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Factors Influencing Acceptance of Mobile Learning as a Measure to Slow Down the Spread of SARS-COV-2

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The SARS-COV-2 has changed the way we work, learn, socialize, travel, and do business. Most governments closed all non-essential services including schools and encouraged teachers and students to use mobile learning to minimize notional time lost during this period. The study's goal was to determine which factors teachers and students consider important when adopting mobile learning, as well as whether there is a significant difference in educators' and students' adoption of mobile learning. The study utilised a survey design, with data collected using a questionnaire. A survey was utilised to generate a quantitative picture of educators' and students' attitudes toward mobile learning. When embracing mobile learning as a measure to slow the spread of SARS-COV-2, educators and students regarded perceived usefulness, perceived attitude toward, perceived ease of use, perceived social influence, perceived skills readiness, perceived psychological readiness, and perceived resources as vital. These variables accounted for 43.7% of educators' and students' behavioural intentions to use mobile learning. Perceived attitude towards played a mediation role between the other factors and behavioural intention to use mobile learning. There was no discernible difference between educators' and students' path coefficients except for the path perceived resources to perceived attitude towards.

Key words: *Mobile learning; SARS-COV-2; Acceptance; Educators; Students.*

INTRODUCTION

The SARS-COV-2 has transformed how we work, learn, socialise, travel, and conduct business. The World Health Organization (WHO) recommended public health and social interventions to limit or halt the spread of the SARS-CoV-2 (also known as SARS-COV-2). These procedures included; detecting and isolating cases, contact tracking and quarantine, social and physical distance, including precautions for public gatherings, and international travel restrictions (World Health Organization, 2020).

Social and physical distancing methods attempt to reduce the spread of SARS-COV-2 by inhibiting virus chain transmission and the emergence of new cases (World Health Organization, 2020). According to the WHO, governments should develop flexible working practices such as teleworking and e-learning, reduce and avoid crowding, and close non-essential facilities and services. (World Health Organization, 2020). The closure of non-essential services affected teaching and learning as schools were closed, as they were deemed non-essential services. Most governments encouraged educators and students to use mobile learning (M-learning) to minimize notional time lost during this period. However, limited information is available about the factors that influence rural high school educators' and students' acceptance of mobile learning as a measure to slow down the spread of SARS-COV-2. This study sought to predict rural high school educators' and students' determinants of M-learning acceptance as a measure to slow down the spread of SARS-COV-2.

The term M-learning was coined to describe "learning that occurs when students have access to information anytime and anywhere via mobile technologies to perform authentic activities in the context of their learning" (Al-Emran, Arpaci, & Salloum, 2020, p. 2). M-learning can enhance the learning process by making educational material and services available to educators and students through mobile devices at any time and place. This enables teaching and learning to take place without educators and students being in contact with each other. M-learning can be used to kill two birds with one stone, slowing down the spread of SARS-COV-2 by minimising physical contact between educators and students, and yet teaching and learning continues.

Despite the obvious advantages provided by M-learning to educators and students during this period when the world is under attack from SARS-COV-2, its adoption rate is substantially lower than expected (S´anchez-Prietoa, Hern´andez-Garcíab, García-Pe˜nalvoa, Chaparro-Pel´aezb, & Olmos-Miguel´a˜neza, 2019), especially in developing countries. The acceptance of M-learning by educators and students is critical if schools are to keep the academic project alive, according to Aburub and Alnawas (2019). Users' attitudes about M-learning determine its acceptance (Sánchez-Prietoa et al., 2019). It could be argued, based on the suggestions of Aburub and Alnawas (2019) and Sánchez-Prietoa et al. (2019), that the acceptability of M-learning as a tool to restrict the spread of SARS-COV-2 is dependent on educators' and students' attitudes toward it.

Research was conducted to identify factors that educators (Mac Callum, & Jeffrey, 2014; Sánchez-Prietoa et al., 2019) and students (Aburub, & Alnawas, 2019; Alenezi, Karim, & Veloo, 2010), deem vital when accepting M-learning. Despite the fact that various research has been conducted to identify educators' and students' determinants of M-learning, the relevance of these determinants in predicting M-learning acceptance as a measure to slow down the spread of SARS-COV-2, continue to be limited. Furthermore, while educators' and students' views of M-learning might exist as distinct studies, comparison analysis among these groups (educators and students) is limited, and multi-group insights are still missing from the corpus of knowledge. Multi-group analysis assists in the identification of substantial and relevant differences in the relationships between the determinants. Hair, Hult, Ringle, & Sarstedt (2017), talks of M-learning acceptance as a measure to slow down the spread of SARS-COV-2 across rural high school educators' and students' results, in the case of this study. Consequently, the current study investigated rural high school educators' and students' determinants of acceptance of M-learning as a measure to slow down the spread of SARS-COV-2. Consequently, the following questions were addressed in this study.

Question 1: What are the determinants of rural high school educators' and students' acceptance of M-learning as a measure to slow down the spread of SARS-COV-2?

Question 2: Is there a substantial difference in the acceptance of M-learning as a tool to slow the spread of SARS-COV-2 among rural high school educators and students?

This study proposed and evaluated a technology acceptance model and used the results to answer the first question. By answering the second question, the study sought to examine if there are intergroup differences in the acceptance of M-learning as a measure to slow down the spread of SARS-COV-2. The findings of this study could assist Ministry of Education authorities in developing countries in determining how to successfully adopt M-learning as a measure to slow down the spread of SARS-COV-2 and other related pandemics in the future.

REVIEW OF THE LITERATURE AND MODEL DEVELOPMENT

Davis, Bagozzi, and Warshaw (1989) proposed the Technology Acceptance Model (TAM) to explicate users' intentions to adopt new systems. The TAM theorises structural relations between the PEOU, PU, ATT, BI, and actual usage (Davis et al.., 1989). The TAM is the basis for describing the mechanisms behind information system acceptance as it pervades all other subsequent technology acceptance models. The TAM theorizes that external variables particular to the information system in issue influence PEOU and PU. The TAM postulates that PEOU has a positive effect on PU and they both affect attitude towards using. PU and ATT influence BI, which in turn affect the actual system use. The TAM was chosen for this study because it is regarded to be effective at predicting mobile learning acceptance (Sánchez-Prietoa et al., 2019).

Behavioural Intention (BI)

The belief that one will perform a certain behaviour is characterized as the behavioural intention (Davis, Bagozzi, & Warshaw, 1989). BI is the best single predictive of users' actual usage of data systems (Davis et al, 1989). The willingness of educators or students to use M-learning has been shown to be highly correlated with M-learning acceptance and, as a result, utilization (Cheng, 2019). According to Cheng (2019) and Davis et al. (1989), factors that influence rural high school educators' and students' BIs indirectly influence their actual usage of M-learning to limit the spread of SARS-COV-2.

Perceived attitude towards (ATT)

Perceived attitude towards the use of a data system was defined by Al-Emran et al (2020) as one’s desirability to use the system. Educators' and students' attitudes contribute significantly to the acceptance or rejection of M-learning. Studies showed that students’ (Ku, 2009; Sivo et al., 2018) and educators’ (Fathema et al., 2015; Mac Callum et al., 2014) ATT has a positive impact on their BIs. On the contrary, Teo (2008) reported that educators’ ATT towards M-learning does not affect their BI to use M-learning. Therefore, the hypothesis:

H1: Rural high school educators’ and students’ ATT influences their BI to use M-learning as a measure to slow down the spread of SARS-COV-2.

Perceived usefulness (PU)

PU was defined in the context of M-learning as an individual's belief that using M-learning will enhance their teaching and learning (Cheng, 2019). Studies have shown that PU influences both perceived attitude and BI to use M-learning (Cheng, 2019; Fathema et al., 2015; Montrieux, et al., 2014). Consequently, the hypotheses:

H2: Rural high school educators’ and students’ PU influences their ATT towards the use of M-learning as a measure of slowing down the spread of SARS-COV-2.

H3: The PU of rural high school educators and students impacts their BI to use M-learning to slow the spread of SARS-COV-2.

Perceived ease of use (PEOU)

PEOU was described as the extent to which individuals believe that adopting M-learning will be effortless (Mutambara & Bayaga, 2020). Studies by Ku (2009) and Fathema et al. (2015) confirmed the positive effect of students’ and educators’ PEOU on ATT, PU, and BI. In the early phases of adopting a new information system, users' attitudes, usefulness, and BI might be conditioned by the notion that the system is difficult to use (Davis et al., 1989). In the current study, rural high school educators and students are accustomed to using mobile phones in their everyday lives, but they are not accustomed to using mobile devices for learning. Therefore, M-learning is in its early stages. Hence, the hypotheses:

H4: Rural high school educators' and students' PEOU influences their ATT towards the use of M-learning as a measure of slowing down the spread of SARS-COV-2.

H5: Rural high school educators' and students' PEOU influences their PU to the use of M-learning as a measure of slowing down the spread of SARS-COV-2.

H6: The PEOU of educators and students impacts their BI to use M-learning to slow the spread of SARS-COV-2.

Perceived resources (PR)

Perceived resources were described as an individual's belief in private and organisational resources required to utilise an information system (Sivo et al., 2018). In a study by Sivo et al. (2018), the researchers extended the TAM with the construct PR. The results showed that students' PR influences their PEOU, PU, and ATT towards the use of World Wide Web Course Tools (WebCT). The results also confirmed all the TAM hypotheses. As a result, the following hypotheses were made:

H7: Rural high school educators' and students' PR influences their ATT towards the use of M-learning as a measure of slowing down the spread of SARS-COV-2.

H8: Rural high school educators' and students' PR influences their PU towards the use of M-learning as a measure of slowing down the spread of SARS-COV-2.

H9: Rural high school educators' and students' PR influences their PEOU of M-learning as a measure of slowing down the spread of SARS-COV-2.

Perceived social influence (PSI)

Perceived social influence is defined as an individual's belief that important individuals in his or her life believe he or she should or should not engage in a particular behaviour. Perceived social influence was found to be a predictor of ATT towards M-learning use (Mutambara & Bayaga, 2020). If educators and students believe that their peers, community, parents, and Department of Education officials believe that M-learning should be used to slow down the spread of SARS-COV-2, they have a favourable attitude toward M-learning. Hence, the hypothesis:

H10: Rural high school educators' and students' PSI influences their ATT to use of M-learning as a measure of slowing down the spread of SARS-COV-2.

Perceived psychological readiness (PPR)

When a person is confronted with the possibility of having to use an information system, they have a perceived psychological readiness. These emotions might vary from uneasiness to despair, according to Alenezi et al. (2010). Educators and students who have had extensive experience with mobile devices are more confident in their ability to use mobile devices effectively. As a result, the hypotheses:

H11: Rural high school educators' and students' PPR influences their PU to the use of M-learning as a measure of slowing down the spread of SARS-COV-2.

Perceived skills readiness (PSR)

Students are digital natives who can use mobile devices with ease and motivation. This was also highlighted by Odiakaosa et al. (2017)'s study, which discovered that 91.1 percent of students could use mobile devices and start exploring their extended capabilities. This suggests that the majority of students have the necessary skills for M-learning deployment. Students who have the necessary technical abilities will engage in M-learning more than those who do not (Mutono & Dagada, 2016). When taking online classes, students who have the appropriate technological abilities suffer less anxiousness and dissatisfaction than those who do not (Mutono & Dagada, 2016). As a result, the following hypothesis was formulated:

H12: Rural high school educators' and students' PSR influences their PPR to use of M-learning as a measure of slowing down the spread of SARS-COV-2.

A hypothetical model for this study is shown in Figure 1 based on the theoretical underpinning discussed herein.

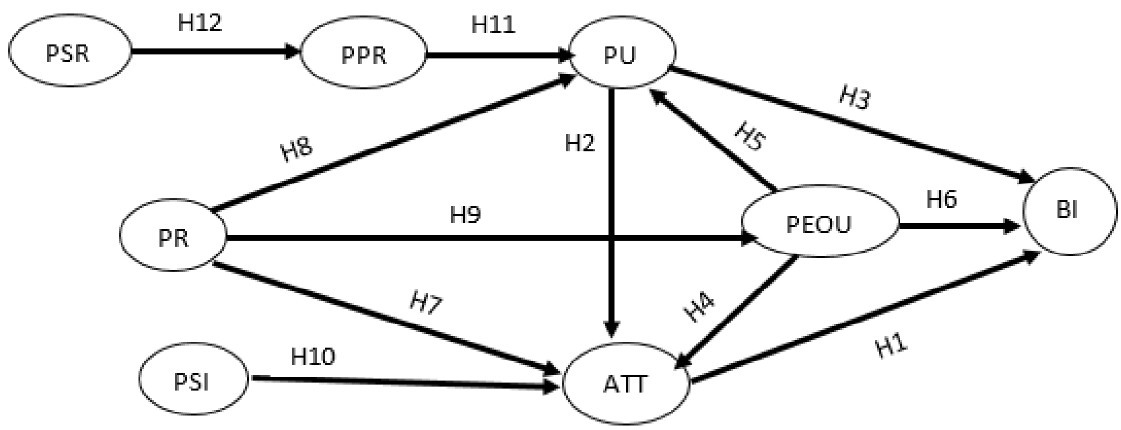

Figure 1: The hypothetical model

METHODOLOGY

Research Design

The survey design was utilised for this paper. It was used in this paper to show a quantitative representation of rural educators' and students' opinions towards M-learning as a measure of slowing down the spread of SARS-COV-2. The survey enabled the researchers to obtain a huge amount of data from respondents in a relatively short period of time and at a minimal cost. This study centered on a cross-sectional survey.

Measures

There were two sections to the questionnaire. The first portion requested demographic information from rural high school educators and students. In the second section, respondents completed the main portion of the questionnaire, which consisted of scales evaluating the model's latent variables. The questionnaire items were developed from Al-Emran et al. (2020) and Sivo et al. (2018) and then fine-tuned to meet requirements of this study. The items in the survey were all directly related to using M-learning to prevent the spread of SARS-COV-2.

Respondents were asked to choose one of seven answers ranging from strongly disagree to strongly agree using a 7-point Likert-type scale. As a result, the lower the respondent's reported score, the lower the value assigned to the variable by the respondent. There were nine latent variables and a total of 31 items in the questionnaire.

Participants

To collect data for the study, stratified sampling was used (Creswell, 2015). Using their quintiles, all rural high schools in one of South Africa's districts were grouped. A stratum was formed by grouping all rural high schools in the same quintile. This was done to ensure that schools with similar properties were placed in the same stratum. Putting homogeneous elements in the same stratum, according to Creswell (2015), lowers estimation errors. There were three strata that were developed. Using simple random sampling, four high schools from each stratum were picked. A simple random selection method was also used to select 200 students from the 12 schools. The same method used to pick students was utilized to pick 150 high school teachers. A total of 350 participants were chosen to participate in the survey.

A total of 307 (88%) of the 350 questionnaires distributed to respondents were found to be legitimate. Among the respondents, 123 (40%) were high school educators and 184 (60%) were high school students. About 191 (62%) were female and the remaining 116 (38%) were males.

Analysis technique

The software SmartPLS 3.2.8 was utilised to analyse data using Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM is defined as "a family of statistical models that seek to explain the relationships among multiple variables" Rahi (2012, p. 5). The goal of PLS-SEM is to optimise the covariance between the exogenous and endogenous latent variables (Hair et al., 2017). The primary objective of PLS-SEM is to forecast the endogenous variable, in this case, high school educators' and students' BI to utilize M-learning. PLS-SEM was also used in this research to analyse the predictive relevance of the antecedent factors and to see if there is a substantial difference in the path coefficients of rural high school educators and students.

To determine overall model fit, the researchers employed Hair et al. (2017)'s two-stage model analysis approach. The measurement model was evaluated first, then the structural model. The structural model examines the relationships among the constructs, whereas the measure measurement model describes the relationships between constructs and their associated items (Hair et al., 2017).

DATA ANALYSIS RESULTS

Measurement model

The relationship between constructs and their items is explored using the measurement model. The measurement model was evaluated using internal consistency, indicator reliability, convergent validity, and discriminant validity. The reliability of an indicator is assessed to see if it is consistent with what it is supposed to measure (Rahi, 2012). The factor loadings were utilized to measure the indicator's dependability. Figure 2 shows that, with the exception of PR2 (0.590) and PR4 (0.618), all factor loadings were higher than the threshold value of 0.7. Because eliminating the two items had no effect on the composite reliability (CR) or average variance extracted (AVE) scores, the two indicators were retained. The findings show that indicator reliability is adequate. Internal consistency was assessed using the CR. All of the CR values in Table 1 were greater than 0.7, indicating that the constructs' items all had the same meaning (Rahi, 2012). The AVE was used to assess convergent validity. Table 1 shows that all the AVE values were higher than 0.5, indicating that convergent validity has been established (Hair et al., 2017).

Table 1: CR and AVE results

	ATT	BI	PEOU	PPR	PR	PSI	PSR	PU
CR	0.918	0.898	0.941	0.918	0.803	0.959	0.890	0.941
AVE	0.692	0.746	0.762	0.789	0.510	0.886	0.730	0.761

Discriminant validity is used to determine whether latent variables are genuinely distinct from one another (Rahi, 2012). Discriminant validity was evaluated using the Heterotrat-Monotrait (HTMT) ratio. All of the HTMT readings were below the 0.85 criterion, as shown in Table 2. The results demonstrate that the constructs were separate and measured different aspects of rural high school educators' and students' acceptance of M-learning as a strategy of decreasing SARS-COV-2 spread.

Table 2: HTMT results

	ATT	BI	PEOU	PPR	PR	PSI	PSR	PU
ATT								
BI	0.751							
PEOU	0.487	0.352						
PPR	0.127	0.097	0.183					
PR	0.691	0.402	0.469	0.182				
PSI	0.211	0.238	0.103	0.100	0.100			
PSR	0.107	0.124	0.087	0.431	0.173	0.104		
PU	0.398	0.369	0.207	0.117	0.247	0.095	0.124	

The measurement model presents acceptable indicator reliability, convergent validity, discriminant validity and internal consistency. As a result, the measurement model proved the adequate resilience required to assess the structural model.

Structural model

To evaluate collinearity concerns, the variance inflation factor (VIF) values have been utilized. Collinearity happens when two latent variables that are thought to be causally connected and assess the same thing are used together in the single model (Rahi, 2012). The lack of collinearity concerns is shown by a VIF value of lower than four (Hair et al., 2017). The outcomes in Table 3 demonstrate that the VIF values were all lower than four, signifying that collinearity had no effect on the precision of the calculated path coefficients of the hypothesised model. As a result, the hypotheses of the proposed model were investigated. The bootstrapping approach with 5000 subsamples was used to examine the significance level of the hypotheses, as suggested by Hair et al. (2017). The approach is utilised to avoid standard error inflation or deflation caused by non-normal data. Table 3 and Figure 2 summarise the hypotheses testing outcomes. The results showed that three paths (PEOU to ATT ($\beta = 0.019$, $p > 0.1$), PR to PU ($\beta = 0.144$, $p > 0.1$), and ($\beta = 0.105$, $p > 0.1$)) were not statistically significant.

Table 3: Path coefficients

Path	Std Beta	Std Error	T Statistics	P Values	Decision	Q-squared	f-squares	VIF
ATT -> BI	0.607	0.123	4.930	0.000	Accepted	0.471	0.290	1.392
PEOU -> ATT	0.241	0.089	2.699	0.007	Accepted	0.086	0.070	1.193
PEOU -> BI	0.019	0.099	0.189	0.850	Rejected	0.001	0.010	1.254
PEOU -> PU	0.165	0.113	1.988	0.046	Accepted	0.025	0.090	1.200
PPR -> PU	0.130	0.095	1.952	0.049	Accepted	0.018	0.020	1.027
PR -> ATT	0.403	0.102	3.948	0.000	Accepted	0.242	0.040	1.196
PR -> PEOU	0.381	0.096	3.986	0.000	Accepted	0.170	0.090	1.000
PR -> PU	0.144	0.123	1.172	0.242	Rejected	0.019	0.010	1.171
PSI -> ATT	0.126	0.093	2.611	0.009	Accepted	0.028	0.030	1.014
PSR -> PPR	0.363	0.118	3.077	0.002	Accepted	0.152	0.320	1.000
PU -> ATT	0.226	0.081	2.795	0.005	Accepted	0.085	0.110	1.068
PU -> BI	0.105	0.113	0.934	0.351	Rejected	0.017	0.040	1.158

Figure 2 consists of eight constructs. BI is directly projected by PEOU, ATT, and PU, while PU, PSI, PR, and PEOU influence ATT. PR influences PEOU, and they both affect PU. PSR affects PPR, which in turn influences PU.

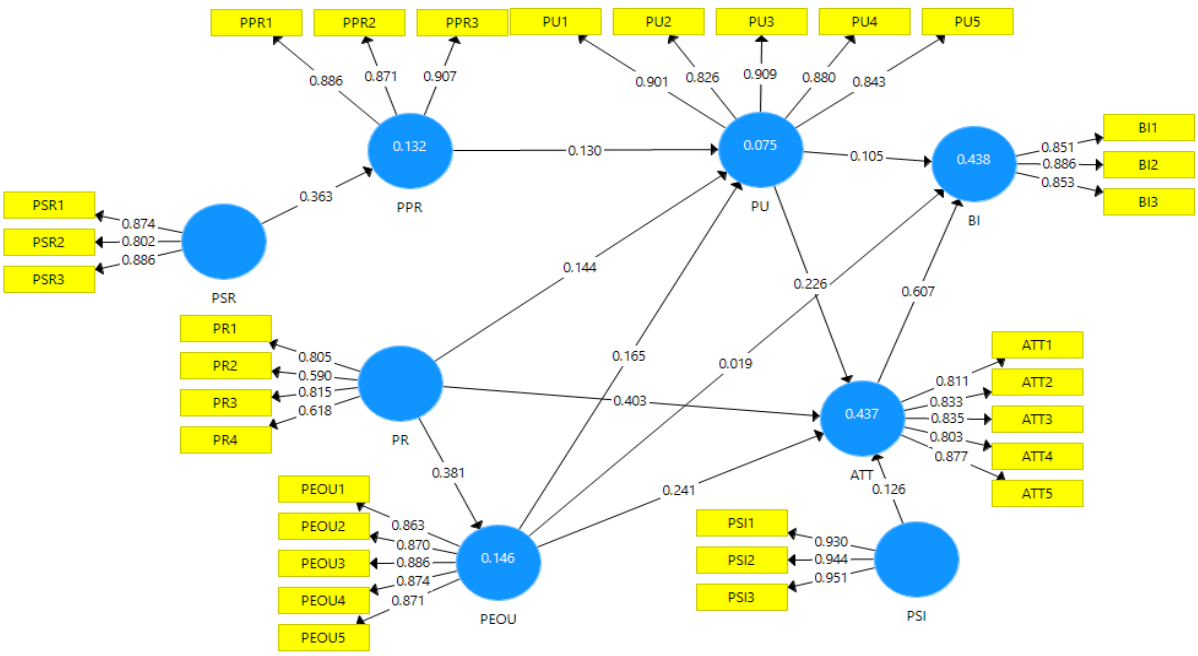

Figure 2: Research model

The R-squared and the paths coefficients are shown in Figure 2. The R-squared value assesses the combined effect of independent latent variables on the dependent latent variable (Rahi, 2012). In our case, the R-squared value assesses the collective effects of PEOU, PU, PR, PSI, ATT, PSR, and PPR on rural high school educators' and students' BI to use M-learning as a measure to slow down the spread of SARS-COV-2. According to Cohen (1988) the R-squared value of 0.02, 0.13, 0.26 respectively, portray weak, moderate, or high degrees of accuracy in prediction. The R-squared value of BI is 0.438, according to the results displayed in Figure 2. This R-squared value is considered substantial (Cohen, 1988). This implies that the joint effect of the predictors PEOU, PU, PR, PSI, ATT, PR, PSR, and PPR in predicting educators' and students' BI to utilise M-learning as a measure to slow down the spread of SARS-COV-2, was 43.8%.

The study used the blindfolding rules proposed by Hair et al. (2017) to measure the predictive relevance of the postulated model. The values of cross-validated redundancy (Q-squared) were employed. The Q-squared values were all greater than zero, indicating that the suggested model can be used to predict the elements that rural high school educators and students value when deciding to accept M-learning.

To answer question 2, the Welch-Satterthwait test was utilised. The Welch-Satterthwait test was done to test if there was a considerable difference in the path coefficients of rural high school students and educators in the hypothesised model. Except for PR to ATT, the results in Table 4 reveal that there was no statistical difference between all educators' and students' path coefficients. The path, however, is significant for each group, showing that the model can be used to predict M-learning adoption as a measure to curb the spread of SARS-COV-2.

Table 4 Welch- Satterthwait test

Path	Path Coefficients-diff	T-Value	p-Value	Decision
ATT -> BI	0.179	1.291	0.199	Rejected
PEOU -> ATT	0.150	1.242	0.216	Rejected
PEOU -> BI	0.120	1.049	0.296	Rejected
PEOU -> PU	0.183	1.190	0.236	Rejected
PPR -> PU	0.022	0.185	0.853	Rejected
PR -> ATT	0.274	2.082	0.039	Accepted
PR -> PEOU	0.203	1.613	0.109	Rejected
PR -> PU	0.068	0.464	0.643	Rejected
PSI -> ATT	0.198	1.873	0.063	Rejected
PSR -> PPR	0.217	1.467	0.145	Rejected
PU -> ATT	0.186	1.507	0.134	Rejected
PU -> BI	0.148	1.065	0.289	Rejected

DISCUSSION

Research question 1: The research intended to know what factors influenced rural high school educators' and students' adoption of M-learning as a way to slow the spread of SARS-COV-2.

This study constructed and tested a proposed model to answer this research topic. The results revealed that all of the Q-squared values were greater than zero, indicating that the model is predictive (Hair et al., 2017). The findings suggest that the model can be used to predict educators' and students' willingness to embrace M-learning as a measure of slowing down the spread of the SARS-COV-2. This means that the factors: ATT, PU, PEOU, PR, PSI, PSR, and PPR are good determinants of high school educators' and students' BI to use M-learning as a measure to slow down the spread of the SARS-COV-2. The combined effect of these factors (ATT, PU, PEOU, PR, PSI, PSR, and PPR) on rural high school educators' and students' BI was 43.8%. This means that these factors explain a moderate 43.8% of the variance in rural high school educators' and students' behavioural intention to use M-learning as measure to slow down the spread of the SARS-COV-2.

The best predictor of rural high school educators' and students' BI to utilise M-learning was found to be perceived attitude towards use. The results supported hypothesis H1 but were contradicting the findings of Teo (2008), who reported that ATT towards use does not influence BI. Additionally, ATT played a mediating role between factors (PU, PR, PSI, PPR, and PSR) and BI to use M-learning as a measure of slowing down the spread of SARS-COV-2. The Education Ministry officials should take into consideration factors that influence educators' and students' attitudes towards the use of M-learning as a measure of slowing down the spread of SARS-COV-2.

ATT towards use was influenced by PSI. This result supported hypothesis H10 but was differing to the results of Ma et al. (2005), who reported that educators' attitudes towards M-learning were not influenced by what they hear from people close to them. The findings suggest that what influential people around them say about the adoption of M-learning as a measure to prevent the spread of SARS-COV-2 has a significant impact on rural high school educators and students. The Ministry of Education should therefore run awareness programs on the benefits that M-learning can bring into teaching and learning during the SARS-COV-2 pandemic. When educators and students think that the Education Ministry officials and the community expect them to use M-learning as a measure of slowing down the spread of SARS-COV-2, they will have a positive attitude towards it, which in turn positively influences their acceptance and use of M-learning.

Perceived usefulness influenced ATT but not BI to use M-learning as a measure of slowing down the spread of SARS-COV-2. The results supported the hypothesis H2 but not H3. The results partially contradict the findings of Cheng (2019) and those of Fathema et al. (2015), who independently stated that educators' and students' PU influences their attitudes and BI. The results indicated that the usefulness of M-learning does not necessarily influence rural high school educators' and students' intentions to use it, however, it influences their attitudes. As a result, makers of M-learning platforms should make their platforms as valuable as possible by including as much learning and assessment material as possible. If rural high school educators and students find that there is a lot of teaching and assessing material on the platforms they will have positive attitudes towards M-learning, which in turn influences their intentions and actual usage.

Educators' and students' PEOU influence their BI, PU, and ATT towards use of M-learning as a measure of slowing down the spread of SARS-COV-2. These results supported hypotheses H4, H5, and H6. The findings were in line with those of Fathema et al. (2015). These findings suggest that, despite the fact that educators and students use mobile devices in their everyday undertakings, they value the effort required to learn how to use M-learning when considering it as a means of slowing the spread of SARS-COV-2. A possible reason for this finding is that the spread of the SARS-COV-2 caused abrupt closure of schools and a switch from physical contact teaching and learning to online learning without proving educators and students the opportunity to be trained to use M-learning. As a result, educators and students are more likely to reject M-learning platforms that are difficult and complicated to use, so M-learning developers should create user-friendly platforms.

Perceived resources influenced all the antecedents (PEOU, PU, and ATT) of BI. The results supported hypotheses H7, H8, and H9. The results endorsed the results of Sivo et al. (2018) who made the claim that students considered availability of resources when accepting WebCT. The main reason for this finding is that most students use shared mobile devices at home (Odiakaosa et al., 2017). SARS-COV-2 can be spread through sharing of mobile devices, in trying to slow down the spread of SARS-COV-2, the owners of the shared mobile devices at home might not be willing to share their devices. This leaves students without devices that can support M-learning. The Ministry of Education should try to source and supply mobile devices to those educators and students who cannot afford these gadgets. This will improve rural high school educators' and students' attitudes towards the use of M-learning, which in turn influences their intentions to use this technology as a measure to slow down the spread of SARS-COV-2.

Perceived skills readiness influenced PPR, which in turn influenced PU. The results supported hypotheses H11 and H12. The results echoed the findings of Mutono and Dagada (2016) and Alenezi et al. (2010), who stated that students and educators with skills needed for M-learning, are psychologically ready for it, and they will realise its usefulness. The results imply that the Ministry of Education should run to equip needy educators and students with the necessary skills for the use of M-learning.

Research questions 2: Contrary to the belief that students had a more positive outlook towards M-learning than their educators (Montrieux et al., 2014), the findings revealed that all educators' path coefficients were not significantly different from students' path coefficients, except PR to ATT. A possible explanation for this finding is that both educators and students perceived M-learning as a useful tool they can use to continue teaching and learning in the face of abrupt school closures due to SARS-COV-2. The findings suggest that educators and students consider the same factors when considering M-learning as a measure to slow down the spread of SARS-COV-2. The results imply that the unavailability of resources affect students more than it does educators. As a result, it can be argued that the Ministry of Education should provide resources to students for M-learning to be effectively implemented as a measure to slow down the spread of SARS-COV-2.

THEORETICAL IMPLICATIONS

This study presents an important contribution to the Technology Acceptance Model by providing four external factors (PSR, PSI, PPR, and PR) that may be used to forecast users' acceptance of M-learning. These four factors are antecedents of the two main pillars (PU and PEOU) of the Technology Acceptance Model. All of behavioural intention's antecedents (PEOU, PU, and ATT) are influenced by perceived resources. Through the mediation of ATT, perceived resources have an indirect effect on behavioural intention. In order to apply M-learning, ATT additionally mediates the link between PSI and BI. Perceived skills readiness influences PPR, which in turn influences PU. The multi-group analysis findings revealed that there was no substantial distinction between rural high school educators' and students' path coefficients, except PR to ATT. This means that the developed model can be used to predict M-learning acceptance for both rural high school educators and students.

FUTURE STUDIES AND LIMITATIONS

The study was only carried out in rural high schools, the generalisation of the results to urban high schools should be carried out with caution. Future research could focus on both rural and urban educators and students, and investigate if there is a statistically significant distinction between the rural and urban educators' and students' acceptance of M-learning as a measure to slow down the spread of SARS-COV-2 or other related pandemics.

CONCLUSION

The results of this study showed that all the TAM hypotheses were supported except on perceived usefulness to behavioural intention to use M-learning as a measure to slow down the spread of SARS-COV-2. Furthermore, the findings also revealed that rural high school educators and students take into consideration similar factors when accepting M-learning as a measure of slowing down the spread of SARS-COV-2. The predictors of rural high school educators' and students' acceptance of M-learning as a measure to slow down SARS_COV-2 are PU, ATT, PSI, PEOU, PR, PSR, and PPR. The results showed that educators' and students' perceived ease of use influences their attitude and belief that M-learning will help to slow down the rapid spread of SARS-COV-2, can enhance their level of performance, and hence prop up their intent to use this technology. The accessibility of resources positively influences rural high school educators' and students' perception that M-learning is helpful and simple for the students to use. The availability of resources influences students' attitudes towards M-learning

more than their educators. The results revealed that for M-learning to be implemented successfully as a measure of slowing down the spread of SARS-COV-2, it is essential that resources be provided to needy rural high school educators and students.

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