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Rural STEM Preservice Teachers' Acceptance of Virtual Learning

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Abstract. Teaching and learning of Science, Technology, Engineering and Mathematics (STEM) to preservice teachers in rural universities has always been a challenge, resulting in poor student performance. The outbreak of COVID-19 has made it exacerbated this owing to lockdown restrictions in most institutions including universities. Consequently, universities switched to virtual learning (VL), even though most of them (especially rural universities) were not ready for it. This worsened the plight of struggling rural STEM students who had to make do with this new VL. Hence, this study focussed on rural STEM preservice teachers' acceptance of virtual learning. Prior studies have shown that adoption of a new information system depends on its acceptance by users; however, very little is known about the acceptance of VL by rural STEM preservice teachers. Based on the technology acceptance model, the study proposed and used the STEM preservice teacher acceptance virtual learning model to investigate factors that predict rural STEM preservice teachers' actual use of VL. Partial least squares structural equation modelling was used to analyse data from 250 valid questionnaires. The model explained 74.6% of the variance in rural STEM pre-service teachers' actual use of VL. Latent variables, facilitating conditions, attitude towards use, and perceived ease of use had a direct impact on the actual use of VL. Attitude to use also played a mediating role between actual use and predictors, perceived enjoyment, perceived social influence, computer self-efficacy, and perceived usefulness. It was concluded that rural STEM pre-service teachers embrace VL given the desperate pandemic situation.

Keywords: preservice teachers; STEM; virtual learning; technology acceptance model; COVID-19

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1. Introduction

The coronavirus (COVID-19) pandemic has changed our way of life, social interactions, travel, and work. It is caused by the recently discovered SARS-CoV-2 coronavirus. Since the 1918 influenza pandemic, this virus has been regarded as the world's most serious public health threat (Greenstone & Nigam, 2020). In a bid to slow down the spread of the virus, most governments worldwide closed all nonessential services, including universities. In a bid to breathe life into academia, universities switched to virtual learning (VL), even though most of them (especially rural universities) were not prepared for this. Virtual learning is a type of learning that is supported by the use of computers and the Internet, both beyond and within the educational institutions' faculties (Govindarajan & Srivastava, 2020).

The use of VL has exacerbated the plight of rural STEM students who previously struggled while being helped by teachers and are now forced to rely solely on VL. According to Mutambara and Bayaga (2021), STEM education in developing countries faces numerous challenges, resulting in low student performance, particularly in rural regions. Some of the challenges with VL in rural universities include a lack of technical support and resources such as computers, laptops, and mobile devices, erratic network connections, and lecturers who are not trained to use VL (Joo et al., 2018; Maphalala & Adigun, 2021). In the midst of all these challenges, rural STEM preservice teachers were forced to turn to VL owing to the spread of COVID-19. Moreover, student acceptance is critical to the success of any educational programme (Eksail & Afari, 2019; Mutambara & Bayaga, 2020).

Unfortunately, very little is known regarding the adoption of VL among STEM preservice teachers, particularly in rural areas. Previous research (Benadé & Liebenberg, 2017; Govender, 2010; Maphalala & Adigun, 2021) focused on the use of learning management systems in developing countries. Govender (2010) used a qualitative approach to study the attitudes of students towards learning management systems while Maphalala and Adigun (2021) investigated instructors' experiences with the use of e-learning to promote teaching and learning. In an Excel course, Benadé and Liebenberg (2017) studied students' intents to utilise an ebook and a specialised learning management system (SLMS). Despite the fact that some technological studies have been conducted in universities in developed countries, their usefulness in explaining VL acceptance in rural areas remains limited. Furthermore, these studies were not carried out during a pandemic during which VL was the only mode of learning available.

Developing countries should not blindly follow developed countries' technology acceptance models, but must instead forge their own path (Belgheis & Kamalludeen, 2018; Mutambara & Bayaga, 2020; Wu & Chen, 2017). Any information system's adoption is dependent on its users' acceptance (Davis et al. (1989). Based on the findings of Mutambara and Bayaga (2020) and those of Davis et al. (1989), it can be argued that students' attitudes must be considered for VL to be successfully implemented in the rural universities of developing countries. As a result, determining what factors influence rural STEM preservice teachers' acceptance of VL is critical. Furthermore, VL is now an integral part of modern teaching and learning in tertiary institutions; hence it is important to identify the factors that affect it and embrace them. The technology acceptance model (TAM) was used in this study to investigate what variables rural STEM preservice teachers consider important when accepting VL. The study specifically seeks to answer the following research questions:

1. What factors influence the use of virtual learning by rural STEM pre-service teachers?
2. To what extent do these factors explain the actual use of virtual learning by rural STEM preservice teachers?

The results of this study may shed some light on the acceptance of VL in developing countries' rural universities. The findings may also assist rural universities in successfully implementing and continuing VL after the COVID-19 pandemic.

2. Literature Review

Virtual learning is swiftly becoming an important part of teaching and learning, especially in universities (Van Raaij & Schepers, 2008). Universities benefit from VL for a variety of reasons, including the ability to extend contact time across geographical borders and improve face-to-face instruction (Mutambara & Bayaga, 2020; Sánchez-Prieto et al., 2017). It also facilitates more efficient communication between learners and educators, as well as amongst learners themselves (Mutambara & Bayaga, 2020; Van Raaij & Schepers, 2008). It became the most widely used mode of teaching and learning for most universities during the COVID-19 pandemic lockdown (Mulenga & Marbán, 2020).

The acceptance of technology by students is a critical factor in its successful implementation in universities (Van Raaij & Schepers, 2008). However, only a few previous studies have looked into the factors that influence university students' willingness to accept VL (Van Raaij & Schepers, 2008). The majority of studies (Bradshaw & Mundia, 2006; Chen, 2010; Fang et al., 2019a; Mutambara & Bayaga, 2020; Raman & Don, 2013; Scherer et al., 2019; Teo et al., 2012) focused on the acceptance of different technologies in education. Fang et al. (2019a) explored the influence of culture on technological acceptability in schooling while Mutambara and Bayaga (2020) concentrated on the acceptance of mobile learning. In addition, Scherer et al. (2019) explored the adoption of digital technology in education using the TAM while Chen (2010) used structural equation modeling to investigate preservice teachers' use of technology to support student-centered learning. Finally, Teo et al. (2012) assessed preservice teachers' acceptance of technology in Turkey.

The most acceptable factors of technology acceptance in education are the perceived ease of use (PEOU) and perceived usefulness (PU) (Mutambara & Bayaga, 2021; Teo et al., 2012). Prior research (Maphalala & Adigun, 2021; Mutambara & Bayaga, 2020) has also confirmed that PU and PEOU are the most powerful predictors of technology acceptance in education. PU and PEOU are also influenced by other external factors such as social influence (SI), computer self-efficacy, and facilitating conditions (PR) (Al Kurdi et al., 2020; Chen, 2020; Lim, 2018a, 2018b). According to Chen (2010), the strongest predictor of preservice teachers' acceptance of technology in the classroom is their self-efficacy. The perceived attitude of preservice teachers towards technology integration was reported to mediate the relationship between actual use and predictors and between SI and PR (Scherer et al., 2019).

This study seeks to extend the body of knowledge by evaluating the effects of preservice teachers' perceived enjoyment (PEN) on their acceptance of VL. Furthermore, all these factors were assessed when learners had a choice between face-to-face instruction and technology-assisted instruction. However, owing to the COVID-19 pandemic, VL has become the most widely used method of instruction. As a result, this research is significant because it clarifies the nature of the factors that must be overcome when considering VL activities for pedagogy, as well as determining whether these factors are still valid predictors of technology acceptance during the COVID-19 pandemic. During a pandemic, educational innovations are critical in order that the academic endeavour does not suffer.

2.1 Theoretical Framework

The most commonly used models to explain technology acceptance are the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003b) and the TAM (Davis et al., 1989). Davis et al. (1989) developed the TAM to predict information systems acceptance. The TAM hypotheses that PEOU influences PU and that they both influence perceived attitude (ATT) towards the use of VL (Davis et al., 1989) were key findings of the model. The perceived attitude towards and perceived usefulness predicts behavioural intention to use the information system (Davis et al., 1989). Behavoural intention (BI) is the best single known predictor of users' actual usage (Mutambara & Bayaga, 2020; Venkatesh et al., 2003a).

The TAM is thought to be reliable in predicting user acceptance of a new system (Al Kurdi et al., 2020; Mutambara & Bayaga, 2021; Venkatesh et al., 2003). Other academics, however, have criticised the TAM in an educational context for assuming that the use of technology in educational contexts is mandatory (Mutambara & Bayaga, 2021; Venkatesh et al., 2003). The TAM is more general and can be used in a wide range of situations (Mutambara & Bayaga, 2021). According to Mutambara and Bayaga (2021), educational contexts are becoming more individual, personalised, and focused on system services. Venkateshet al. (2003) criticised the TAM for having a low explanatory power. What these criticisms teach us is that the TAM alone is insufficient to explain the acceptance of VL by rural STEM preservice teachers.

Venkatesh et al. (2003) developed the UTAUT as an improvement to the TAM to explain user acceptance of technology. The UTAUT hypothesises that behavioral intention is influenced by performance expectancy, effort expectancy, and social influence. Behavioural intention and facilitating conditions predict behaviour. Gender, age, experience, and the voluntariness of use act as moderators in the relationships between the determinants (performance expectancy, effort expectancy, and social influence) and behavioural intention.

The UTAUT was successful in increasing the explanatory power of users' acceptance of a new system (Venkatesh et al., 2003). Other academics, however, criticised it (Lim, 2018b; Mutambara & Bayaga, 2021). Lim (2018b) contended that the UTAUT was too difficult to meet all of its assumptions. Mutambara and Bayaga (2021) faulted the UTAUT for failing to anticipate actions beyond the user's control. Because of the university closures caused by COVID-19, preservice teachers were forced to use VL. UTAUT could not be used in this study because it does not explain why people adopt technology when forced to do so.

2.2 Conceptual Framework

According to Lim (2018b), the TAM offers a conceptual lens that gives the key pillars of user interactions (PU and PEOU), which should be expanded to create a fully-fledged model that can describe and predict technology acceptance in many situations. Furthermore, Venkatesh et al. (2003) reported that by including an external variable in the TAM, the explanatory power of the TAM can be improved. Prior research has shown that including an external variable improves the TAM's explanatory power (Al Kurdi et al., 2020; Mutambara & Bayaga, 2020). Following the recommendations by Lim (2018b) and Venkatesh et al. (2003), this study broadened the TAM by including some UTAUT variables such as facilitating conditions (PRs) and social influences (SIs). The TAM was also expanded to include PEN and self-efficacy as external variables in this study. Other investigations have demonstrated that these variables are predictors of educational technology acceptance (Al Kurdi et al., 2020; Maphalala & Adigun, 2021; Mutambara &Bayaga, 2021). This study hypothesises that adding context-related external variables to the TAM will improve its explanatory power.

The proposed model posits that computer self-efficacy predicts both perceived usefulness and perceived ease of use. Perceived enjoyment and social influence are determinants of perceived usefulness. Facilitating conditions predict actual usage, perceived attitude toward and perceived ease of use. Perceived ease of use predicts perceived usefulness, and both predict perceived attitude toward and actual usage. Perceived attitude toward use plays a mediating role between actual usage and predictors as well as perceived enjoyment and social influence. Figure 1 shows the conceptual model.

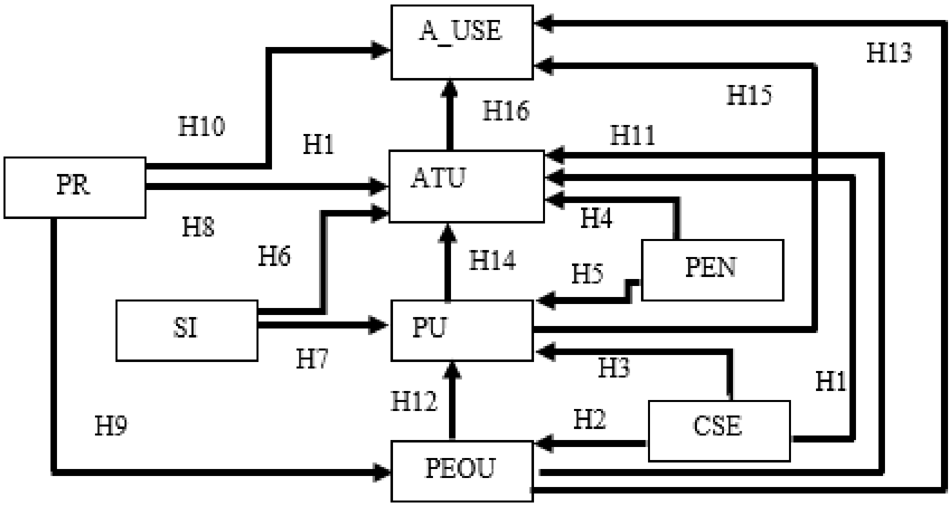

Figure 1: Conceptual model

ATU–perceived attitude towards, C_USE-actual usage, PU-perceived usefulness, PEOU–perceived ease of use, SI-social influence, PR–facilitating conditions, PEN–perceived enjoyment, CSE–self efficacy.

2.2.1 Computer Self-efficacy

In this study computer self-efficacy (CSE) can be defined as rural STEM preservice teachers' self-assurance in their command of information technology and their ability to handle a variety of computer-related tasks (Teo et al., 2015). CSE is critical because it influences the attitudes of rural STEM preservice teachers toward VL. Teo et al. (2012) investigated the impact of CSE on preservice teachers' PEOU, PU, and ATU towards the use of educational technology. The findings revealed that preservice teachers' CSE predicts their PEOU, PU, and ATU toward the use of technology in education. This study postulates that rural preservice teachers with low CSE are more likely to be anxious about learning STEM using computers. This is more likely to have an impact on their perceived ease of use, perceived usefulness, and attitude towards use. As a result, the hypotheses for this construct are as follows:

H1: Rural preservice teachers' self-efficacy predicts their perceived attitude towards the use of VL;

H2: Rural preservice teachers' self-efficacy predicts their perceived ease of use of VL;

H3: Rural preservice teachers' self-efficacy predicts their perceived usefulness of VL.

2.2.2 Perceived Enjoyment

The degree to which a student or instructor finds the interaction of educational technology intrinsically engaging or intriguing was characterised as perceived enjoyment (PEN) (Mutambara & Bayaga, 2021). PEN is a form of intrinsic motivation, and it has a major influence on the attitudes of rural preservice teachers on the use of VL and its utility for STEM learning. PEN has no effect on STEM teachers' and learners' PU (Fang et al., 2019b). This study assumes that rural STEM preservice teachers who enjoy using technology are more likely to

consider VL useful and to have a positive attitude toward the use of VL for STEM learning. Consequently, the hypotheses for this construct are as follows:
H4: Rural preservice teachers' perceived enjoyment predicts their perceived attitude towards the use of VL;

H5: Rural preservice teachers' perceived enjoyment predicts their perceived ease of use of VL.

2.2.3 Social Influence
Social influence (SI) is defined in this study as rural STEM preservice teachers' perceptions that people important to them expect them to use VL for learning (Sánchez-Prieto et al., 2019). Mutambara and Bayaga (2020) found that parents' SI influences their PU and attitude toward their children's use of mobile learning for STEM. This study postulates that rural preservice teachers are not immune to what their parents and lecturers say about the use of VL for STEM learning. Rural preservice teachers' PUs and attitudes toward the use of VL for STEM learning are more likely to be influenced by what their parents and lecturers say about VL. As a result, the hypotheses for this construct are as follows:
H6: Rural preservice teachers' social influence predicts their perceived attitude towards the use of VL;

H7: Rural preservice teachers' social influence predicts their perceived ease of use of VL.

2.2.4 Facilitating Conditions
Facilitating conditions (PR) was 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). There are some inconsistencies in the body of knowledge on the effect of PR on PU and PEOU (Mutambara & Bayaga, 2020; Sivo et al., 2018). According to Mutambara and Bayaga (2020), PR influences ATU but not PU or PEOU. Chen (2020) and Sivo et al. (2018), on the other hand, found that PR influences ATU, PU, and PEOU. This investigation was carried out in rural locations where resources are very limited (Bhattarai & Maharjan, 2020). During the COVID-19 pandemic many people lost their jobs; thus, the availability of resources is most likely to influence the acceptance of VL for STEM learning. Therefore, the hypotheses for this construct are as follows:
H8: Rural preservice teachers' facilitating conditions predict their perceived attitude towards the use of VL;

H9: Rural preservice teachers' facilitating conditions predict their perceived ease of use of VL;

H10: Rural preservice teachers' facilitating conditions predict their actual use of VL.

2.2.5 Perceived Ease of Use
Mutambara and Bayaga (2021) describe perceived ease of use (PEOU) as the extent to which users believe that adopting educational technology will be effortless. According to Davis et al. (1989), users' PEOU influences their PU and ATU of technology. Several studies (Al Kurdi et al., 2020; Mutambara & Bayaga, 2020; Sivoet al., 2018) in the educational context have confirmed the effect of effort required to learn to use educational technology on PU and ATU. This

study assumes that the amount of effort required to learn to use VL for STEM learning will influence rural preservice teachers' PU, actual usage, and perceived attitude toward the use of VL. As a result, the hypotheses for this construct are as follows:
H11: Rural preservice teachers' perceived ease of use predicts their perceived attitude towards the use of VL;

H12: Rural preservice teachers' perceived ease of use predicts their PU of VL;

H13: Rural preservice teachers' perceived ease of use predicts their actual use of VL.

2.2.6 Perceived Usefulness

Perceived usefulness (PU) was described as the belief that using educational technology boosts learners' performance in STEM-related subjects (Mutambara & Bayaga, 2021). In the educational context, Al Kurdi et al. (2020) confirmed the findings of Sivoet al. (2018), who reported that PU influences both ATU towards use and behavioural intention. This study hypothesises that PU influences rural STEM preservice teachers' actual use of VL. Therefore, the hypotheses for this construct are as follows:

H14: Rural preservice teachers' perceived usefulness predicts their perceived attitude towards the use of VL;

H15: Rural preservice teachers' perceived usefulness predicts their actual use of VL.

2.2.7 Perceived attitude towards

Perceived attitude towards (ATU) can be described as rural STEM preservice teachers' overall affective reaction to the use of VL. According to Davis et al. (1989), users' attitudes play an important role in their acceptance of new technology. Several studies in the educational context have found that ATU influences behavioural intention and the actual usage of educational technologies (Al Kurdi et al., 2020; Mutambara & Bayaga, 2020; Sivoet al., 2018). As a result, the hypothesis for this construct is:
H16: Rural preservice teachers' perceived attitude towards the use of VL predicts their actual use of VL.

3. Methodology

In this study, a cross-sectional survey design was utilised. A survey design examines a subset of the population to produce a quantitative account of the population's views (Creswell, 2014). In this study, a survey was employed to obtain a quantitative picture of how rural STEM preservice teachers feel about VL. A survey was chosen because it allows for the collection of a significant amount of data from rural STEM preservice teachers in a short period of time and at a low cost. A cross-sectional survey was conducted to obtain opinion-related data from rural STEM preservice teachers using a questionnaire. The data were firstly examined using descriptive statistics on all the constructs and demographics. Secondly, the postulated model was evaluated using the partial least squares–structural equation model (PLS-SEM).

3.1 Participants
All the 263 fourth-year STEM preservice teachers at the university under study were invited to participate in this study. A total of 250 valid questionnaires were collected, giving a questionnaire return rate of 95%. Of the 250 respondents, 157 (63%) were females and 93 (33%) were males. Among the respondents, 182 (73%) were below 25 years old, 52 (20%) were between 26 and 30 years of age, nine (4%) were between 31 and 35 years old, and seven (3%) were between 35 and 40 years old.

The latent variable with the most indicators in the model is actual usage with five indicators. Using the suggestion by Hair et al. (2017) that a sample size should be 10 times greater than the number of indicators on the construct with the most indicators, the required minimum sample size for this study would be 50 (five indicators of actual usage construct X 10 times). This study's actual sample size was 263, far surpassing the suggested minimum requirement of 50.

3.2 Research instrument
The questionnaire was divided into two sections. The first section requested rural STEM preservice teachers to provide their biographical data. In the second section, respondents were asked to choose one of seven answers ranging from 'strongly disagree' to 'strongly agree' on a seven-point Likert-type scale. The questionnaire used in this study was adapted from existing literature (Mutambara & Bayaga, 2021; Sivo et al., 2018; Van Raaij & Schepers, 2008), the validity and reliability indices of which were 0.975 and 0.753 respectively. Furthermore, multiple questionnaire items were adapted and modified in order to have the variety of items needed for each construct suitable for this study. Owing to the large number of items needed in the research instrument, it was also necessary to adapt and modify questions from multiple questionnaires. The research instrument, for example, contained a total of 51 items. As a result, it was assumed that using and modifying only one questionnaire would be insufficient. The questionnaire items were therefore adapted from previous studies (Mutambara & Bayaga, 2021; Sivo et al., 2018; Van Raaij & Schepers, 2008) and modified to suit the needs of the current study.

4. Data Analysis Technique
Data screening was done using Statistical Package for the Social Sciences (SPSS). This was also used for the descriptive statistics. The data set was then transferred to the SmartPSL software for analysis using partial least squares structural equation modelling (PLS-SEM). The main function of PLS-SEM, according to Hair et al. (2017), is to predict the target variable, in this case, the actual usage of VL by rural STEM preservice teachers. The PLS-SEM methodology was also used to determine the factors that rural preservice teachers consider important when deciding whether to accept VL.

This study followed a two-stage model analysis approach (Hair et al., 2017). To confirm the quality of the measurement model, the reliability and validity of several model variables were initially assessed. The measurement model defines the link between the constructs and their corresponding indicators. The links within the structural model were evaluated in the second stage by examining the significance of the path coefficients, the explained variance of the endogenous variables, and the predictive powers of different variables (Hair Jr. et al., 2016).

4.1 The Measurement Model
The measurement model was evaluated to ensure that the constructs added to the model were valid. This was accomplished by evaluating the measurement model's convergent validity, internal consistency, indicator reliability, and discriminant validity (Shmueli et al., 2019).

4.1.1 Indicator Reliability
Indicator reliability indicates how much of the item's variance can be explained by the underlying latent construct (Hair et al., 2017). According to Chin (1998), a construct should explain a significant portion of the variance in each item, usually at least 50%. Hair et al. (2017) proposed a threshold value for the outer loadings of 0.7. Table 1 shows that all of the items had outer loadings greater than the threshold value of 0.7 (Hair et al., 2017), indicating that the constructs adequately explained all of their items.

4.1.2 Internal Consistency Reliability
The composite reliability (CR) and Cronbach's alpha (CA) tests were used to determine internal consistency reliability. Composite reliability is preferred over Cronbach's alpha because it provides more accurate results (Hair Jr et al., 2016). Table 1 shows that all of the constructs used had fair internal consistency reliability because their CR and CA values were all above the cut-off value of 0.7 (Hair et al., 2017).

4.1.3 Convergent Validity
Convergent validity is the degree to which one measure positively correlates with other measures of the same construct (Hair et al., 2014, p.102). For convergent validity evaluation, outer loadings and average extracted variance (AVE) were used. As shown in Table 1, all outer loadings were higher than the cut-off value of 0.70. All AVE values were higher than 0.50 (Hair et al., 2017). The results show an acceptable convergence validity.

Table 1: Measurement model

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
ATU	ATU1	0.866	0.805	0.919	0.943	Yes
	ATU2	0.886				
	ATU3	0.918				
	AUT4	0.918				
CUSE	CUSE1	0.930	0.801	0.936	0.929	Yes
	CUSE2	0.756				
	CUSE3	0.933				
	CUSE4	0.906				
	CUSE5	0.937				

SI	SI1	0.925	0.836	0.805	0.911	Yes
	SI2	0.905				
CSE	CSE1	0.940	0.867	0.847	0.952	Yes
	CSE2	0.922				
PEN	PEN1	0.907	0.805	0.758	0.892	Yes
	PEN2	0.887				
PU	PU1	0.845	0.692	0.852	0.900	Yes
	PU2	0.850				
	PU3	0.830				
	PU4	0.801				
PEOU	PEOU1	0.753	0.696	0.855	0.901	Yes
	PEOU2	0.791				
	PEOU3	0.895				
	PEOU4	0.889				
PR	PR1	0.912	0.836	0.804	0.911	Yes
	PR2	0.917				

ATU–perceived attitude towards, C_USE-actual usage, PU-perceived usefulness, PEOU–perceived ease of use, SI-social influence, PR–facilitating conditions, PEN–perceived enjoyment, CSE–self efficacy.

4.1.4 Validity in Discrimination
Discriminant validity refers to the degree to which a construct is actually distinct from other constructs based on empirical standards (Hair Jr et al., 2014, p. 104). The heterotrait-monotrait ratio of correlations (HTMT) values were utilised to determine discriminant validity (Garson, 2016). The HTMT readings were all less than 0.90. The results verified the discriminant validity. Overall, the measurement model's indicator reliability, internal consistency, convergent validity, and discriminant validity tests were successful. As a result, the measurement model demonstrates the sturdiness required to test the structural model.

4.2 The Structural Model
After confirming the measurement model's suitability, the structural model was evaluated. Collinearity was assessed using the variance inflation factor (VIF). Collinearity in PLS-SEM inflates standard errors, makes significance tests of independent constructs inaccurate, and makes it difficult to determine the relative importance of one independent construct compared to another, according to Hair et al. (2017). Table 2 shows that the VIF values range from 1.16 to 2.77. All the VIF values were less than 4 (Garson, 2016), demonstrating that collinearity in the structural model was not an issue among the predictors. As a result, path coefficients can be assessed.

Bootstrapping (with 5000 subsamples) was used to assess the statistical significance of each path coefficient using t-tests (Chin, 1998), and the results are shown in Table 2. Out of 16 hypotheses that were tested, only five path coefficients are not statistically significant, as shown in Table 2. PEOU to C_USE (β = -0.023, $p > 0.05$), PEOU to PU (β = -0.003, $p > 0.05$), PR to PEOU (β = 0.208, $p > 0.05$), PU to ATU (β= 0.007, $p > 0.05$), SI to PU (β = --0.092, $p > 0.05$) were the non-significant pathways.

The f-squared statistic was used to assess each exogenous construct's contribution to the explained variance of its endogenous construct. Table 2 displays the results. Cohen (1988) defined acceptable effect size values of 0.02, 0.15, and 0.35 as small, medium, and substantial respectively. According to Cohen's guidelines, the effect size of ATU to C_USE (0.76) was considered the most effective (Cohen, 1988). PEN to PU (0.193) had a medium effect size and the rest had small effect sizes.

Table 2: Bootstrapping results

Path	Std Beta	Std error	T-values	P-Values	Decision	VIF	f-squired
ATU -> C_USE	0.666	0.048	13.737	0.000	Accepted	2.288	0.761
CSE -> ATU	0.243	0.074	3.280	0.001	Accepted	2.771	0.057
CSE -> PEOU	0.361	0.098	3.686	0.000	Accepted	2.376	0.083
CSE -> PU	0.327	0.067	4.909	0.000	Accepted	1.679	0.053
PEN -> ATU	0.152	0.066	2.311	0.021	Accepted	2.125	0.029
PEN -> PU	0.369	0.077	4.776	0.000	Accepted	1.770	0.193
PEOU -> ATU	0.234	0.072	3.228	0.001	Accepted	1.548	0.000
PEOU -> C_USE	-0.023	0.043	0.536	0.592	Rejected	1.331	0.059
PEOU -> PU	-0.003	0.069	0.044	0.965	Rejected	1.535	0.000
PR -> ATU	0.257	0.079	3.234	0.001	Accepted	2.513	0.067
PR -> C_USE	0.187	0.045	4.120	0.000	Accepted	1.964	0.069
PR -> PEOU	0.208	0.109	1.909	0.057	Rejected	2.376	0.018
PU -> ATU	0.007	0.066	0.111	0.912	Rejected	1.781	0.077
PU -> C_USE	0.141	0.052	2.734	0.006	Accepted	1.646	0.001
SI -> ATU	0.100	0.043	2.332	0.020	Accepted	1.200	0.022
SI -> PU	-0.092	0.053	1.755	0.080	Rejected	1.155	0.031

ATU–perceived attitude towards, C_USE-actual usage, PU-perceived usefulness, PEOU–perceived ease of use, SI-social influence, PR–facilitating conditions, PEN–perceived enjoyment, CSE–self efficacy.

The bootstrapping method was also used to test the indirect effect of exogenous variables on the actual use of virtual learning by rural STEM preservice teachers. The results in Table 3 show that all four of the indirect paths tested were statistically significant at the 0.05 level of significance. According to the findings, all of the model constructs had a positive direct and/or indirect influence on rural STEM preservice teachers' actual use of virtual learning.

Table 3: Indirect path coefficient

Path	Std Beta	Std error	T-Value	P-Value	Decision
CSE -> ATU -> C_USE	0.162	0.052	3.126	0.002	Accepted
PEN -> ATU -> C_USE	0.101	0.044	2.323	0.021	Accepted
CSE -> PEOU -> ATU -> C_USE	0.056	0.026	2.183	0.029	Accepted
PEOU -> ATU -> C_USE	0.156	0.053	2.948	0.003	Accepted

The R-squared value shows the total contribution of all the independent variables on the explained variance of the dependent variable (Hair et al., 2017). Figure 2 shows that the R-squared value of the model was 0.746. This result implies that all the identified model variables explain 74.6% of the variance in rural STEM preservice teachers' acceptance of virtual learning. According to Hair et al. (2017), the variance explained by the variables identified in this study is considered substantial.

A cross-validated redundancy predictor was used to assess the model's predictive relevance. The results revealed that all Q-squared values were greater than zero, implying that the model could be used to explain and predict virtual learning acceptance by rural STEM preservice teachers. The standardised path coefficients are also shown in Figure 2. The structural model is made up of eight constructs (ATU, PEN, CSE, C_USE, PR, ATU, PEOU, and PU). PU, ATU, PR, and PEOU all predict C_USE. ATU is predicted by PR, SI, CSE, PEN, PU and PEOU. PEC and PR predict PEOU, which in turn predicts PU. PU is also predicted by PEN, SI and CSE.

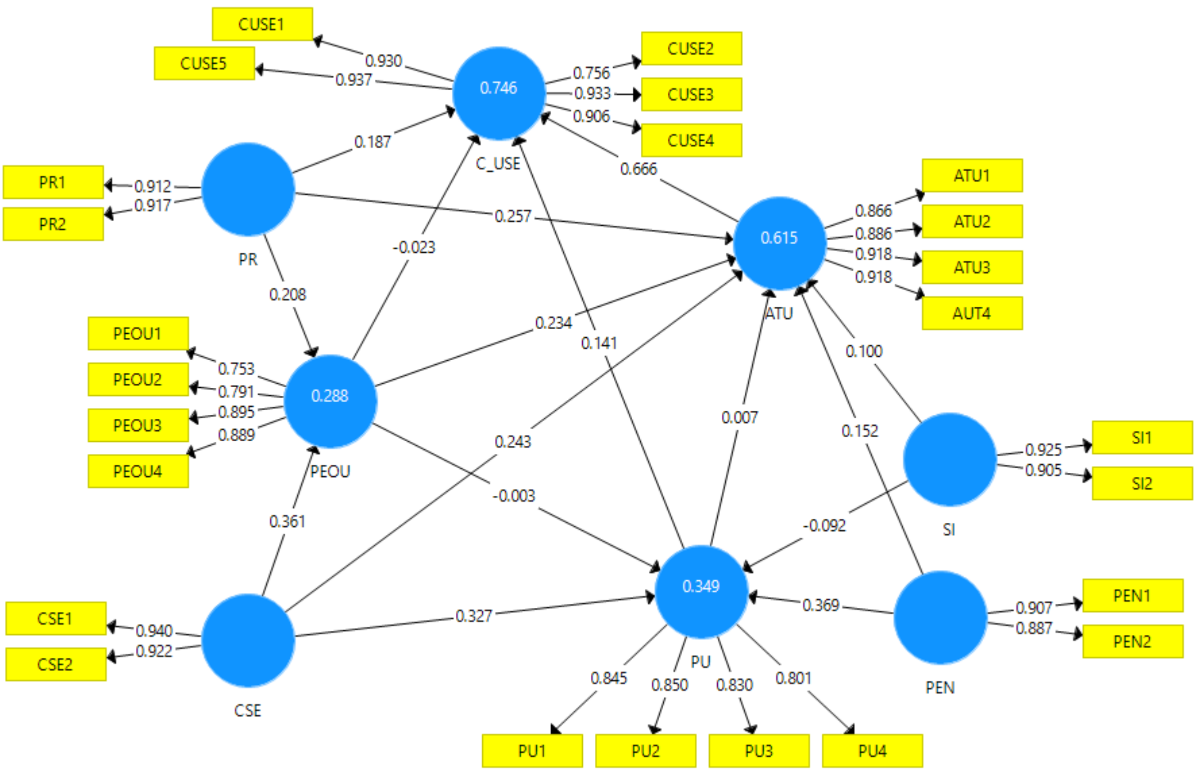

Figure 2: Structural model

ATU–perceived attitude towards, C_USE-actual usage, PU-perceived usefulness, PEOU–perceived ease of use, SI-social influence, PR-facilitating conditions, PEN–perceived enjoyment, CSE–self efficacy.

5. Discussion

Research question 1: The first goal of this research was to investigate the factors that influence rural STEM preservice teachers' use of virtual learning. According to the findings in Table 2, facilitating conditions, perceived usefulness, and perceived attitude toward VL had a positive effect on actual usage among rural STEM preservice teachers. Although perceived ease of use was found to have an insignificant direct effect on rural STEM preservice teachers' actual use of virtual learning, the results in Table 2 show that it has an indirect effect via the mediating effect of perceived attitude toward the use. The computer self-efficacy, perceived enjoyment, and social influence of rural STEM preservice teachers had an indirect effect on their use of virtual learning. These findings suggest that perceived usefulness, perceived ease of use, perceived attitude toward VL, social influence, computer self-efficacy, perceived enjoyment, and facilitating conditions are all good predictors of rural STEM preservice teachers' actual use of virtual learning.

Consistent with the findings of Chen (2010), PEOU had no direct significant effect on actual use. One possible explanation for the findings is that the rural STEM preservice teachers who took part in this study had more than a year of experience using virtual learning. As a result, the effort required to learn and master virtual learning is no longer an important factor for them to consider when accepting or rejecting virtual learning. This finding is also consistent with the findings of Mutambara and Bayaga (2021) and Venkatesh et al. (2003), who separately found that the effect of PEOU on actual use diminishes with user experience with the system. However, through the mediating effect of perceived attitude toward use, PEOU had a positive indirect effect on actual use. This finding implies that a user-friendly virtual learning environment is still required for rural STEM preservice teachers to accept and use virtual learning.

Rural STEM preservice teachers' PR influences their actual use and attitude towards use but not their perceived ease of use. The availability of resources influences rural STEM preservice teachers' attitude towards virtual learning, which reinforces teachers' use of virtual learning. This finding was consistent with that of Mutambara and Bayaga (2021) whose observation was that in rural areas, most people cannot afford to use technology in education. This finding suggests that the availability of resources influences the actual use of virtual learning.

The findings revealed that attitude towards use among preservice teachers has an effect on actual use. The findings were in accordance with those of Pittalis (2020) and Sivo et al. (2018), who both stressed the importance of improving university students' attitude towards learning technologies. According to the findings, rural STEM preservice teachers must have a positive attitude towards virtual learning in order to benefit from it. Rural STEM preservice teachers' attitudes toward virtual learning can be improved by providing resources, training them on how to use virtual learning, and making virtual learning platforms enjoyable.

Perceived enjoyment and computer self-efficacy had an indirect effect on actual use via the mediation of perceived attitude. One possible explanation is that the vast majority (93%) of respondents in this study are members of the 'digital generation' who are confident in their ability to handle a variety of computer-related tasks and enjoy using technology in their daily lives. The findings are consistent with those of Mutambara and Bayaga (2021), namely that the usefulness and pleasure that educational technologies bring to learning influence their acceptance among the digital generation.

In contrast to the study by Sánchez-Prieto et al. (2019) and that of Van Raaij and Schepers (2008), this study found that the perceived social influence of rural STEM preservice teachers influences their perceived usefulness and attitude towards the use of virtual learning. The findings indicate that rural STEM preservice teachers are susceptible to what they have heard about the use of virtual learning during the COVID-19 pandemic from their lecturers, university administrators, and their countrymen at large. Information system users internalise their colleagues' opinions about the system (Venkatesh et al., 2003). Since the study's rural STEM preservice teachers have been hearing about the benefits of using virtual learning in the face of COVID-19, they have internalised it and it has become part of their belief system, resulting in a positive impact on their attitude towards virtual learning.

The perceived usefulness of rural STEM preservice teachers prognosticates their practical use. This result is consistent with that of Sánchez-Prieto et al. (2019), who found that the utility of virtual learning has an effect on its actual use by students. Rural STEM preservice teachers in this study found that, even though universities were closed owing to the COVID-19 pandemic, they could still learn virtually. Furthermore, rural STEM preservice teachers have realised that virtual learning enables them to access their learning materials from anywhere at any time. Moreover, rural preservice teachers can learn at their own pace with virtual learning. These benefits of virtual learning influence its use by rural STEM preservice teachers.

Research question 2: The R-squared statistic was used to assess the extent to which the model factors explain the actual use of virtual learning by rural STEM preservice teachers. The model's R-squared value was 0.746, as shown in Figure 2. According to Chin (1998), this R-squared value is statistically significant. This means that the total contribution of the model variables (perceived usefulness, perceived ease of use, perceived, social influence, perceived attitude towards VL, computer self-efficacy, and perceived enjoyment by rural STEM preservice teachers) to the variance of the actual use of virtual learning is 74.5%. The model's explanatory power exceeds that of Van Raaij and Schepers (2008), who reported that their model explained 31% of virtual learning acceptance. The explanatory power of this model is also greater than the 40% of the original TAM developed by Davis et al. (1989). This finding supports the proposal made by several authors (Chibisa et al., 2021; Venkatesh et al., 2003a; Zarafshani et al., 2020), who proposed that adding context-related external variables to the TAM improves its explanatory power.

6. Implications

6.1 Practical Implications

These findings have a number of practical implications, especially for university information communication technology managers who use virtual learning as a central knowledge hub. Since universities have invested considerably in virtual learning, it is critical that students take advantage of these systems and learn to their full potential. The first requirements are, of course, that the system has features that improve study efficiency and that its interface is simple to use. It is the system designer's responsibility to ensure that these fundamental requirements are met. Secondly, virtual learning should be given relevant and up-to-date material by teaching personnel on how to use it. This increases the actual use of the system by students. Internal motivation for the system's continued use during and after the COVID-19 pandemic should be included. Furthermore, course administrators should emphasise the importance of students using the system extensively. Course management, on the other hand, has the potential to make a difference by providing adequate training to students, especially new students, thereby increasing their perceived ease of use and their computer self-efficacy.

6.2 Theoretical Implications

The findings backed up Lim's (2018) suggestion that the TAM be expanded to include context-related antecedents of perceived ease of use and perceived usefulness to clarify technology acceptance in a different context. According to the findings of this study, perceived enjoyment and social influence predict rural STEM preservice teachers' perceived usefulness and attitude towards use and have a positive effect on actual use via the mediation of attitude towards use. The study also found that facilitating conditions predict perceived ease of use, attitude towards use, and actual use. Finally, computer self-efficacy influences the TAM's main pillars, namely perceived ease of use, perceived usefulness, and attitude towards use.

7. Limitation

The study's limitation is that it only looked at one rural university and its STEM preservice teachers. As a result, generalising the study's findings to all universities in developing countries and their STEM preservice teachers should be done with caution.

8. Recommendations for Further Studies

Future research should focus on faculties other than education. It is also intended to conduct the same study at urban universities and compare the results. The research model explained 74.6% of the variance; future studies may consider other factors that account for the remaining 25.4% of the variance in explaining the use of virtual learning by preservice teachers.

9. Conclusion

The constructs perceived usefulness, perceived ease of use, facilitating conditions, perceived attitude toward VL, self-efficacy, perceived enjoyment, and perceived social influence are the factors that were found to influence rural STEM preservice teachers' acceptance of virtual learning. The research model accounted for 74.6% of the variance in rural preservice teachers' use of virtual learning. Just as in the case of the original TAM, perceived usefulness and perceived ease of use influenced perceived attitudes of rural STEM preservice teachers. Perceived usefulness and perceived attitude of rural STEM preservice teachers have a direct impact on their actual use.

This study concluded that computer self-efficacy, perceived enjoyment, facilitating conditions, and perceived social influence have an impact on rural STEM pre-service teachers' use of virtual learning. According to the findings, facilitating conditions predict actual use, perceived attitude, and perceived ease of use. It was found that computer self-efficacy influences perceived ease of use, perceived usefulness, and perceived attitude toward use. Perceived enjoyment and social influence also have a considerable influence on perceived usefulness and perceived attitude towards use. It can be concluded that the factors identified in the model are good predictors of rural STEM pre-service teachers' acceptance of virtual learning.

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Appendix 1

STEM preservice teachers' acceptance of virtual learning

The purpose of this questionnaire is to collect data that will be used to determine the acceptance of virtual learning among Sciences, Mathematics, Engineering and Technology (STEM) pre-service teachers in rural universities. Any information provided will be treated with utmost confidentiality and will not be used for any purpose other than this. Your participation in this survey will be highly appreciated. All data obtained from participants and their personal details will be treated with utmost confidentiality. You are free to withdraw from this survey any time you feel like doing so, without any consequences. You need approximately 5-10 minutes to complete this survey.

DEMOGRAPHIC DATA
(Please tick the appropriate box)

Gender	Male	Female
	1	2

Age	18 Years & below	19-20 Years	21-22 Years	23-24 Years	25 Years & above
	1	2	3	4	5

CONSTRUCTS AND INDICATORS
(Please indicate your level of agreement or disagreement with the following by placing **X** in the appropriate box, where 1 = entirely disagree, 2 = mostly disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 =somewhat agree, 6 = mostly agree, and 7 = entirely agree)

No	**Facilitating conditions (PR)**	1	2	3	4	5	6	7
1	I have access to the Internet that I can use it for virtual learning.							
3	I would be able to use virtual learning for learning if I wanted to.							
4	I have a virtual device to use for virtual learning.							
5	I have a data bundles that I can use for virtual learning.							
6	I can get help from others when I have difficulties using virtual learning.							

No	**Perceived social influence (PSI)**	1	2	3	4	5	6	7
1	My friends think that I should use virtual learning							
2	My parents think that I should use virtual learning							
3	My lecturers think that I should use virtual learning							
4	My classmates think that I should use virtual learning							

No	**Perceived usefulness (PU)**	1	2	3	4	5	6	7
1	Using virtual learning enhanced the quality of my learning							
2	Using virtual learning increased my productivity							
4	Using virtual learning would enhance my effectiveness in learning							
5	Using virtual learning would make it easier for me to learn							
6	I would find virtual learning useful in learning							

No	**Perceived ease of use (PEOU)**	1	2	3	4	5	6	7
1	It would be easy to learn how to use virtual learning							
3	I would find virtual learning easy to use in learning all my modules							
4	I would find virtual learning to be flexible to interact with.							
5	It would be easy to access my learning materials using virtual learning							

No	**Perceived Attitude (PA)**	1	2	3	4	5	6	7
1	I believe it is beneficial to use virtual learning							
2	My experience with virtual learning to learn will be good							
3	I feel positive about using virtual learning for learning							
4	I have a positive attitude toward using virtual learning							

No	**Perceived enjoyment (PE)**	1	2	3	4	5	6	7
1	Learning using virtual learning would be enjoyable							
2	I would find it fun to learn using virtual learning							
3	I would find using virtual learning interesting							

No	**Behavioural intention (BI)**	1	2	3	4	5	6	7
1	In future I intend to increase my time working virtually							
2	I intend to use virtual learning whenever I am studying in future							
3	I intend to use virtual learning for my future studies							

No	**Actual use (AU)**	1	2	3	4	5	6	7
1	I go onto the Internet several times per week for my studies							
2	On average I spend more than 2 hours each time I am working virtually							
3	I access all my notes virtually							
4	All my lessons were offered virtually							