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Factors Influencing Adoption of e-Learning for Teaching and Learning Among First-Year Students at A Historically Disadvantaged University in South Africa: Applying the UTAUT Model

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ABSTRACT

The rapid growth in information communication technology (ICT) usage has brought remarkable changes in higher education. Many higher education institutions around the globe are adopting e-learning platforms as one of the primary ways of delivering teaching and learning among students. During the COVID-19 pandemic, South African higher education institutions utilised the e-learning platform for effective collaborative teaching and learning between teachers and learners. This study investigates the factors that influenced the adoption of technology by first-year Walter Sisulu University (WSU) students. Interviews were conducted with students to explore their perceptions of the use of e-learning and what factors positively or negatively affected their e-learning experiences. The unified theory of acceptance and use of technology (UTAUT) model was used to interpret the results. The findings show that, in general, the students have a very positive attitude towards e-learning, and they perceived that e-learning enhanced their educational experience. The communication aspect was especially important for historically disadvantaged universities in South Africa, as it facilitated a feeling of belonging to the global community of students and scholars and alleviated the former apartheid-torn country's isolation. However, some socio-cultural aspects of students' communities negatively affected their e-learning experience.

Keywords: *unified theory of acceptance and use of technology; e-learning, information communication technology; historically disadvantaged universities; first-year students*

INTRODUCTION

Information and communication technology (ICT) is fast becoming essential in our daily lives and our educational system (Lawrence and Tar, 2018). Author (Livingstone, 2012) alluded to its ability to improve the quality of teaching, learning, and management in schools. In the contemporary period, there has been a significant shift in education practices from a teacher-centred pedagogy-based approach to a learner-centred pedagogy approach (Moate and Cox, 2015, Amponash, 2018) This implies that the learner's needs, abilities, and learning styles are acknowledged to motivate and engage students in their learning activities. Earlier studies suggest that the introduction of modern technology in education and the emergence of electronic learning (e-learning) platforms have contributed to an important role in facilitating the broad adoption of learner-centred approaches in the educational environment (Buabeng-Andoh, 2012, Esan and Masombuka, 2025).

Technology adoption has been used to refer to the stage in which a technology is selected for use by an individual or an organisation (Eneh, 2010). There have been studies such as (Dastjerdi, 2016), on factors influencing ICT adoption by students at universities and employees at various organisations. Some of these studies have explored similar factors, which include perceived usefulness and perceived ease of use (Kelly and Palaniappan, 2023). Other factors influencing adoption include perceived benefits, perceived compatibility, personal innovativeness, and attitudes toward the use of these technologies, among others.

CONTEXT OF INSTITUTION/UNIVERSITY

It has been noted that the racialised structure of the apartheid system influenced the historical development of the South African educational system (Mbaleki & Mbodila, 2023). The South African higher education system is the backdrop for this case study. Because of the university's disparate geographic locations, resource levels, and cultural, ethnic, and political backgrounds, there is significant disparity within the system (Mbaleki & Mbodila, 2023, Songca et al., 2021). The historically disadvantaged university (HDU), also called historically disadvantaged institution (HDI), is defined by (Mbaleki & Mbodila, 2023) in the South African context as a cluster of universities that were established during the apartheid regime to cater for African and non-white populations.

The current HDU under study is a comprehensive university that offers various qualifications in the form of degrees, diplomas, and certificates. The Walter Sisulu University (WSU) results from a merger between various institutions around the Eastern Cape Province. WSU was established on 1 July 2005 through a merger of two polytechnics and a university, that is, the former Border Technikon, Eastern Cape Technikon, and University of Transkei, in accordance with the Higher Education Act 101 of 1997, as amended (Songca et al., 2021). This HDU is seeking to play a vital role by offering a responsive curriculum that will help make a difference in its surrounding communities and beyond (Songca et al., 2021, WSU, 2020). The institution comprises four campuses, with two of those campuses situated in rural settings. They mainly cater for students from rural disadvantaged communities. As such, most campus feeder schools are public schools that generally lack proper technology infrastructure and adequate personnel. Approximately 88% of the first-time entering students (FTENs) who were admitted at WSU in 2021 were from disadvantaged circumstances and were the first in their families to attend college, according to student tracking unit data on the FTENs profiles (Mbodila et al., 2023).

During COVID-19, the institution shifted from using only face-to-face teaching and learning to a blended approach - both face-to-face and e-learning (Songca et al., 2021). This was done to reduce the spread of the coronavirus among the learners, lecturers, and support staff. During this period, only 40% of education activities were conducted face-to-face, while the remaining 60% was done using the e-learning platform WiseUp LMS (Songca et al., 2021, Mbodila et al., 2023). The WiseUp tool was used frequently for various purposes such as disseminating information to the learners, uploading files to the system, uploading learning content to the system, making announcements, creating assessments for students and facilitating class interactions between students and teachers, and uploading quizzes and assignments for students (Mbodila et al., 2023, Esan & Esan, 2025). However, during this period, many students and lecturers migrated quickly to adopting WiseUp technology for teaching and learning, while some found it challenging. Research has demonstrated that many students experienced challenges in joining live lectures because of issues such as IT skills and network coverage since most of them are based in the rural areas in the Eastern Cape province (Mbodila et al., 2023). Hence, these issues remain significant factors delaying the adoption of LMS for teaching and learning at WSU (WSU, 2020, Mbaleki & Mbodila, 2023, Mbodila et al., 2023, Mbaleki et al., 2023)). To address this challenging issue of technological adoption of e-learning LMS in historically disadvantaged universities, it is imperative to consider the factors influencing the adoption of the technology. In this study, the unified theory of acceptance and use of technology (UTAUT) model was used to interpret the results.

THEORETICAL FRAMEWORK

This study explores the factors influencing the adoption of an e-learning tool among first-year students for teaching and learning. This section reviews the theories that underpin technology adoption/acceptance and selects the theory that is best suited for this study. Different models of technology acceptance were developed and tested in the 1980s (Al-hamazani, 2020). However, (Venkatesh et al., 2003) developed and tested the unified theory of acceptance and use of technology (UTAUT) model. UTAUT is the integration of eight (8) technology models, namely, the theory of reasoned action (TRA), the technology acceptance model (TAM), the motivational model (MM), the theory of planned behaviour (TPB), a model combining the TAM and the TPB, the model of PC utilization (MPCU), the innovation diffusion theory (IDT), and the social cognitive theory (SCT).

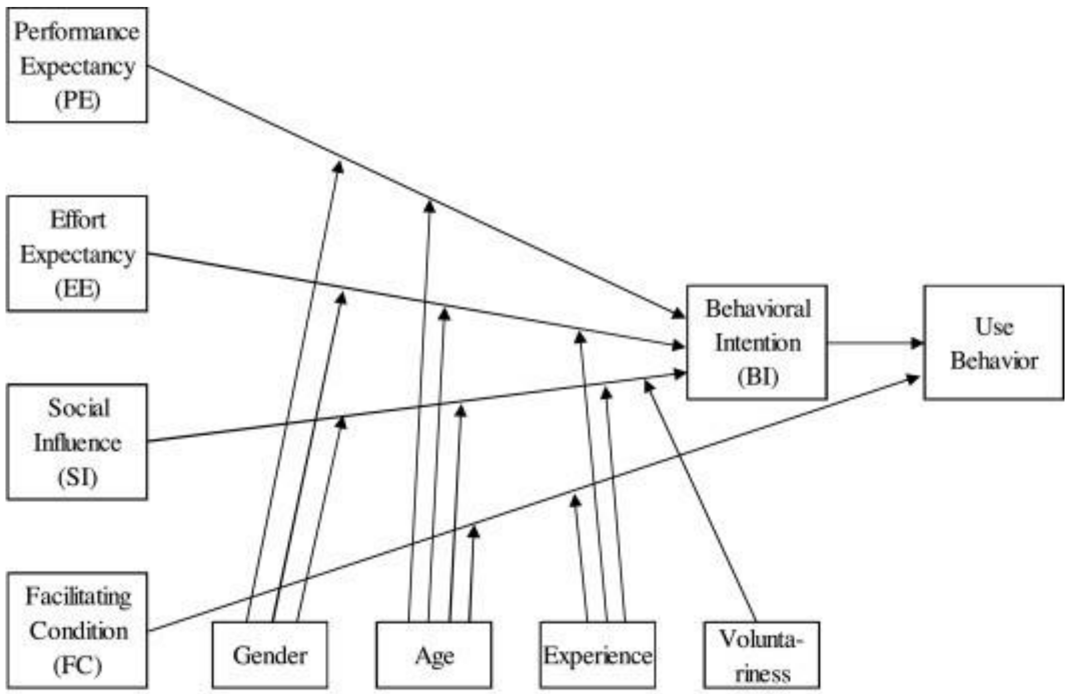

Figure 1: The Conceptual Framework

Performance Expectancy (PE)

Performance expectancy can be viewed as the level at which an individual perceives the benefits one can attain in using a particular system for job performance. The PE constructs are based on predictor intention, which is obtained from 5 constructs in 8 different models used for the development of the UTAUT model (Qamar et al., 20220, Davis, 1989). These constructs include extrinsic motivation from MM, job fit from MPCU, usefulness from TAM, relative merit from IDT and expectations outcomes from SCT. The research has shown the relationship between PE and behavioural intentions about educational technologies, and that PE can help students migrate smoothly from the traditional teaching and learning approach to e-learning. This implies that the student's behavioural intention to use e-learning will be influenced by the perception of its usefulness in their educational performances.

Behavioural Intention (BI)

The UTAUT model shown in Figure 1 indicates that PE, EE, and SI have a significant influence on the individual's behavioural intention to use technology (Qamar et al., 20220, Davis, 1989, Esan & Esan, 2025). BI involves the level at which individuals are willing to participate in a specific behaviour. The TAM, TPB and TRA models testify that the BI positively impacts system users. The

Behavioural intention is the most significant factor that determines the actual behaviour, and it is expected that the BI will have a positive influence on the actual usage of e-learning by students, especially post the COVID-19 pandemic for effective teaching and learning between teachers and students as well as collaborative learning between students and students.

Effort Expectancy (EE)

Effort expectancy is the level of comfort an individual experiences with the use of the system (Qamar et al., 20220). At the initial stage, the effort expectancy is a strong predictor of behavioural intention when using the system. The more the user becomes acquainted with the system, the less significant the EE becomes. The EE was created with the ease of use and complexity of use found in the TAM (Davis, 1989) and MPCU models (Rahmaningtyas et al., 2020). The research conducted by (Jaradat & Banikhale, 2013), indicated that EE has a positive influence on the behavioural intentions to use the technology.

Social Influence (SI)

This is the individual's perception of the user of the system since those who are important to the users believe the user should use the system (Venkatesh et al., 2003). This Social influence was obtained from TRA (Fishbein & Ajzen, 1975), TPB (Ajzen, 1985) and C-TAM-TPB. From all the derived theories, the SI is a direct determinant of behavioural intentions. In the UTAUT model shown in Figure 1, the SI was identified as the voluntary use of the technology by individuals (Davis, 1989). It is, therefore, expected that the SI might have a positive influence on behavioural intention on the use of the WiseUp technology tool for e-learning.

Facilitating Condition (FC)

The FC refers to an individual's perception of the level of support received from an organisation's technical support to encourage technology use (Qamar et al., 20220, Rahmaningtyas et al., 2020, Davis, 1989). The constructs were derived from TPB and C-TAM as perceived behavioural controls, IDT as compatibility, and MPCU as facilitating conditions. The FC was not found to have a direct influence on behavioural intention when EE is present in the model (Rahmaningtyas et al., 2020). (Kim & Lee, 2020) also used UTAUT as a model to build a conceptual model for effective ICT-based instruction. In the context of e-learning, this study was in line with the research conducted by (Jaradat & Banikhale, 2013) with the difference in application to the students in one of the historical universities in Jordan.

Hypotheses Development

From Figure 1, relationships between constructs were suggested. Firstly, it was suggested that there is a relationship between behavioural intention, perceived ease of use and perceived usefulness. From this understanding, five hypotheses were suggested as follows:

> ***H1:*** Performance expectancy does not influence the adoption of e-learning in a historically disadvantaged institution in South Africa.
>
> ***H2:*** Effort expectancy does not influence the adoption of e-learning in a historically disadvantaged institution in South Africa.
>
> ***H3:*** Social influence does not impact the adoption of e-learning in a historically disadvantaged institution in South Africa.
>
> ***H4:*** Facilitating conditions do not influence the adoption of e-learning in a historically disadvantaged institution in South Africa.

H5: Behavioural intention does not influence the adoption of e-learning in a historically disadvantaged institution in South Africa.

METHODOLOGY

An explanatory sequential mixed-methods paradigm approach was used in this research study to investigate the factors that affect the acceptance of e-learning among first-year students in one of the disadvantaged universities (WSU) in South Africa. The sequential mixed method design involves incorporating the collection of both quantitative and qualitative data with quantitative data collected to triangulate the data and solicit rich data from respondents (Dawadi et al., 2021). The qualitative data was obtained through the open-ended questionnaire.

Population and Sampling

A systematic sampling procedure was used to determine the sample size. This method is appropriate because a complete list (class lists) of sampling subjects (students) is arranged in an orderly manner (student numbers) to investigate the acceptance of information communication technologies in learning and teaching. The sample comprises 7 programmes in the Economics and Information Technology Systems Faculty; 20 students were selected using the systematic sampling procedure to make a population size of 141. The demographic characteristics of respondents are shown in Table 1.

Table 1: *Demographic characteristics of respondents (n = 141)*

Variable	**Frequency**	**Percentage (%)**
Gender		
• Male	91	64.5
• Female	50	35.5
Age group		
• 17 – 20	61	43.3
• 21 – 24	53	37.6
• 25 – 28	21	14.9
• Above 28	6	4.3
Qualification stream		
• Main programme	53	37.6
• Extended programme	88	62.4
Registered qualification		
• Internal Auditing	24	17.0
• Accountancy	7	5.0

• ICT in App Development • Public management • Human Resource Development • Local Government Finance • BCom (General)	20 8 14 62 6	14.2 5.7 9.9 44.0 4.3
Type of High School Attended • Government/Public • Former Model C • Private	 130 6 5	 92.2 4.3 3.5
Where students live • Urban • Rural • Township	 13 87 41	 9.2 61.7 29.1
Computer competency • Not yet competent • Moderately competent • Competent	 38 67 36	 27.0 47.5 25.5
Devices students own • Smartphone • Laptop/desktop • combination	 61 31 49	 43.3 22.0 34.8
Where students access WiseUp • At home • In the library • Computer lab • Internet café • School residence	 122 3 4 4 8	 86.5 2.1 2.8 2.8 5.7
Access to high-speed Wi-Fi		

• Yes • No • Sometimes	61 7 73	43.3 5.0 51.8

Table 1 shows the demographics of the respondents. A vast majority of students, 90.8% come from both rural and township areas with an overwhelming 92.2% of students who participated being students in public schools (also known as government schools). This finding is in line with studies such as that conducted by (Songca et al., 2021, WSU, 2020), which confirm that most of the students admitted to WSU come from disadvantaged socio-economic backgrounds and schools in both rural and township areas. Only 4.3% and 3.5% went to the former model C and private schools, respectively. Public schools depend on the government for funding and supply of materials. In rural areas and townships, they tend to have less equipment, lack Internet connectivity, have no interactive whiteboards, fewer teaching resources, and fewer specialised rooms, such as libraries, computer laboratories, and sciences laboratories, compared to private schools (Mampane & Bouwer, 2011, Zenda, 2020). 86.5% of students in the survey accessed the Internet and subsequently WiseUp at home. This contradicts the findings of (Oyedemi & Mogano, 2018), whose study revealed that about 83.7% of students in rural areas had no Internet access at home. However, this contradiction can be explained, as students in this study were mainly taught online due to the COVID-19 induced teaching and learning environment and had access to the Internet through data provided by the institution.

However, the rural Eastern Cape still lags in terms of Internet access and adoption. Statistics SA's (2019) general household survey revealed that only 3.2% of households have Internet access at home in the province. The number drastically drops to 0.3% if you are considering only rural households. 11.3% accessed the Internet and WiseUp from computer labs, school residences, and Internet cafés compared to 3.1% (Internet cafés and/or educational facilities) in EC (Statistics SA, 2021). Results also revealed that about 47.5% of students are moderately equipped to operate computers (or computer literate) on a basic level. In comparison, (Oyedemi & Mogano, 2018) reported that about 56% of students had challenges with using computers upon their arrival. The number increased to 60.2% when referring to students from rural backgrounds. This is in line with the WSU FTENs profiles report from the student tracking unit data, which indicated that most students are computer illiterate and face challenges in the use of computers for learning and teaching (Mbodila et al., 2023). Table 1 shows that only 25.5% consider themselves to be computer-competent, closely followed by 27% of students who consider themselves to be incompetent. Computer incompetency can lead to computer anxiety, which will subsequently affect student performance (Katsarou, 2021). According to research by Mbaleki & Mbodila (2023), about 93% of FTENs in the same settings were seeking help in their first year for computer-related skills to enable them to be ready in their studies (Mbaleki et al., 2023).

Data Collection

The data was collected through a semi-structured questionnaire administered to the students through Google Forms sent via their WhatsApp platform on their cell phones. A total of 141 questionnaires were received out of the total number of 150 questionnaires sent out. Using the sequential mixed methods approach, the pre-coded questionnaire was sent to respondents. Building on the assertion that the person's belief towards a system may be influenced by other factors referred to as external variables [14], the pre-coded questionnaire was designed to solicit information from participants on external factors to the system itself. The five-point Likert-type scale (1= Strongly Agree, 2 = Agree, 3 = Neutral, 4 = Disagree, 5 = Strongly Disagree) on the actual variables were used as coded responses. The total number of TAM variables used in this study was five including factors influencing the adoption of the e-learning technology, particularly the WiseUp learning management system (LMS), by students at the historically disadvantaged university, Walter Sisulu University, as shown in Table 2.

Table 2: *Scale items used in the research*

	Variables	Description of Items
1.	Performance Expectancy (PE)	**PE 1:** I find the LMS useful in my study
		PE 2: I Use LMS to accomplish my learning activities quickly.
		PE 3: My learning productivity increases with the use of LMS
		PE 4: The use of LMS increases my chances of getting better marks in all my courses
2.	Effort Expectancy (EE)	**EE 1:** My interaction with LMS is clear and understandable
		EE 2: I have the skills and knowledge of LMS
		EE 3: Using LMS is easy for me
		EE 4: I find it easy and convenient to use LMS to do my study
3.	Social Influences (SI)	**SI 1:** People who influenced my behaviour think I should use LMS
		SI 2: The senior students in my university are helpful in the use of the LMS
		SI 3: People who are important to me think I should use LMS
		SI 4: In general, the university has supported the use of the LMS
4.	Facilitating Conditions (FC)	**FC 1:** I have the resources necessary
		FC 2: I know it is necessary to use LMS
		FC 3: LMS is not compatible with other systems I use

		FC 4: The IT department in my university is always available for assistance with LMS difficulties
5.	Behavioural Intension (BI)	**BI 1:** I intend to use the LMS in the future
		BI 2: I predict I would use the LMS in the future
		BI 3: I plan to use the LMS in the future
		BI 4: I would recommend the LMS to my colleagues.

All the UTAUT factors were measured by the items listed in Table 1 in accordance with the literature reviewed on mobile learning systems. Finally, the Statistical Package for the Social Sciences (SPSS) tool was used for data analysis and evaluation.

Data Analysis

To analyze the data and test the hypotheses, the structural equation modelling (SEM) approach was utilized in this study for various reasons. SEM is the most rigorous and powerful statistical research approach for dealing with complicated models (Madge et al., 2019). SEM is a set of statistical models aimed at explaining correlations between a large number of variables. Furthermore, the SEM was utilized for hypothetical testing of relationships among several constructs and observable factors. This analysis was done using the two-step approach by (MOKHTAR et al., 2019). The assessment of the validity and reliability of the model measurement was the first step, and structural model analysis to test the research hypothesis was the second step.

Structural Model and Testing Hypotheses

After conducting a confirmatory factor analysis, items with poor loadings were eliminated, and the most parsimonious model was achieved with 20 items maintained. In short, 4 items measured performance expectancy (PE) (Factor 1), 4 items measured effort expectancy (EE) (Factor 2), 4 items measured social influence (SI) (Factor 3), 4 items measured facilitating conditions (FC) (Factor 4), and 4 items measured behavioural intentions (BI) (Factor 5). All factor loadings exceeded 0.60 (See Table 3 below). Factor loadings should ideally be greater than 0.5 (preferably greater than 0.7) to indicate a strong relationship between items and their latent constructs. The factor loading range of >0.70 and <0.90 was retained in the model because it ensures that the retained items exhibit both strong convergent validity and low multicollinearity risks (Hair et al., 2020). Thus, retaining items within this range ensures that the model is both statistically sound and theoretically meaningful**,** improving its overall validity and interpretability. On that basis, we accepted those above 6 as well, as they are greater than the ideal cut-off points of 0.5.

Table 3: *Confirmatory factor analysis and internal consistency output*

Factors and corresponding items	**CODE**	**CFA Loadings**	**Alpha if Item Deleted**
Performance Expectancy (PE)			
I find the LMS useful in my study	PE 1	0.843	0.821

I Use LMS to accomplish my learning activities quickly.	PE 2	0.960	0.874
My learning productivity increases with the use of LMS	PE 3	0.871	0.852
The use of LMS increases my chances of getting better marks in all my courses	PE 4	0.742	0.878
Cronbach's Alpha = ***0.910***; *Joreskog rho* = ***0.930***; *Average Variance Extracted (AVE)* = ***0.742***			
Effort Expectancy (EE)			
My interaction with LMS is clear and understandable	EE 1	0.720	0.930
I have the skills and knowledge of LMS	EE 2	0.891	0.898
Using LMS is easy for me	EE 3	0.941	0.897
I find it easy and convenient to use LMS to do my study	EE 4	0.869	0.922
Cronbach's Alpha = ***0.919***; *Joreskog rho* = ***0.928***; *Average Variance Extracted (AVE)* = ***0.745***			
Social Influences (SI)			
People who influenced my behaviour think I should use LMS	SI 1	0.946	0.967
The senior students in my university are helpful in the use of the LMS	SI 2	0.676	0.985
People who are important to me think I should use LMS	SI 3	0.949	0.975
In general, the university has supported the use of the LMS	SI 4	0.962	0.972
Cronbach's Alpha = ***0.915***; *Joreskog rho* = ***0.938***; *Average Variance Extracted (AVE)* = ***0.754***			
Facilitating Conditions (FC)			
I have the resources necessary	FC 1	0.945	0.967
I know necessary to use LMS	FC 2	0.866	0.975
LMS is not compatible with other systems I use	FC 3	0.942	0.959
IT department in my university is always available for assistance with LMS difficulties	FC 4	0.955	0.971
Cronbach's Alpha = ***0.912***; *Joreskog rho* = ***0.927***; *Average Variance Extracted (AVE)* = ***0.734***			
Behavioural Intension (BI)			
I intend to use LMS in future	BI 1	0.933	0.945
I predict I will use LMS in future	BI 2	0.892	0.953
I plan to use LMS in future	BI 3	0.938	0.961

I would recommend LMS to my colleagues.	BI 4	0.962	0.977
*Cronbach's Alpha = **0.968**; Joreskog rho = **0.975**; Average Variance Extracted (AVE) = **0.818***			

As shown in Table 3 above, the average variance extracted for all the items is greater than the required minimum of 0.50, that is, performance expectancy (AVE = 0.742), effort expectancy (AVE = 0.745), social influences (AVE = 0.754), facilitating conditions (AVE = 0.734), and behavioural intention (AVE = 0.818). Therefore, the convergence validity for the factors is deemed adequate since the average variance extracted figures for the five factors is greater than the required minimum of 0.50.

To measure the internal consistency of these factors, the Cronbach alpha coefficient was used, and the value was at least 0.910 for all the constructs analysed, that is, performance expectancy (Alpha = 0.910), effort expectancy (Alpha = 0.919), social influences (Alpha = 0.915), facilitating conditions (Alpha = 0.912), and behavioural intention (Alpha = 0.968). The recommended cut-off for reliability is 0.70, and with the foregoing Cronbach data, the reliability of the established factors is indicative of good and satisfactory reliability. Composite reliability was measured using the values of the Joreskog rho and these were greater than 0.900 for all the reviewed constructs, that is, performance expectancy (*CR* = 0.930) effort expectancy (*CR* = 0.928), social influences (*CR* = 0.938), facilitating conditions (*CR* = 0.927), and behavioural intention (*CR* = 0.975). Thus, the composite reliability is adequate for the established measurement model which justifies construct reliability.

As shown in Table 4 below, the standard root mean residual (SRMR) is 0.077, which is regarded as a satisfactory model fit. The good fit index (GFI) and its associated average good fit index (AGFI) were all above 0.95, which also suggests model fit. The appropriate or normed fit index (NFI = 0.966) and the suitable or relative fit index (RFI = 0.964) were also above 0.95, suggesting a good model fit for the established measurement model.

Table 4: *The fitness measures assessment for the factor's measurement model*

Name of index	**Index value**	**Cut-off points**	**Comments**
SRMR	0.085	0.05 < SRMR ≤ 0.09	**Acceptable fit**
GFI	0.974	≥ 0.95	**Good fit**
AGFI	0.969	≥ 0.95	**Good fit**
NFI	0.972	≥ 0.95	**Good fit**
RFI	0.970	≥ 0.95	**Good fit**

Note: ***SRMR*** *= The Standardised Root Mean Square Residual.* ***GFI/AGFI =*** *The (Adjusted) Goodness of Fit.* ***NFI*** *= The (Non) Normed Fit Index.* ***RFI*** *= The Relative Fit Index, also known as RHO1* Source: Compiled by the authors

Descriptive Analysis of Major Theoretical Variables and Construct

A means analysis of respondents' perceptions regarding the factors was conducted. Table 5 shows the summary of the descriptive statistics for these factors.

Table 5: *Summary of descriptive statistics for the factors*

Factor	Mean	S. D	Skewness	Kurtosis	SW.Sig
Performance Expectancy (PE)	4.1314	0.53375	- 1.467	0.586	< 0.0001
Effort Expectancy (EE)	4.4438	0.54887	- 1.162	- 0.085	< 0.0001
Social influences (SI)	4.5825	0.54430	- 1.535	1.178	< 0.0001
Facilitating conditions (FC)	4.6225	0.5320	- 1.541	0.759	< 0.0001
Behavioural intention (BI)	4.3427	0.53872	- 1.456	1.255	< 0.0001

Note: Factors were measured on a 5-point Likert scale. SW. Sig is the significance of the Shapiro-Wilk test. Source: Compiled by the authors.

The information is displayed as a summary of the mean scores and the respective standard deviation, the skewness and kurtosis coefficients, and the p-value for the Shapiro-Wilk test for normality. The factors were measured on a 5-point Likert scale. Conclusively, the findings revealed that mean ratings for the factors were high. In the sample, the mean ratings were as follows: Performance expectancy (PE) -4.1314, effort expectancy (EE) -4.4438, social influences (SI) -4.5825, Facilitating conditions (FC) -4.6225 and behavioural intention (BI) -4.3427. Notably, the mean ratings were all above four, meaning that the participants perceived high levels of performance expectancy, effort expectancy, social influences, facilitating conditions and behavioural intention. Also, the Shapiro-Wilk test and the skewness and kurtosis coefficients showed that the factors were inconsistent with the normal distribution, thus justifying the use of non-parametric statistics to analyse the data.

Correlation Analysis

As the data has been proven inconsistent with normality, Spearman's Rho correlation coefficient was applied to assess the relationship between the factors and the adoption of e-learning. A two-tailed test was conducted, and Table 6 below indicates the results of the established correlation coefficients.

Table 6: *Spearman's correlation coefficient for relationships between factors and the adoption of e-learning*

Theoretical Constructs/Factors	**Adoption of e-learning**
	Spearman's correlation (*rs*)
Performance expectancy	0.844**
Effort expectancy	0.775**
Social influences	0.821**
Facilitating conditions	0.814**
Behavioural intention	0.805**

*Note: **. Correlation is significant at the 0.01 level (2-tailed).* Source: Compiled by the authors

The data in Table 6 above reflects the results of Spearman's correlation coefficients for the relationship between the factors and the adoption of e-learning. The adoption of e-learning has a strong, positive, and significant relationship with all the factors listed in Table 6. In short, the results in the table suggest that improving performance expectancy, effort expectancy, social influences, facilitating conditions and behavioural intention leads to more efficient adoption of e-learning in the institution of higher learning. Given this outcome, the hypothesis on how the factors influence the adoption of e-learning in an institution of higher learning can now be tested. The path beta estimate for the performance expectancy to the adoption of the e-learning path is statistically significant (β = 0.850; SE = 0.084; 90% CI = [0.684 – 0.925]; p = 0.003). Thus, the regression weight for performance expectancy in the prediction of e-learning adoption is significantly different from zero at the 5% significance level. The squared multiple correlations of 71.0% with 90% bias-corrected CI = [0.582-0.911] indicate that the structural model explains 71.0% of the variation in levels of e-learning adoption (see Table 7 below).

Table 7: *Bootstrapped R-squared (squared multiple correlation) estimate and 90% bias-corrected confidence intervals for the performance expectancy on e-learning adoption default structural model*

Estimate	**Bootstrap SE**		**Bootstrapped 90% CI**		**Effect Size**
	SE	**Bias**	**LL**	**UL**	**Cohen's f^2**
0.710	0.122	0.014	0.472	0.867	2.320

Note: S.E. and Bias are the standard error and estimated bias for the bootstrapped R-squared (Squared Multiple Correlation) standardised estimates, respectively. Bias-corrected confidence
Source: Compiled by the authors.

According to Cohen's f^2, the effect size of 2.320 is greater than 0.35 and is regarded as a significant effect. This result supports the alternative hypothesis since the beta parameter for the performance expectancy to the e-learning adoption path is positive and substantial. Hence, there is satisfactory statistical evidence to reject the null hypothesis and conclude that the performance expectancy factor has a statistically significant and positive predictive effect on e-learning adoption in a historically disadvantaged higher education institution in South Africa. The path beta estimate for the effort expectancy to adopt the e-learning path is statistically significant (β = 0.861; SE = 0.078; 90% CI = [0.674 – 0.945]; p = 0.004). Thus, the regression weight for performance expectancy in the prediction of e-learning adoption is significantly different from zero at the 5% significance level. The squared multiple correlations of 70.0% with 90% bias-corrected CI = [0.580-0.923] indicates that the structural model explains 70.0% of the variation in levels of e-learning adoption (see Table 8 below).

Table 8: *Bootstrapped R-squared (squared multiple correlation) estimate and 90% bias-corrected confidence Intervals for the performance expectancy on e-learning adoption default structural model*

Estimate	**Bootstrap SE**		**Bootstrapped 90% CI**		**Effect Size**
	SE	**Bias**	**LL**	**UL**	**Cohen's f^2**
0.700	0.102	0.016	0.482	0.857	1.504

Note: S.E. and Bias are the standard error and estimated bias for the bootstrapped R-squared (Squared Multiple Correlation) standardised estimates, respectively. Bias-corrected confidence
Source: Compiled by the authors.

According to Cohen's f^2, the effect size of 1.504 is greater than 0.35 and is regarded as a significant effect. This score supports the alternative hypothesis since the beta parameter for the effort expectancy to the e-learning adoption path is positive and substantial. Henceforth, there is reasonable statistical evidence to reject the null hypothesis and conclude that the effort expectancy factor has a statistically significant and positive predictive effect on e-learning adoption in a historically disadvantaged higher education institution in South Africa. The path beta estimate for the social influence on the adoption of the e-learning path is statistically significant (β = 0.750; SE = 0.074; 90% CI = [0.685 – 0.935]; p = 0.004). Thus, the regression weight for social influence in the prediction of e-learning adoption is significantly different from zero at the 5% significance level. The squared multiple correlations of 72.0% with 90% bias-corrected CI = [0.582-0.911] indicate that the structural model explains 72.0% of the variation in levels of e-learning adoption (see Table 9 below).

Table 9: *Bootstrapped R-squared (squared multiple correlation) estimate and 90% bias-corrected confidence intervals for the performance expectancy on e-learning adoption default structural model*

Estimate	Bootstrap SE		Bootstrapped 90% CI		Effect Size
	SE	**Bias**	**LL**	**UL**	**Cohen's f^2**
0.720	0.132	0.018	0.482	0.897	2.068

Note: S.E. and Bias are the standard error and estimated bias for the bootstrapped R-squared (Squared Multiple Correlation) standardised estimates, respectively. Bias-corrected confidence
Source: Compiled by the authors.

According to Cohen's f^2, the effect size of 2.320 is greater than 0.35 and is regarded as a significant effect. This result supports the alternative hypothesis since the beta parameter for the social influence on the e-learning adoption path is positive and substantial. Hence, there is satisfactory statistical evidence to reject the null hypothesis and conclude that the social influence factor has a statistically significant and positive predictive effect on e-learning adoption in a historically disadvantaged higher education institution in South Africa. The path beta estimate for the effort expectancy to adopt the e-learning path is statistically significant (β = 0.864; SE = 0.076; 90% CI = [0.684 – 0.955]; p = 0.004). Thus, the regression weight for social influence in the prediction of e-learning adoption is significantly different from zero at the 5% significance level. The squared multiple correlations of 72.0% with 90% bias-corrected CI = [0.678-0.891] indicates that the structural model explains 72.0% of the variation in levels of e-learning adoption (see Table 10 below).

Table 10: *Bootstrapped R-squared (squared multiple correlation) estimate and 90% bias-corrected confidence intervals for the social influence on e-learning adoption default structural model*

Estimate	Bootstrap SE		Bootstrapped 90% CI		Effect Size
	SE	**Bias**	**LL**	**UL**	**Cohen's f^2**
0.720	0.112	0.015	0.491	0.860	2.068

Note: S.E. and Bias are the standard error and estimated bias for the bootstrapped R-squared (Squared Multiple Correlation) standardised estimates respectively. Bias-corrected confidence
Source: Compiled by the authors.

According to Cohen's f^2, the effect size of 2.068 is greater than 0.35 and is regarded as a significant effect. This score supports the alternative hypothesis since the beta parameter for the social influence on the e-learning adoption path is positive and substantial. Henceforth, there is reasonable statistical evidence to reject the null hypothesis and conclude that the social influence factor has a statistically significant and positive predictive effect on e-learning adoption in a historically disadvantaged higher education institution in South Africa. The path beta estimate for the facilitating condition to the adoption of the e-learning path is statistically significant (β = 0.810; SE = 0.080; 90% CI = [0.715 – 0.974]; *p* = 0.003). Thus, the regression weight for facilitating conditions in the prediction of e-learning adoption is significantly different from zero at the 5% significance level. The squared multiple correlations of 68.0% with 90% bias-corrected CI = [0.489-0.812] indicates that the structural model explains 68.0% of the variation in levels of e-learning adoption (see Table 11 below).

Table 11: *Bootstrapped R-squared (squared multiple correlation) estimate and 90% bias-corrected confidence intervals for the facilitating condition on e-learning adoption default structural model*

Estimate	Bootstrap SE		Bootstrapped 90% CI		Effect Size
	SE	Bias	LL	UL	Cohen's f^2
0.680	0.172	0.028	0.581	0.910	1.964

Note: S.E. and Bias are the standard error and estimated bias for the bootstrapped R-squared (Squared Multiple Correlation) standardised estimates, respectively. Bias-corrected confidence
Source: Compiled by the authors.

According to Cohen's f^2, the effect size of 1.964 is greater than 0.35 and is regarded as a significant effect. This result supports the alternative hypothesis since the beta parameter for the facilitating condition to the e-learning adoption path is positive and substantial. Hence, there is satisfactory statistical evidence to reject the null hypothesis and conclude that the facilitating condition factor has a statistically significant and positive predictive effect on e-learning adoption in a historically disadvantaged higher education institution in South Africa. The path beta estimate for the effort expectancy to adopt the e-learning path is statistically significant (β = 0.823; SE = 0.072; 90% CI = [0.664 – 0.859]; *p* = 0.004). Thus, the regression weight for facilitating conditions in the prediction of e-learning adoption is significantly different from zero at the 5% significance level. The squared multiple correlations of 68.0% with 90% bias-corrected CI = [0.712-0.922] indicate that the structural model explains 68.0% of the variation in levels of e-learning adoption (see Table 12 below).

Table 12: *Bootstrapped R-squared (squared multiple correlation) estimate and 90% bias-corrected confidence intervals for the facilitating condition on e-learning adoption default structural model*

Estimate	Bootstrap SE		Bootstrapped 90% CI		Effect Size
	SE	Bias	LL	UL	Cohen's f^2
0.680	0.112	0.015	0.491	0.860	1.964

Note: S.E. and Bias are the standard error and estimated bias for the bootstrapped R-squared (Squared Multiple Correlation) standardised estimates respectively. Bias-corrected confidence
Source: Compiled by the authors.

According to Cohen's f^2, the effect size of 1.964 is greater than 0.35 and is regarded as a significant effect. This score supports the alternative hypothesis since the beta parameter for the facilitating condition to the e-learning adoption path is positive and substantial. Henceforth, there is reasonable statistical evidence to reject the null hypothesis and conclude that the facilitating condition factor has a statistically significant and positive predictive effect on e-learning adoption in a historically disadvantaged higher education institution in South Africa. The path beta estimate for the behavioural intention to adopt of e-learning path is statistically significant (β = 0.780; SE = 0.082; 90% CI = [0.740 – 0.889]; *p* = 0.004). Thus, the regression weight for behavioural intention in the prediction of e-learning adoption is significantly different from zero at the 5% significance level. The squared multiple correlations of 73.0% with 90% bias-corrected CI = [0.388-0.712] indicates that the structural model explains 73.0% of the variation in levels of e-learning adoption (see Table 13 below).

Table 13: *Bootstrapped R-squared (squared multiple correlation) estimate and 90% bias-corrected confidence intervals for the behavioural intention on e-learning adoption default structural model*

Estimate	**Bootstrap SE**		**Bootstrapped 90% CI**		**Effect Size**
	SE	**Bias**	**LL**	**UL**	**Cohen's f^2**
0.730	0.072	0.012	0.321	0.760	1.841

Note: S.E. and Bias are the standard error and estimated bias for the bootstrapped R-squared (Squared Multiple Correlation) standardised estimates, respectively. Bias-corrected confidence
Source: Compiled by the authors.

According to Cohen's f^2, the effect size of 1.841 is greater than 0.35 and is regarded as a significant effect. This result supports the alternative hypothesis since the beta parameter for the facilitating condition to the e-learning adoption path is positive and substantial. Hence, there is satisfactory statistical evidence to reject the null hypothesis and conclude that the facilitating condition factor has a statistically significant and positive predictive effect on e-learning adoption in a historically disadvantaged higher education institution in South Africa. The path beta estimate for the behavioural intention to adopt an e-learning path is statistically significant ($\beta = 0.693$; SE = 0.065; 90% CI = [0.671 – 0.872]; $p = 0.003$). Thus, the regression weight for behavioural intention in the prediction of e-learning adoption is significantly different from zero at the 5% significance level. The squared multiple correlations of 73.0% with 90% bias-corrected CI = [0.712-0.922] indicates that the structural model explains 73.0% of the variation in levels of e-learning adoption (see Table 14 below).

Table 14: *Bootstrapped R-squared (squared multiple correlation) estimate and 90% bias-corrected confidence intervals for the behavioural intention on e-learning adoption default structural model*

Estimate	**Bootstrap SE**		**Bootstrapped 90% CI**		**Effect Size**
	SE	**Bias**	**LL**	**UL**	**Cohen's f^2**
0.730	0.142	0.019	0.522	0.760	1.841

Note: S.E. and Bias are the standard error and estimated bias for the bootstrapped R-squared (Squared Multiple Correlation) standardised estimates, respectively. Bias-corrected confidence
Source: Compiled by the authors.

According to Cohen's f^2, the effect size of 1.841 is greater than 0.35 and is regarded as a significant effect. This score supports the alternative hypothesis since the beta parameter for the behavioural intention to e-learning adoption path is positive and substantial. Henceforth, there is reasonable statistical evidence to reject the null hypothesis and conclude that the behavioural intention factor has a statistically significant and positive predictive effect on e-learning adoption in a historically disadvantaged higher education institution in South Africa (see Table 15 below).

Table 15: *Summarised results for the hypotheses on the predictive effect of factors on the adoption of e-learning in higher education institutions*

	Description (Null Hypothesis)	**Test Statistic**	***p*-value**	**Decision**
H_0	Performance expectancy does not influence the adoption of e-learning in a historically disadvantaged institution in South Africa.	β = 0.844	*p* = 0.003*	Reject
H_0	Effort expectancy does not influence the adoption of e-learning in a historically disadvantaged institution in South Africa.	β = 0.823	*p* = 0.004*	Reject
H_0	Social influence does not impact the adoption of e-learning in a historically disadvantaged institution in South Africa.	β = 0.780	*p* = 0.004*	Reject
H_0	Facilitating conditions do not influence the adoption of e-learning in a historically disadvantaged institution in South Africa.	β = 0.810	*p* = 0.003*	Reject
H_0	Behavioural intention does not influence the adoption of e-learning in a historically disadvantaged institution in South Africa.	β = 0.780	*p* = 0.003*	Reject

Note: (*) Statistically significant effects at alpha = 0.05. The beta coefficients are standardised estimates of the structural default models. Source: Compiled by the authors

DISCUSSION AND RECOMMENDATIONS

Discussion

The study's main aim was to test the extent to which the factors in Table 15 above influence the levels of e-learning adoption in a historically disadvantaged institution of higher learning in South Africa. The study used deductive logic, whereby the research commenced with a null hypothesis for each of the five factors and then data collection ensued to determine whether empirical evidence supported the hypothesis. It permitted logical analysis and conclusions based on the relationships derived from the variables. Hereunder follows the discussion of the findings for each of the factors.

Performance Expectancy (PE)

It has been confirmed that performance expectancy influences the adoption of e-learning in this historically disadvantaged institution in South Africa. This result is consistent with (Asare et al., 2016), who determined that PE plays a vital role in shaping students' behavioural intentions regarding e-learning at a university in Ghana. At North-West University in South Africa, (Liebenberg et al., 2018) reached a similar conclusion when they showed that PE had a significant and direct relationship with behavioural intention in adopting eBooks and Specialized Learning Management Systems (SLMS) among 738 ICT students. (Maphosa, 2021) also found PE to be the dominant determinant of Moodle usage in Zimbabwe.

Therefore, it can be deduced that students are aware that e-learning brings an immeasurable proportion of advantages to the institution as it speeds up data capturing, storage, and retrieval for students and staff alike. There is elevated performance in all university activities, which provides a context for e-learning to be consistent with the advent of artificial intelligence and other forms of advanced computer applications in the work and learning environments.

Effort Expectancy (EE)

Effort expectancy does influence the adoption of e-learning in the historically disadvantaged institution in South Africa. (Chatti & Hadoussa, 2021) found in a similar study conducted during the COVID-19 pandemic that there is a significant and direct relationship between perceived ease of use and intention to adopt e-learning among university students in Saudi Arabia. Also, the finding is consistent with (Abbad, 2020), who concluded in a developing country from 370 students using Moodle that EE was one of the most critical determinants of behavioural intentions. However, (Oyede et al., 2023) at the Vaal University of Technology (South Africa) found that EE does not influence student's use of e-learning technology. They attributed this to students' digital literacy background.

In this study, however, lecturers and students know that their workload and effort will be reduced as they apply the power of computers and connectivity when they engage in e-learning. Educational proficiency and accessibility would become an automatic reality as a result.

Social Influence (SI)

Social influence impacts the adoption of e-learning in the historically disadvantaged institution in South Africa since the students are driven by technology in their quest for modernisation and adherence to present-day civilisation. However, there have been mixed results regarding this construct's influence on behavioural intentions and adoption. For example, (Oyede et al., 2023, Asare et al., 2016) also concluded that social influence positively and directly influences behavioural intentions to use e-learning systems if students believe their peers and teachers support and promote their use. However, Chatti & Hadoussa (2021) found in their study that only the teacher can significantly influence the intention to adopt e-learning systems, whereas Abbad, (2020) found that SI has no meaningful effect on behavioural intentions for adopting e-learning systems. Evans & Roux (2015) found the relationship between the two variables (SI and behavioural intention) to be the weakest (but still significant) in using e-learning resources. In this study, however, for university students to be accepted in their social circles, computer usage is key to the new generation of scholars.

Facilitating Conditions (FC)

Facilitating conditions significantly influence the adoption of e-learning in the historically disadvantaged institution in South Africa. Several studies (Oyatade et al., 2023, Chatti & Hadoussa, 2021, Maphosa, 2021, Liebenberg et al., 2018, Evans & Roux, 2015) have also reached similar conclusion regarding behavioural intention.

Among numerous facilitating conditions, those that stand out include the availability of high-tech computer hardware and software, knowledgeable personnel, fast Internet connectivity and plentiful incentives for those who adopt e-learning. The university's role is to ensure that these conditions are available and accessible to guarantee a smooth adoption of e-learning, especially among new students.

Behavioural Intention (BI)

Behavioural intention has a bearing on the adoption of e-learning by students of the historically disadvantaged institution in South Africa. This is consistent with Abbad (2021), who found that BI had the most direct and significant effect on students' usage of Moodle. Also, Evans & Roux (2015) found similar results at the University of Zululand, another historically disadvantaged university in South Africa.

Students see technology adoption as behaviour consistent with modernisation and upward mobility on the social strata. Most students tend to mimic behaviours that allow them positive social and economic mobility, and adopting technology is key to such behaviours. The university must ensure that the students fulfil their behaviour intentions of superior computer literacy and other technological advancements relevant to present and future civilisation forms.

RECOMMENDATIONS

Given the findings, any disadvantaged university must adhere to the following recommendations to successfully facilitate the adoption of e-learning as a tool of trade. To start with, the university must ensure that the improvements in the new learning mode guarantee performance enhancement among the students in terms of pass rate and accessibility of learning. There is a need for institutions of higher learning to enforce curriculum transformation based on a coordinated education system that permits skills mobility between basic and higher education, which is necessary to increase preparation. With the increasing use of technology in higher education, data-driven practices should be introduced to identify students with technological needs and provide early intervention before they begin classes. In addition to system changes, society should be ready to support students' fundamental academic and skill development so they can compete globally. Frequent surveys on learner performance are highly recommended to track the impact of e-learning, and the outcomes of the surveys must be made available to students to motivate them.

Another vital recommendation is that the university must allow learners to access technology with ease by lobbying for funding from both the state and private funders to finance the e-learning programmes. Students must find it easy to obtain a laptop, smartphone, and Internet connection throughout the day. Extensive fund-raising projects may also be engaged to broaden financial sources. To promote social influence, the university may select some learners for training so that they can influence their peers in the use of technology in the form of peer-assisted learning. Social influence goes a long way in establishing lifelong learning and habits. It also helps in creating a competitive learning environment that aggrandises learners' performance standards. In this fourth industrial revolution, no institution can leave an indelible footprint without embracing electronic technology.

The last recommendation is that future researchers on the use of e-technology may focus on improving e-learning among the new generation of learners who are sometimes more innovative than their instructors due to knowledge proliferation and accessibility.

CONCLUSION

The study explored the factors influencing the adoption of electronic learning among students and lecturers in a historically disadvantaged university in South Africa. The identified factors to be tested were hypothesised, and statistical approaches were used to test the hypotheses and capture the findings. As revealed, the factors significantly influenced the adoption of e-learning and teaching at the university.

LIMITATIONS

Whatever insights this study may provide, it is not without limitations. The results should be interpreted with caution, as this study only looked at students at one South African historically underprivileged university. Because behaviour with other universities may differ, a multi-university study should be conducted to make comparisons easier. To prevent discrepancies between research themes, researchers should employ qualitative data (such as observations or interviews) in place of the quantitative data that this study emphasizes. Furthermore, this study did not take into account moderators that could improve the prediction of students' behaviour, such as age, gender, experience, and voluntariness. The impact they have on behavioural intention can be examined in future research. To fix its shortcomings and expand the scope of its findings, future research should replicate this study in multiple countries, areas, and cultures.

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