African Perspectives of Research in Teaching and Learning Journal
Issue 1, Volume 8, 2024
ISSN Print: 2521-0262
ISSN Online: 2662-012X
ORIGINAL RESEARCH

A conceptual model towards acceptance of mobile learning in Ekurhuleni municipality secondary schools

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Abstract

Nowadays, smartphones represent the fastest technology accepted and utilized by humans. The utilization of mobile devices (m-devices) has revolutionized communication, and existing literature suggests that the successful implementation of mobile learning (m-learning) depends on teachers' willingness to embrace new technologies for teaching and learning. In this study, the researchers conceptualized a model informed by the related theoretical frameworks through an extensive literature review (content analysis). Constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) model were explored in designing the model. A quantitative research approach was adopted, and a closed-ended questionnaire was distributed. A total of 145 completed responses were used after thorough data cleaning. Data analysis (reliability test, descriptive analysis, correlation analysis, and regression analysis) was done using the Statistical Package for Social Scientists (SPSS) version 25. The findings highlighted that performance expectancy, effort expectancy, social influence, perceived usefulness, and perceived ease of use are the most critical factors that may influence the acceptance of mobile learning in Ekurhuleni Municipality secondary schools.

Keywords: Mobile Learning, Information Technology, Technology acceptance, Secondary schools, Ekurhuleni Municipality.

Introduction

The education sector is currently experiencing continuous growth, potentially attributed to the impact of technology on students in the digital age. Compared to previous approaches taken by Tortorella and Graf (2017), the age of technology brings a distinct perspective to the learning process. Teaching and learning involve various factors, including performance expectancy, social influence, and effort expectancy. These factors interact with new information to support learners in achieving their goals and enhancing their skills. Nawaz and Mohamed (2020) assert that teaching and learning occur within specific settings crucial to the learning methodology.

Mobile applications are software programs created to operate on mobile devices like smartphones. They offer users various functionalities and services, providing convenience and accessibility in various domains. Ahmad, Feng, Tao, Yousif, & Ge (2017) highlight the dynamic nature of mobile application development, which is experiencing rapid changes due to significant economic and scientific interest and continuous innovation. Scholars such as Ferreira, Moreira, Santos-Pereira, & Natércia (2015) and Vrana (2018) define mobile devices as handheld computers, indicating their capability to perform various computing tasks while being compact and portable. These devices have become an integral part of everyday life.

According to Alhajri, Al-Sharhan, & Al-Hunaiyyan (2017), m-learning is defined as an educational process facilitated through the use of mobile devices. It serves as a means to support both distance learning and traditional learning methods. Through the adoption of m-learning, learners are no longer passive recipients of information within the confines of a teacher's classroom; instead, they actively engage as dynamic participants in their learning environment. M-learning, or mobile learning, has emerged as a crucial academic technology in various educational contexts. Its adoption has extended to several learning environments, reflecting the increasing recognition of its benefits in enhancing learning outcomes. Traditionally, mobile devices primarily facilitated basic communication features such as text messages and voice recording. However, with recent advancements, as noted by Parajuli (2016), the portable nature of handheld devices, combined with internet connectivity, has revolutionized the accessibility and opportunities for learning among students. This evolution in mobile technology has facilitated the seamless integration of m-learning in educational settings, enabling learners to engage with educational content in a more flexible and interactive manner.

Despite the numerous advantages of mobile learning (m-learning), some of the generic problems schools face relate to maintaining mobile devices. Also, a significant concern arises from unwanted websites that permit movie downloads, resulting in substantial disruptions during learning sessions.

Consequently, teachers must devote excessive time to preventing students from accessing unrelated websites in the classroom (Burden & Hopkins, 2017). Another challenge, as highlighted by Alkahtani (2017), pertains to internet infrastructure in different schools. When numerous students attempt to access the network simultaneously, connectivity issues overwhelm the system. Additionally, secondary schools often lack electricity backup necessary for the maintenance of SMART boards.

Significance of the study

Significant challenges persist despite the ongoing efforts to promote acceptance and successful utilization of m-learning in secondary schools within the SA Ekurhuleni Municipality. The focus of the Gauteng Department of Education (GDE) appears to be primarily on investing in new technologies while providing less emphasis on post-deployment. As a result, acceptance challenges tend to recur. Through empirical evidence, this study identifies contextual factors that may enable the acceptance of mobile learning platforms.

Literature review and theory of the study

According to Osakwe et al. (2017), the primary goal of incorporating technology in education is to enhance learners' technology literacy and expand the range of options available in educational services. The use of technology also aims to facilitate global distance education and foster a culture of learning within schools, encompassing the development of learning skills and the expansion of optional educational opportunities. Furthermore, Kaliisa and Picard (2017) noted that technical factors, such as teachers' limited knowledge of ICT utilization, interplay with other factors such as beliefs regarding the integration of ICT into teaching methods. Various learning platforms are employed in the academic environment, including e-learning, online learning, and m-learning.

Abdallah, Elleuch, and Guermazi (2021) concurred that m-learning has the potential to enhance flexibility in teaching and learning processes. It enables users, particularly learners, to access information across various environments, including classrooms, workplaces, and residences. Additionally, Alghazi, Wong and Kamsin, (2020) emphasized that the application of mobile technology extends beyond teaching and extends to diverse fields such as hospitality, travel, and tourism.

The evolution of the relationship between e-learning and m-learning began with the advent of digital learning and subsequently transitioned to e-learning in the 1980s. Nowadays, the latest technology in this domain is referred to as m-learning.

Figure 1 below illustrates that mobile learning is a subset of e-learning called digital learning. On the other hand, m-learning is often seen as a distinct paradigm that transforms the framework of teaching and learning. Typically, e-learning is associated with internet connectivity through desktop computers.

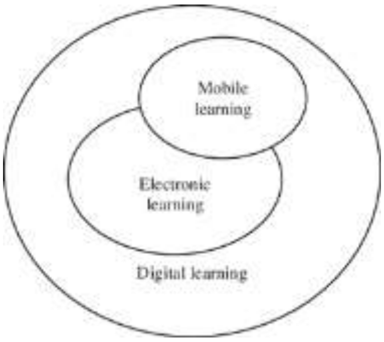


Figure 1: Relationship of e-learning, m-learning, and d-learning (Source: Sujit et al., 2018)

Kumar-Basak, Wotto, and Bélanger (2018) provided a distinction between the two: e-learning is a self-paced form of learning, encompassing both synchronous and asynchronous approaches. In contrast, m-learning is characterized as a learning modality that assumes the collaborative exchange of information through mobile devices. Additionally, e-learning, such as computer-managed learning, is typically delivered formally (Parajuli, 2016). In contrast, m-learning is more self-paced and tends to have a more casual approach.

Review of generic factors influencing acceptance of m-learning

The study examined the various factors that commonly impact the acceptance of m-learning within organizations.

Effort Expectancy (EE) refers to the level of trust individuals have in the ease of use of the innovative structure (technology) being employed. A study conducted at Makerere University revealed that learners exhibited a positive attitude towards accepting m-learning when they could use their cellphones to access study materials, complete learning tasks, and communicate with fellow learners, even outside of school premises (Kaliisa & Picard, 2017). In line with this, Chatterjee et al. (2020) identified EE as a crucial factor influencing the acceptance of m-learning. This perception has been supported by other studies such as those conducted by Alotaibi et al. (2019), Chao (2019), and Kamalasena & Sirisena (2021).

Social Influence (SI) encompasses a wide range of systems within the humanities, including compliance and conformity. Understanding the characteristics of SI is crucial when considering learners' curiosity, as Almaiah et al. (2020) highlighted. BrizPonce et al. (2017) observed that learners are more inclined to accept m-learning if it is made user-friendly, especially when it provides larger screens and better keyboards. Their findings suggest that there are other factors beyond SI that influence the acceptance of m-learning. Abdallah et al. (2021) discovered that the social influence construct reflects the behavior of participants connected to acceptance, emphasizing its significant impact on the behavioral intention toward m-learning acceptance. Additionally, Khlaif and Salha (2022) asserted that teachers in higher educational institutions must possess adequate knowledge and resources to effectively use and embrace m-learning, highlighting the importance of accessibility.

Perceived Usefulness (PU) significantly influences user acceptance and cannot be overlooked when striving to implement a successful system. The perceived usefulness of an application is a critical factor, as users are unlikely to adopt it if they do not perceive it as beneficial or advantageous. Davis (1989) emphasizes that for an application to be objectively deemed as bringing improvements, users must perceive it as useful and see the value in using it.

Perceived Ease of Use (PEOU) refers to the belief held by an individual that utilizing a particular system would require minimal physical and mental effort. In the context of this paper, PEOU relates to teachers experiencing fewer difficulties when using m-learning on their mobile phones within pedagogical settings. Chatterjee et al. (2020) affirm that PEOU directly influences the behavioral intention to use. Additionally, Briz-Ponce et al. (2017) assert that PEOU is one of the key constructs that positively impact teaching and learning. Moreover, Almaiah et al. (2020) discovered that accessibility and perception significantly influence the acceptance of m-learning. Their findings indicate a positive connection between PEOU factors and the acceptance of m-learning.

The content analysis carried out in this study resulted in several outcomes, some of which are presented in Table 1. Only outputs with the highest frequencies were considered, and any redundant factors were also eliminated during this process.

Table 1: Content analysis and their sources

Factors / Construct	Frequency	Sources
Performance expectancy	119	Alghazi et al., (2021); Kamalasena and Sirisena (2021); Almaiah et al., (2020); Alotaibi et al., (2019) and Chao (2019)
Effort expectancy	93	Khlaif and Salha (2022); Alghazi et al., (2021) Abdallah et al., (2021); Kamalasena and Sirisena (2021); Chatterjee et al., (2020); Alotaibi et al., (2019) and Chao (2019)
Social influence	101	Khlaif and Salha (2022); Navarro et al., (2016); Alghazi et al., (2021); Abdallah et al., (2021); Almaiah et al., (2020); Briz-Ponce et al., (2017) and Al-Zoubi (2016)
Perceived usefulness	99	Navarro et al., (2016); Chatterjee et al., (2020); Almaiah et al., (2020); Briz-Ponce et al., (2017) and Al-Zoubi (2016)
Perceived ease of use	112	Navarro et al., (2016); Chatterjee et al., (2020); Almaiah et al., (2020); Briz-Ponce et al., (2017) and Al-Zoubi (2016)

Review of related Information Systems frameworks

Through an in-depth review of pertinent studies, the research extensively examined the factors that have an impact on the acceptance of m-learning. Subsequently, the study identified generic factors that emerged from this review process. Furthermore, the research identified information systems frameworks that aligned with these identified factors, thereby establishing a connection between the two.

The Technology Acceptance Model (TAM) is a theoretical framework that illustrates how users can readily adopt an information system and embrace technology. Davis (1989) has described TAM as an attitude that aligns with an individual's core beliefs regarding the outcomes of specific behavior, along with their evaluation of these consequences.

Researchers have adopted the Technology Acceptance Model (TAM) to align with the requirements of their specific studies. For instance, Senaratne and Samarasinghe (2019) conducted an empirical study in Taiwan, investigating the factors that influence the acceptance of m-learning and validate the success of information systems. Al-Emran et al. (2020) state that while additional variables may be incorporated as determinants of TAM constructs, the fundamental objective of TAM remains unchanged. This objective is to comprehensively contribute to the acceptance of information systems within their respective environments.

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been employed by several studies to investigate the acceptance of m-learning. Venkatesh et al. (2003) defined the UTAUT model as the intention of users to engage in the practice of an information system, which reflects their behavioral usage. This theory encompasses four

key constructs: performance expectancy, social influence, effort expectancy, and facilitating conditions.

To align the theories with the current study, the constructs were carefully chosen based on the earlier discussed related work. These selected constructs formed the foundation of the research model, which was utilized to design the questionnaire. The collected data was subsequently employed to evaluate the applicability of each factor within the study domain.

Operationalization of the hypothesis

Performance Expectancy (PE) is characterized as an individual's perception of the extent to which acceptance of new technology will yield advantages. In the UTAUT model, the PE construct is often integrated to predict the behavioral intention to embrace a new change. Almaiah et al. (2019) conducted a study that demonstrated a positive correlation between PE and the user's behavioral intention to accept m-learning. The researchers argued that incorporating PE within the context of m-learning could significantly enhance pedagogy, enabling teachers to enhance their teaching skills and performance promptly. Therefore, the following hypothesis is formulated: H1: Performance expectancy will influence the behavioural intention to accept m-learning

Effort expectancy (EE) refers to an individual's perception of how effortlessly they can use new technology. Nawaz and Mohamed (2020) discovered that EE significantly influences the acceptance of m-learning in Saudi Arabia. In this study, we will examine how the EE of m-learning influences the acceptance of m-learning in secondary schools within the Ekurhuleni Municipality. Based on this, the following hypothesis has been formulated: H2: Effort expectancy will influence the behavioural intention to accept m-learning.

Social Influence (SI) refers to the extent to which an individual recognizes the significance of adopting new technology. Based on previous UTAUT studies, SI has consistently emerged as a critical contributing construct to the acceptance of accepting m-learning, as highlighted in the research conducted by Al-Zoubi (2016). As a result, the following hypothesis is subject to testing within the study domain: H3: Social influence will influence the behavioural intention to accept m-learning

Perceived Usefulness (PU) is defined as the extent to which an individual believes that the acceptance of m-learning will improve their performance. The PU construct is closely associated with factors such as quality, reliability, and performance. Additionally, Navarro et al. (2016) emphasized that PU measures the degree to which individuals perceive technology as beneficial. PU originates from the TAM framework and is considered a critical factor that strongly influences behavioral requirements. Drawing upon the insights gained from this study, the following hypothesis has been formulated: H4: Perceived usefulness will influence the behavioural intention to accept m-learning

Perceived ease of use (PEOU) is described as the extent to which an individual believes that utilizing a specific system would require minimal physical and mental effort (Almaiah et al., 2016). Building upon the concept of effort expectancy, it is suggested that PEOU can influence teachers' intention to adopt m-learning. Therefore, the following hypothesis is formulated: H5: Perceived ease of use will influence the behavioural intention to accept m-learning.

Research problem

The acceptance of mobile devices is steadily increasing, extending from higher education to secondary schools. M-learning has played a significant role in enhancing flexibility in learning, providing students with real-time learning experiences (Abdallah et al., 2021). The general benefits of m-learning, such as flexibility, accessibility, and personalized learning activities, have been highlighted by Baek et al. (2017) and S. Criollo-C (2021). These advantages are anticipated to enhance engagement, productivity, and overall effectiveness within the teaching and learning environment. Al-Emran et al. (2016) have emphasized that the acceptance of mobile devices in secondary schools can positively impact teachers' attitudes towards m-learning, leading to its purposeful integration within the educational environment. Handheld devices support the constructive principle by ensuring that each learner has access to the necessary information to achieve educational goals.

Despite the evident benefits of m-learning, Alghazi et al. (2020) suggest that it is crucial to evaluate critical factors within the specific context of each study. Tarhini et al. (2017) also highlight the need for further research to examine the strength of the correlation between various factors and the acceptance of m-learning in different domains. Based on the reviewed articles, there is a clear gap in understanding the contextual factors that influence the acceptance of m-learning in Ekurhuleni municipality secondary schools. Therefore, this study aims to address this gap by developing a conceptual model that elucidates the acceptance of m-learning within this specific domain.

Research design and Methodology

Given the goal of the study, a positivist philosophy was adopted to generate quantitative data, to enable generalization of outcome. Sürücü and MaslakÇI (2020) suggest that a theoretical framework is one of the most reliable predictors and outcomes in quantitative research. In this paradigm, greater emphasis is placed on quantitative analysis rather than qualitative analysis. Nardi (2018) explains that positivism aims to provide mathematical representations of the relationships between factors. Specifically, a survey strategy was employed due to its advantages, including ensuring anonymity, facilitating replication of the study, and enabling comparison with similar studies using similar questionnaires. This strategy also allows for the collection of data from large population samples.

Unit of Analysis

This study aimed to analyze the perceptions of participants regarding the factors or variables that influence the acceptance of m-learning. This aligns with the assertion of Ndenje-Sichalwe and Elia (2021) that the unit of analysis refers to a specific item or individual within the sample being analyzed. In this case, the unit of analysis is the organization, specifically the secondary schools within Ekurhuleni municipality, and the population consists of teachers from these schools. The target population for this research study encompasses teachers from Grade 08 to Grade 12. The group of teachers from which the researcher intends to draw conclusions is referred to as the target population.

Sampling techniques

Sampling is the procedure of choosing a group of representatives or participants from the population under study. Considering resources and the domain, respondents were selected from the estimated population size of 235 teachers from six randomly selected secondary schools based on the target population outlined in the unit of analysis. The study utilized Krejcie and Morgan's (1970) tool to decide the sample size from the estimated population. In light of the Krejcie and Morgan (1970) tool delineated in Table 2, the estimated population of teachers was 235 with the corresponding sample size between 144 to 148. The study was able to gather 159 feedbacks however, 145 responses were usable after screening (data cleaning). It should be noted that during the data gathering phase, there was still some low-level restriction due to government policies to mitigate the spread of coronavirus limiting access to resources.

Table 2: Krejnie & Morgan's (1970) Tool for Determining Sample Sizes (s) for Finite Population (N)

Total	*Sample*	*Total*	*Sample*	*Total*	*Sample*
10 ⇒	10	220 ⇒	140	1200 ⇒	291
15 ⇒	14	230 ⇒	144	1300 ⇒	297
20 ⇒	19	240 ⇒	148	1400 ⇒	302
25 ⇒	24	250 ⇒	152	1500 ⇒	306
30 ⇒	28	260 ⇒	155	1600 ⇒	310
35 ⇒	32	270 ⇒	159	1700 ⇒	313
40 ⇒	36	280 ⇒	162	1800 ⇒	317
45 ⇒	40	290 ⇒	165	1900 ⇒	320
50 ⇒	44	300 ⇒	169	2000 ⇒	322
55 ⇒	48	320 ⇒	175	2200 ⇒	327
60 ⇒	52	340 ⇒	181	2400 ⇒	331
65 ⇒	56	360 ⇒	186	2600 ⇒	335
70 ⇒	59	380 ⇒	191	2800 ⇒	338
75 ⇒	63	400 ⇒	196	3000 ⇒	341
80 ⇒	66	420 ⇒	201	3500 ⇒	346
85 ⇒	70	440 ⇒	205	4000 ⇒	351
90 ⇒	73	460 ⇒	210	4500 ⇒	354
95 ⇒	76	480 ⇒	214	5000 ⇒	357
100 ⇒	80	500 ⇒	217	6000 ⇒	361
110 ⇒	86	550 ⇒	226	7000 ⇒	364
120 ⇒	92	600 ⇒	234	8000 ⇒	367
130 ⇒	97	650 ⇒	242	9000 ⇒	368
140 ⇒	103	700 ⇒	248	10000 ⇒	370
150 ⇒	108	750 ⇒	254	15000 ⇒	375
160 ⇒	113	800 ⇒	260	20000 ⇒	377
170 ⇒	118	850 ⇒	265	30000 ⇒	379
180 ⇒	123	900 ⇒	269	40000 ⇒	380
190 ⇒	127	950 ⇒	274	50000 ⇒	381
200 ⇒	132	1000 ⇒	278	75000 ⇒	382
210 ⇒	136	1100 ⇒	285	100000 ⇒	384

Analysis and presentation of results

Demographics of the participants

The demographics section gathered general information about the participants, including their gender, the grade they taught, their designation, and years of experience.

The table presented below indicates that the majority of respondents were female (68.3%), while males accounted for 31.7% of the participants. In terms of the grade they taught, Grade 10 had the highest number of respondents (25.5%). Regarding designation, the largest proportion of participants were teachers (60.7%), and among them, Grade 10 teachers represented

25.5% of the total respondents. Additionally, a significant portion of the participants (33.1%) reported having less than 3 years of experience.

Table 3: Demographics of the Participants

Characteristics	Item	Frequency	Percentage (%)
Gender	Male	46	31.7
	Female	99	68.3
Grade	Grade 8	23	15.9
	Grade 9	24	16.6
	Grade 10	37	25.5
	Grade 11	28	19.3
	Grade 12	33	22.8
Designation	Teacher	88	60.7
	Assistant teacher	25	17.2
	Principal / HOD	18	12.4
	ICT Coordinator	6	4.1
	Other	8	5.6
Years of Experience	Below 3yrs	48	33.1
	4 -6yrs	35	24.1
	7 - 9yrs	22	15.2
	Over 9yrs	40	27.6

Reliability of the data collection instrument

Cronbach's alpha, as mentioned by Taber (2018), is a widely used reliability measure in the field of communal and structural knowledge. It assesses the internal consistency of the collected data. The reliability value can vary depending on the specific application, with the emphasis placed on the reliability of the population rather than the reliability of the sample. In this study, the questionnaire demonstrated a high reliability value of 0.879, surpassing the recommended threshold of 0.7 suggested by Bonett and Wright (2015). The reliability was tested on a set of 23 items. Furthermore, the table presented below displays the overall results of the five variables or constructs that were examined.

Reliability Statistics

Cronbach's Alpha	N of Items
.879	23

Descriptive analysis

The mean value, as defined by Muijs (2010), represents the sum of all given values divided by the total number of values. On the other hand, the standard deviation is a measure of variability for a set of data with similar measurements. In this study, the skewness of the data was also examined to gain insights into the participants' responses.

The results indicate that the mean values of all the constructs mentioned above were higher than 4 when rounded off to the nearest whole number. This suggests that the respondents' answers spanned from uncertain to strongly agree. The highest mean value of 4.2644 was observed for the BIAML construct, indicating that a majority of teachers have a high level of interest in using mobile learning. Furthermore, the results revealed the highest deviation value of 0.77776, while the lowest deviation was found in the EE construct with a value of 0.46786. The construct with the lowest mean value was PU, which had a value of 3.9517, rounding off to 4.0 when expressed to one decimal place. Therefore, it can be confidently stated that most participants agree that the construct in question has a significant influence on the acceptance of m-learning in secondary schools. All the constructs, including PE, EE, SI, BIAML, PU, and PEOU, exhibit a negatively skewed distribution. The results indicate that most participants are concentrated towards the right side of the mean.

Correlation analysis

The interrelationship between the constructs was examined using bivariate analysis to measure their associations. The correlation value can range from -1 to +1, with a value of 0 indicating no relationship. A positive correlation value signifies a positive relationship between the constructs, indicating that when one construct increases, the other construct also tends to increase.

A significant positive correlation was found between effort expectancy (EE) and performance expectancy (PE) with a value of 0.596 at a significance level of 0.01. This suggests that PE has a considerable impact on effort expectancy in the acceptance of mobile learning. Social influence (SI) exhibited the most significant correlation with a value of 0.667 at a significance level of 0.01, indicating its strong relationship with effort expectancy (EE). Additionally, perceived ease of use (PEOU) showed a significant correlation with perceived usefulness (PU) with a value of 0.459 at a significance level of 0.01. Overall, the correlation results indicated that the hypotheses were highly significant and interrelated with each other.

Table 4: Descriptive statistics

Descriptive Statistics

	N	Min	Max	Mean	Std. Dev	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
PE	145	2.20	5.00	4.0952	.56769	-.778	.201
EE	145	2.20	5.00	4.0331	.46786	-.595	.201
SI	145	2.25	5.00	3.9672	.53785	-.329	.201
BIAML	145	1.67	5.00	4.2644	.64418	-1.025	.201
PU	145	2.00	5.00	3.9517	.77776	-.754	.201
PEOU	145	1.67	5.00	4.1770	.60100	-1.003	.201
Valid N (listwise)	145						

Regression Analysis

Linear regression was used to determine the factors that influence the acceptance of m-learning. The obtained outcomes were then compared, to demonstrate the significant relationship between the dependent and independent variables, deciding whether the variables were impacted negatively or positively. The ANOVA F statistics is 5.866 and the significance level (which is the probability level) level is .000.

Muijs (2010) states that for general statistical analysis, the acceptable level of significance should be below 0.050. This implies that the factors under consideration are highly significant in relation to the dependent variables.

Coefficients of independent constructs

The Variance Inflation Factor (VIF) is used to assess the level of collinearity between variables in a multiple regression analysis. The coefficients table displays the VIF values that remain within the acceptable threshold of VIF <10. Among them, social influence stood out as the most well-maintained construct, with a VIF value of 2.462. Our test results for the variance inflation factors model indicated values below 5, which is significantly lower than the threshold of 10. This aligns with Taber (2018) suggestion that rules of thumb for multicollinearity should be employed to address excessively high analysis results.

Table 5: Correlation statistics

Correlations

		PE	EE	SI	BIAML	PU	PEOU
PE	Pearson's Correlation	1					
	Sig. (2-tailed)						
	N	145					
EE	Pearson's Correlation	.596**	1				
	Sig. (2-tailed)	.000					
	N	145	145				
SI	Pearson's Correlation	.527**	.667**	1			
	Sig. (2-tailed)	.000	.000				
	N	145	145	145			
BIAML	Pearson's Correlation	.297**	.206*	.284**	1		
	Sig. (2-tailed)	.000	.013	.001			
	N	145	145	145	145		
PU	Pearson's Correlation	.394**	.647**	.621**	.018	1	
	Sig. (2-tailed)	.000	.000	.000	.830		
	N	145	145	145	145	145	
PEOU	Pearson's Correlation	.459**	.489**	.521**	.251**	.459**	1
	Sig. (2-tailed)	.000	.000	.000	.002	.000	
	N	145	145	145	145	145	145

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 6: ANOVA result

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10.473	5	2.095	5.866	.000[b]
	Residual	49.277	138	.357		
	Total	59.750	143			

a. Dependent Variable: BIAML

b. Predictors: (Constant), PEOU, PE, PU, SI, EE

Both perceived usefulness (PU) and social influence (SI) were found to have significant effects on the behavioral intention to accept mobile learning (BIAML). Their respective values were below the threshold of 0.05, indicating statistical significance at $P<0.05$. On the other hand, the variables PE, EE, and PEOU did not show significant relationships with the behavioral intention to accept mobile learning (BIAML), as their values were higher than 0.05 at $P<0.05$. As a result, the behavioral intention to accept mobile learning appears to be influenced by perceived usefulness (PU) and social influence (SI), which serve as effective mediating factors.

Table 6: Coefficients of Independent Constructs

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.221	.479		4.634	.000		
	PE	.203	.114	.179	1.775	.078	.590	1.696
	EE	.070	.169	.051	.414	.680	.400	2.501
	SI	.340	.138	.284	2.462	.015	.449	2.228
	PU	-.274	.091	-.329	-3.024	.003	.505	1.980
	PEOU	.158	.103	.148	1.543	.125	.651	1.537

a. Dependent Variable: BIAML

Hypothesis testing

Hypothesis testing refers to a formal method employed by researchers to examine the significance of their research findings, as defined by Hair et al. (2014). In this process, the relationships between the dependent and independent variables are analyzed to identify any numerical significance. The primary objective of the study revolves around the hypothesis, which determines whether the proposed effects have occurred. The table presented below illustrates the significance of the hypothesis relationships and indicates whether they were accepted or rejected based on their p-value at $p<0.05$. The results demonstrate that the dependent variable, along with the independent variables of performance expectancy, effort expectancy, social influence, perceived usefulness, and perceived ease-of-use towards the behavioral intention to accept m-learning, were all accepted. This conclusion is drawn from their p-values being below the threshold value of 0.05.

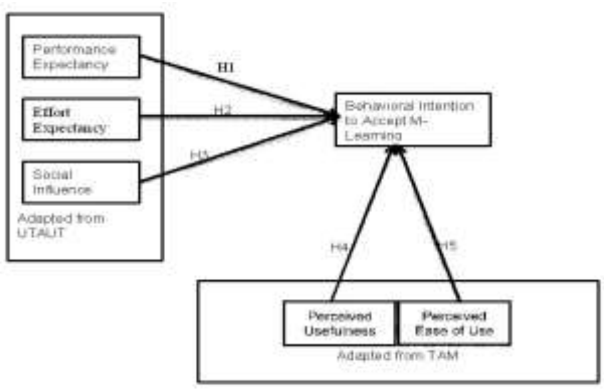
Suggested Hypothesis	**Significant P**	**Comment**
H1: Performance expectancy influence the behavioural intention to accept m-learning	P = 0.000 < 0.05	Accepted
H2: Effort expectancy influence the behavioural intention to accept mlearning	P = 0.000 < 0.05	Accepted
H3: Social influence positively influence the behavioural intention to accept m-learning in secondary schools	P = 0.000 < 0.05	Accepted
H4: Perceived usefulness influence the behavioural intention accept mlearning	P = 0.000 < 0.05	Accepted
H5: Perceived ease of use influence the behavioural intention to accept mlearning	P = 0.000 < 0.05	Accepted

Discussion and Recommendation

The study aimed to develop a conceptual model that could assist secondary school teachers toward seamless acceptance of m-learning. Hence, the study successfully developed a model that informs the acceptance of m-learning in secondary schools located within the Ekurhuleni Municipality. Figure 3 below shows the developed model. Based on the analysis of the hypothesis, this study concluded that the acceptance of m-learning provides teachers within secondary schools with a powerful alternative for teaching and learning. The findings indicate that constructs such as effort expectancy, performance expectancy, perceived usefulness, perceived ease of use, and social influence significantly influence the behavioral intention to accept m-learning.

Hence, it is advised that secondary schools consider the factors in the developed framework to improve the behavioral intention to accept m-learning, thus maximizing the advantages it offers.

Figure 3: Acceptance model for mobile learning in Ekurhuleni municipality secondary schools.



While the study employed rigorous scientific methods, it suggests that future research should explore alternative methodologies to validate the developed model over a longitudinal timeframe. This study focused exclusively on teachers within the Ekurhuleni Municipality, thus limiting the scope of the research domain. Exploring a broader domain could provide further understanding and insights, making it a recommendation for future studies. In conclusion, the findings of this study can be applied and tested in diverse learner settings to determine if the context reveals additional aspects that were not covered in this research

Declaration of interest

The authors affirm that their writing of this article was not inappropriately influenced by any financial relationships.

Ethical considerations

The research adhered to the ethical standards of the university, with approval granted by the ethics committee prior to data collection. Nardi (2018) emphasized the importance of preserving participant confidentiality and privacy, encompassing both information and physical privacy. To maintain ethical considerations, measures such as anonymity, informed consent, and privacy protection were implemented throughout the research process. The study communicated its objectives and assured participants of the confidentiality of their secondary school names.

Moreover, participants were given the option to withdraw from the study at any time without providing a reason. Their participation in answering the questionnaires was voluntary, and there were no consequences for those who chose to withdraw. Additionally, all participants were required to receive a consent form outlining their rights before their involvement in the research.

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