STEM students and educators in grade 12. Therefore, it should be done with caution to generalize the results of this research to educators and students of other lower grades. Educators and students from other lower grades and parents should also be included in future research. It will be important to find variables that impact the continuous use of m-learning by STEM students and educators for STEM learning.

7. Concluding remarks

It is reasonable to assume, based on the study's findings, that grade 12 STEM students and educators have a positive attitude toward m-learning. The model explained 74.1% of the variance in students' and educators' behavioural intentions. Overall, the results provide empirical evidence for the applicability of the TAM in explaining users' acceptance of mobile learning. Students' and educators' behavioural intentions are directly influenced by perceived usefulness, perceived resources, and perceived attitude toward, although perceived ease of use has an indirect impact. Students and educators accepted m-learning for a variety of reasons, including their sentiments about it, the availability of resources, and its potential to improve teaching and learning. This was confirmed by the finding that perceived attitude toward m-learning was the most important factor of acceptance, followed by perceived resources and perceived usefulness for both educators and students. When it comes to accepting m-learning, the survey demonstrates that both students and educators recognize the benefits that m-learning provides to the classroom and are willing to adopt it. Furthermore, the availability of materials has a substantial impact on students' and educators' acceptance of mobile learning. This may imply that they require mobile devices that are specifically designed for learning.

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Appendix A: Questionnaire

Construct	Code	Indicators
Perceived attitude towards	ATT1	I believe it is beneficial to use mobile learning to learn STEM
	ATT2	My experience with mobile learning to learn STEM will be good
	ATT3	I feel positive about using mobile learning for learning STEM
	ATT4	The mobile learning application will improve my online learning experience STEM
Behavioural Intention	BI1	Assuming I have access to mobile learning, I intend to use it to learn
	BI2	I will frequently learn STEM using mobile learning in the future.
	BI3	I would like to use many different mobile applications for learning STEM in the future
	BI4	It is worth it to use mobile learning for learning STEM
	BI5	I am planning to use mobile learning in learning STEM
Perceived Usefulness	PU1	Using mobile learning in class will improved my work efficiency in learning STEM
	PU2	Using mobile learning to learn STEM will enhance the quality of my learning
	PU3	Using mobile learning to learn STEM would increase my productivity
	PU4	Using mobile learning would enhance my effectiveness in learning STEM
Perceived Ease of Use	PEOU1	It will be easy to learn how to use mobile learning to learn STEM
	PEOU2	I will find it easy to use mobile learning to teach STEM.
	PEOU3	I will find mobile learning easy to use in STEM class
	PEOU4	I would find mobile learning to be flexible to interact with.
Resources perceived	R1	I have the mobile learning resources I would need to use for learning STEM.
	R1	I would be able to use mobile learning for learning STEM if I wanted to

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