Millennials' Perceptions of M-learning in Higher Education in Developing Countries: The Role of Social Influence

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***Abstract*—Technology has brought about various changes in the teaching and learning industry. This has further led to a new form of learning known as M-learning. Meanwhile, the attributes of students have changed over time. A new generation of learners known as millennials have varying demands from bodies of knowledge as compared to their preceding generations. millennials have been acquainted with technology for most of their life. Considering these facts, this study seeks to determine factors affecting millennials' perceptions of M-learning in higher education. An online questionnaire based on a fusion of the Technology and Acceptance Model with the Unified Theory of Acceptance and Use of Technology framework was used to survey 103 millennials at a university in a developing country. Structural Equation Modelling was used to analyze data. The findings revealed that social influence has a statistically significant impact on millennials' intention to use M-learning. The geographical location and contextual environment may amplify social influence as a prime factor motivating millennials' intention to use M-learning. Universities, governments, and other learning institutions should consider this for more suited provisioning of M-learning solutions in higher education.**

***Keywords*—social influence, mobile learning, perceptions of millennials, intention of use m-learning, developing countries, higher education**

I. Introduction

Tertiary educational institutions currently cater to the needs of a new group of learners commonly known as the Net Generation or the millennials [1]. Net Generation refers to people born in the 1980s who "have grown up digital" [2]. They know information technology evolution and are acquainted with modern media [3]. Due to their incessant exposure to technology since birth, it is perceived that millennials' demands from bodies of knowledge differ from those of their predecessors because of their distinct preferences and social interaction patterns [4]. Studies have inferred that a Millennial's brain has developed differently compared to other generations, such that they have more acute vision and increased spatial awareness [5]. Organizations in various fields must amend production to cater to the needs of the Net Generation, including learning education institutions.

The radical amendments taking place in learning institutions relating to M-learning have led to several concerns for pedagogy since the landscape is constantly developing [6]. Learning through mobile technology is considered a remedy to the obsolescence of traditional methods of learning and the limitations of distant learning. M-learning reduces inequality since rural learners are not required to travel long distances to schools [7]. Mobile devices have gained immense prominence since their launch in the 1980s, with university students as "the most active users of smartphones" [3]. In this sense, M-learning is an attractive learning tool which offers ubiquity and flexibility in the learning process [8].

To improve the current educational system and ease the adoption of M-learning at universities, it is vital to consider the students' perceptions [8]. The students represent the demand side of M-learning in higher education [9]. In Economics, to optimize the supply side of a service, it is important to understand all the factors affecting the demand side [10]. Nevertheless, the implementation of M-learning from a student's point of view has been given little attention in the literature. Moreover, existing studies have not examined the perceptions of the Net Generation in developing countries enough, despite that application of M-learning has not reached its peak yet in these regions [11].

This research examines the perceptions of millennials in developing countries regarding the adoption of M-learning in higher education to understand the most influencing factor. Such understanding could inform the trend in the demand for this mode of learning and thus contributes to the awareness of millennials' need by legislators in the sector for better provisioning. Hence, universities, government, and other learning institutions are potential beneficiaries of this study. Furthermore, bodies of knowledge could ease M-learning integration with their existing teaching practices and enhance the current education system in developing countries. Therefore, the study's research question is: What factors affect millennials' perceptions in developing countries regarding M-learning in higher education the most?

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The rest of the paper proceeds as follows. The related works section introduces the concept of M-learning, first from the perspective of higher education and then from developing countries with a focus on social influence. Next is a description of the research model, followed by a brief of the research methodology. Then will come the research finding, and lastly, the discussion and conclusion.

II. Literature Review

A. *Mobile Learning (M-learning)*

M-learning has been an attractive research subject to explore as its adoption entails various positive impacts. M-learning consists of learning using small computing portable devices, including smartphones [9]. Learners can "access information independently of time and space through mobile devices", customizing their learning processes based on their preferences and needs [12]. M-learning is a subject that has evolved from distance learning and is now a subset of e-learning that incorporates the adoption of mobile technology [13]. M-learning is considered "a robust component to make learning easy and flexible" [14]. M-learning has potential benefits but also involves some constraints toward its implementation [12].

1) *Benefits*

As its name suggests, one of the main features of m-learning is mobility. Mobility in the context of M-learning can be analyzed from three different angles: learners, learning, and technology [15]. M-learning improves the mobility of learners because it eliminates physical barriers such that the learning process can occur anywhere [4]. Portable devices enable learners to gain access to information and engage in forum discussions in their comfort irrespective of location [16]. With M-learning, "a student can learn whatever, wherever and anytime" through teaching applications installed on a portable device, such as a smartphone, iPod, tablet, notebook, and so on [3, 7]. These devices are equipped with advanced attributes such as Wireless Fidelity (Wi-Fi) and Wireless Application Protocol [8]. Hence, technology allows learners to be 'always-on' through improved connectivity and internet access. Information is readily available at a click or a touch away since mobile devices are portable, have arguably lower costs and offer the opportunity for a customized learning process [12]. Students can tailor their learning tools and the environment as per their preferences [14]. Collaboration between learners is facilitated through the sharing of resources and improved networking connections. Thus M-learning could promote students' learning interests and creativity [17].

2) *Constraints*

M-learning comprises certain limitations including those related to technologies, the internet, infrastructure, and material [12]. Mobile devices require supporting m-learning systems electricity and good network connectivity [18]. Thus, poor internet bandwidth and power failures can be the most challenging issue of mobile learning [7]. A suitable mobile device is necessary to fully optimize the use of M-learning. These are relatively expensive and might not fit a student's budget [19]. The battery life and the screen's size of mobile devices are inconvenient for learning purposes [20]. If used excessively, students might even face vision problems in the long run. Mobile devices are limited in storage and hence hinder the sharing of information and resources [20]. Inconsistency in mobile device platforms and variability in devices could lead to designing mobile learning applications that are lacking in certain functionalities due to the need to accomplish cross-platform operability [21]. From the perspective of learners' attention, M-learning seems to support multi-tasking which is not always a productive way to learn [22]. Subsequently, M-learning may entail some form of distraction as a result of using mobile devices [19].

B. *Mobile Learning in Developing Countries and the Role of Social Influence*

Given the incessant development in technology and the subsequent changes in education, researchers have engaged in various investigations and analyses of the adoption and use of Information and Communication Technologies (ICT). Different studies have assessed the acceptance of various technological advancements, such as e-commerce, e-government, and e-learning, in developed and lately developing countries [23]. Developing countries are countries that are regarded as being economically less advanced in terms of technology, infrastructure, standard of living, and other determinants [24].

Many studies have depicted that the application of technology can boost the socio-economic growth of developing countries [25]. Limited research has been done to explore the acceptance of technology and user perceptions in developing countries as compared to developed countries [23]. It is theoretically supported that e-learning, which includes the subset of M-learning, "is still in the early stages" in developing countries [18]. Thus, M-learning adoption and acceptance in these countries may follow a different pattern. A comparative study investigated how students perceived and used M-learning at two universities and showed that there were "major differences between Uganda and Australia" [26]. These differences mean M-learning provisioning might need different approaches based on their context. Likewise, cultural differences in the adoption of M-learning were found in a comparative study among three universities in different locations [27]. These contextual or cultural differences allude to the factor of social influence which turns out to be part of the UTAUT theory.

Some studies have been done in developing countries concerning the acceptance of M-learning in higher education context using the UTAUT. Bassam Nassuora [28] surveyed Saudi students in tertiary education and proved their readiness to adopt this new form of learning. AlMarwani [29] identified causes of the attitudes and behavioural patterns towards using mobile technology in learning using in Saudi Arabian universities involving both learners and faculty members, resulting in five important determinants of learners' intentions to use mobile technologies: Habit, hedonic motivation, social influence, facilitating conditions and performance expectancy. Elsewhere, perceived usefulness and attitude were found to have a significant effect on M-learning adoption intention [14]. But there have not been enough studies focusing on a developing country with a sub-Saharan context to see if, among other factors, social influence would have any effect on millennials' perception of adopting M-learning. This study seeks to address this knowledge gap.

III. Research Model

Various models have been developed to explore the acceptance and adoption of technology, including Innovation Diffusion Theory, TAM, Theory of Planned Behavior, and UTAUT. The latter is gaining more popularity among researchers because of its relevance in demonstrating the implementation of technology. The model has been used in many studies involving the adoption of mobile technology.

There are various UTAUT factors postulated to affect M-learning, investigated by various researchers, predominantly within the university sector. Behavioural intention might moderate the effect of perceived usefulness, perceived ease of use, subjective norms, information quality, system quality, technical support, and self-efficacy on behavioural intention on use [18]. Only behavioural intention and technical support might directly affect the actual use of M-learning [18].

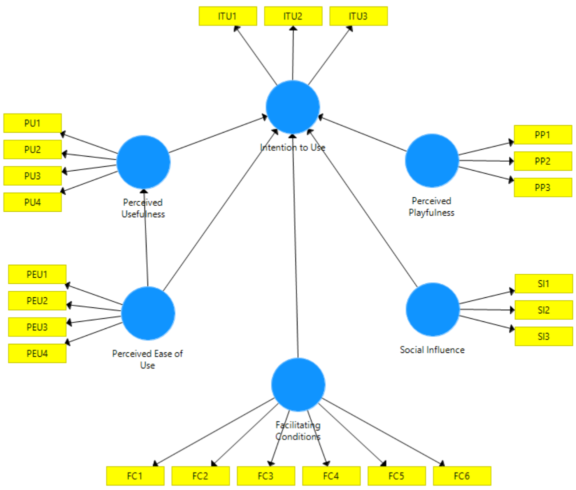

Figure 1. Research model.

In this study, since the perceptions of millennials can be examined by looking at different factors known to affect M-learning, the model of study drives factors from TAM and UTAUT. The model includes a contextual or cultural factor, mentioned earlier as social influence. As shown in Fig. 1, a total of six constructs are measured to understand the perceptions of millennials: Perceived Usefulness (PU), Perceived Ease of Use (PEU), Facilitating Conditions (FC), Social Influence (SI) and Perceived Playfulness (PP) constructs affect Intention to Use (ITU) construct. The common traits which pertain to this research involve collaboration, customization, and innovation.

The model is set to discover the extent to which the independent variables PU, PEU, FC, SI, and PP; affect the dependent variable ITU. These factors of the model comprise various indicators described in Table I. Additionally, the model is set to primarily determine the factors that affect the perceptions of millennials in developing countries towards M-learning in higher education. But since it embeds TAM, it can also determine the effect of PEU on PU. But this relationship was not the focus of this study and thus is not discussed.

TABLE I. Factors and Indicators

Factor	Indicators	Indicators definition
Perceived Usefulness	PU1	Mobile learning tools are quicker in completing a task as compared to computers
	PU2	M-learning increases efficiency.
	PU3	M-learning adds value to your studies
	PU4	M-learning positively affects the learning experience.
Ease of Use	PEU1	Learning is easier with the adoption of M-learning
	PEU2	M-learning is useful for students
	PEU3	It is easier to access information through M-learning tools
	PEU4	It is easier to complete a study-related task using M-learning tools as compared to other means.
Facilitating Conditions	FC1	I am fully equipped with the resources (such as a mobile phone) needed for M-learning.
	FC2	I have the necessary skills and knowledge needed for M-learning
	FC3	I have access to the Internet
	FC4	There is an adequate internet speed on campus for the smooth use of M-learning
	FC5	There is help available concerning the use of M-learning
	FC6	The accessibility and functionality of mobile devices influence my willingness to use M-learning
Perceived Playfulness	PP1	I will not lose track of time when using M-learning
	PP2	I will not forget about tasks/work to be completed when using M-learning
	PP3	M-learning makes the learning experience enjoyable
Social Influence	SI1	The University and the structure of courses impose the use of M-learning on the students
	SI2	My surroundings are in favour of M-learning.
	SI3	I practice M-learning because my friends and classmates use mobile technology for learning
Intention to Use	ITU1	I have the intention to use mobile phones for learning purposes (for education)
	ITU2	I am willing to install software to facilitate learning using mobile technology
	ITU3	I (will) use M-learning because M-learning facilitates access to lecture notes and other academic resources

IV. Materials and Methods

As introduced in the model of study section above, the research uses a conceptual framework built from TAM and UTAUT theories. Hence, the Research Approach was deductive. The study is cross-sectional as it analyses the perceptions of millennials at a point in time. The research population involved students who are categorized as millennials and who study at a university in South Africa. Purposive sampling, also known as judgmental sampling was an appropriate non-probability sampling technique. South Africa was chosen because it is a sub-Saharan country and was proximate to the researcher. In other words, the sample was chosen based on common traits of millennials, including attributes like year of birth and country of study [1]. The common traits were established by a series of questions prior to the actual survey questions.

The study did not necessitate any confidential information and the respondent remained anonymous. Participation in the survey was voluntary and no personal was collected. Participants were given the option to withdraw from the survey at any point in time. The data collected was used purely for academic purposes. Questioners were sent only after approval from the Research Ethics Committee of the University.

A. Data Collection

The data collection method was survey and online questionnaire was the instrument to collect quantitative data. Except for the section dedicated to the demographic information, the questionnaire had a total of six sections a specific question assigned for each of the constructs' indicators as shown in Table I. Respondents were asked to indicate to what extent they agreed or disagreed with several statements representing each indicator of the constructs, on a scale of five values (where 1 is for "strongly disagree" and five for "strongly agree").

B. Data Analysis

Structural Equation Modelling (SEM) was the main data analysis method to assess the relationships between variables and the impact that one variable has on another. SEM is a second-generation multivariate analytical technique that supports causal models [30]. The two models involved in this data analysis model are inner and outer models. While the inner model demonstrates the relationship between endogenous and exogenous latent variables, the outer model showcases the relationship between a certain variable and its indicators. The analysis also involves factor analysis

There are various methods for SEM, of which Partial Least Squares (PLS) consist of a soft modelling method to SEM [31]. SEM-PLS was suitable because there was a limited number of respondents (103). Moreover, SEM-PLS is useful where the correctness of the model cannot be ensured and where predictive accuracy is key to the study. SmartPLS 3 was the software used for executing PLS-SEM, selected because of its user-friendly interface.

V. Results

The study received a total number of 120 responses. However, an initial clean-up of data led to discard invalid responses. Eventually, the sample size consisted of 103 respondents. The findings are subdivided into three main sub-sections: democratic profile to describe the data sample, the evolution of the research model to clean the data and assess validity and reliability, and hypothesis testing to perform the PLS-SEM test and report the findings.

VI. Demographic Profile

The age of the entire sample population lies between the range of 21 and 38 years old. As per the data collected, most of the respondents (59.2%) were in the age group of 21–25 years old. This is explained by the fact that the survey was carried out among university students. University students consist of mostly young people who enter tertiary education institutions immediately after secondary school. Having a high percentage of young respondents is significant and relevant in this study because it is believed that the younger generation is the most active user of mobile technology [3].

Participants were asked whether they studied at a university or a tertiary institution in a developing country. A large proportion (93.2%) of the sample population replied "Yes" to the question asked while only around 6.8% of the respondents are not registered at a university in developing countries. For this study, the fact that most respondents are studying at higher education institutions in developing countries makes the data relevant, since this research is specifically investigating millennials in developing countries.

To get an insight into the level of qualification of the sample population, the respondents were asked to choose their year of study. Most of the respondents (37.9%) were doing their postgraduate studies, 28% were in the fourth year of undergraduate study at university, and the rest were either 1^{st}, 2^{nd} or 3^{rd} year undergraduate students.

VII. Evaluating the Research Model

The first step in PLS-SEM analysis consists of the evaluation of the outer model. This assessment aims to detect how well the respective questions load on each construct. Each factor of the model can be referred to as a variable that comprises several items known as indicators. The reliability of the items of all the variables has been assessed through cross-loadings. Some of the items had a factor loading of less than 0.70 on their constructs as shown in Table II. As a result, they have deleted constructs to increase the reliability of the model: FC3, FC4, and FC5 from Facilitating Conditions; PP1, PP2 from Social Influence; and SI1 from Perceived Playfulness. Subsequently, the cross-loadings were calculated, and a few more items had to be removed because their factor loading was less than 0.70. Including Facilitating Conditions: FC1, FC2, and Perceived Ease of Use: PEU4.

TABLE II. OUTER LOADING

	Facilitating Condition	Intention to Use	Perceived Ease of Use	Perceived Playfulness	Perceived Usefulness	Social Influence
FC1	0.783					
FC2	0.715					
FC3	0518					
FC4	0.534					
FC5	0.433					
FC6	1.052					
ITU1		0.970				
ITU2		0.807				
ITU3		0.755				
PEU1			0.839			
PEU2			0.842			
PEU3			0.747			
PEU4			0.705			
PP1				−0.858		
PP2				0.258		
PP3				0.878		
PU1					0.781	
PU2					1.891	
PU3					0.919	
PU4					0.875	
SI1						0.535
SI2						0.835
SI3						0.891

Thereafter, the cross-loadings were checked again, and the values of factor loading were greater than the cut-off value of 0.70. Conclusively, it can be said that each item is significantly reliable and correctly allocated to the specific latent construct. Furthermore, there is convergent validity due to the shared variance between the indicators and the variables. It is to be noted that the factor loadings were significant at a 5% level of significance. This factor analysis suggested a modification of the mode model for further analysis, as shown in Fig. 2.

In general, there are two different measures in PLS-SEM: reflective and formative. The evaluation of a reflective model involves the examination of indicators' reliability, internal consistency, construct validity, convergent validity, and discriminant validity [30].

(1) Discriminant validity: Discriminant validity measures the extent to which a construct differs from one another analytically [30] and calculates the degree of differences between the intersecting constructs. In this study, discriminant validity was assessed by analyzing the cross-loading of indicators using the method of Heterotrait-Monotrait (HTMT) ratio of correlation because it is more efficient. It has higher specificity and sensitivity rates which varied from 97% to 99% as compared to the Fornell-Lacker criterion which had a rate of only 20.82% [32]. HTMT assumes that the closer the value is to one, the lower the discriminant validity is. It is believed that values higher than 0.85 indicate a deficiency in discriminant validity. As per Table III, it can be observed that the values of the HTMT are all below 0.85 and hence, it can be confirmed that the model entails discriminant validity.

TABLE III. HETEROTRAIT-MONOTRAIT RATIO

	Facilitating Condition	Intention to Use	Perceived Ease of Use	Perceived Playfulness	Perceived Usefulness	Social Influence
FC						
IT	0.657					
PEU	0.510	0.946				
PP	0.600	0.942	0.553			
PU	0.578	0.607	0.776	0.581		
SI	0.684	0.747	0.502	0.622	0.627	

(2) Convergent validity: Convergent validity refers to the degree of correlation of distinct indicators of a construct [30]. The Composite Reliability (CR) and the Average Variance Extracted (AVE) need to be considered when attempting to check for convergent validity. For a model to be satisfactory for convergent validity, the AVE value should exceed 0.50.

TABLE IV. CONSTRUCT RELIABILITY AND VALIDITY

	Crobach's Alpha	Rho_A	Composite Reliability	Average Variance Extracted
Facilitating Condition	1.000	1.000	1.000	1.000
Intention to Use	0.882	0.901	0.885	0.722
Perceived Ease of Use	0.854	0.859	0.856	0.655
Perceived Playfulness	1.000	1.000	1.000	1.000
Perceived Usefulness	0.923	0.928	0.924	0.754
Social Influence	0.802	0.809	0.804	0.673

Table IV shows that all the AVE values are greater than 0.50. Similarly, the CR values of all the items are relatively high ranging from 0.804 to 1. As a result, it can be concluded that all the indicators are suitable for convergent validity.

(3) Internal consistency: Cronbach alpha and composite reliability are the most popular measures for determining internal consistency to establish reliability based on the interrelationship of the indicators [30]. The range of Cronbach alpha values is 0 to 1, where high values indicate more significant reliability. In exploratory research, values of Cronbach alpha are regarded as acceptable when they are above 0.70. Table IV shows that Cronbach's Alpha values exceed the desired minimum value. However, if the value exceeds 0.90, it is undesirable due to redundancy. For constructs of Perceived Usefulness, facilitating conditions and Perceived Playfulness, the values of Cronbach alpha are greater than 0.90 while results for Social Influence, Perceived Ease of Use, and Intention to Use range from 0.802 to 0.882. The alpha values of FC and PP are both one. This can be explained by the fact that these constructs have been limited to only one indicator each during the process of analyzing the outer loadings of the indicators. Conclusively, it can be inferred that SI, PEU, and ITU are the constructs that have internal consistency.

VIII. PARTIAL LEAST SQUARES STRUCTURAL EQUATION MODELLING

(a) Testing the existence of an effect of each factor on Intention to Use: After modifying the model accordingly, the Consistent PLS (Plesk) Algorithm was calculated. PLSc algorithm executes correction of the correlations of

reflective constructs to produce results that are consistent with a factor model [30]. The results of the PLSc algorithm are shown in Fig. 2. The numbers in the circle refer to the extent to which the variance of a certain latent variable is affected by other latent variables. The coefficient of determination, R^2, is 0.615 for the Intention to Use endogenous construct. In other words, 61.5% of the variance of the Intention to Use construct is explained by the latent variables namely: Perceived Usefulness, Perceived Playfulness, Perceived Ease of Use, Social Influence, and Facilitating Conditions. It can be presumed from this value that PU, PP, PEU, SI, and FC constructs when put together do affect Intention to Use to some extent.

Hypotheses have been defined for each construct as described in Table V.

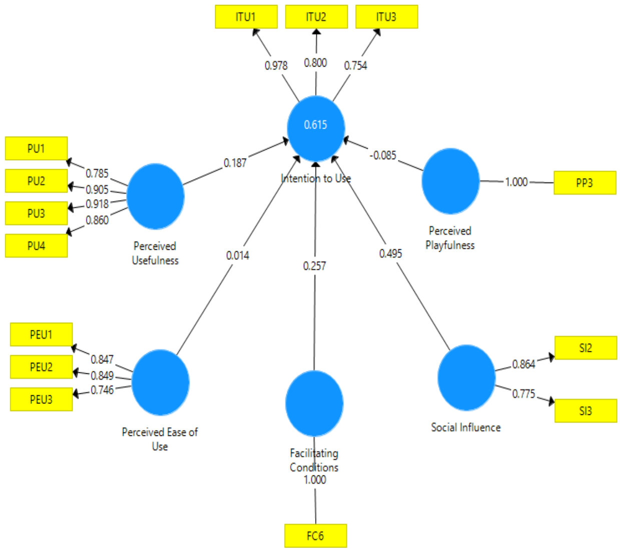

Figure 2. Consistent PLS algorithm result.

To further increase the credibility of the findings derived by calculating the Consistent PLS Algorithm, a PLS Bootstrapping algorithm was run for the model. Bootstrapping refers to a process used by SmartPLS to calculate T-statistics for significance testing of the model. A big number of subsamples are generated from the actual sample with replacement to produce bootstrap standard errors which estimate T-values for significance testing of the structural path.

T statistics values will be examined to determine how significant the path coefficients of the inner model are. For this research study, a two-tailed t-test at a significance level of 1% was used. The path coefficient will be significant for t-statistics greater than 2.58 (or at P-value smaller than 0.01). To proceed with the T-test, a null hypothesis and an alternative hypothesis will be defined. A null hypothesis states that there is no statistical significance between two variables while an alternative hypothesis state otherwise. The null and alternative v from the T-test values as displayed in Table V, it can be observed that for the constructs PEU, PP, and PU, the T statistics of 0.171, 0.268, and 2.038 correspondingly are less than 2.58. This indicates that there is no statistical significance between the PEU, PP, and PU constructs and Intention to Use at a significance level of 1%. Subsequently, the null hypotheses for PEU, PP, and PU are supported. On the other hand, the T statistics of Facilitating Conditions and Social Influence are greater than 2.58. As a result, the null hypotheses for FC and SI are not supported and the alternative hypotheses are accepted at a significance level of 1%. There is statistical significance between both FC and ITU and SI and ITU. However, taking into consideration the previous checks and findings, it is still ambiguous whether FC influences ITU. On the other hand, the T statistics confirm that SI has an impact on ITU.

TABLE V. PATH COEFFICIENT OF PLS BOOTSTRAPPING

	Original Sample	Sample Mean	Standard Deviation	T Statistic	P-Value
Facilitating Condition	0.315	0.306	0.1.3	3.052	0.002
Perceived Ease of Use	0.019	0.020	0.113	0.171	0.664
Perceived Playfulness	0.034	1.036	0.129	0.268	0.798
Perceived Usefulness	1.203	0.199	0.100	2.038	0.042
Social Influence	0.342	0.353	0.129	2.565	0.006

(b) Determining the extent of the effect of each factor on Intension to Use: The next step is to interpret the path coefficients of the inner model. In Fig. 2, the values on the arrows represent path coefficients. Path coefficients determine the degree of the effect of one variable on another [30]. A path coefficient that is lower than 0.1 is statistically insignificant. The results suggest that Social influence has the highest effect on ITU with a path coefficient of 0.495 followed by Facilitation Conditions (0.257). It is noted that the hypothesized path relationship between SI and ITU is statistically significant. It can further be observed that PU predicts ITU to a small extent with a rather low path coefficient of 0.187. However, PEU and PP have both very low path coefficients of 0.014 and -0.085 respectively. Subsequently, at this point, they are not considered to be strong predictors of Intention to Use. Table VI summarises the hypothesis testing results.

TABLE VI. SUMMARY OF HYPOTHESIS TESTING

Factor	T-stat	P-value	Null hypothesis tested	Outcome
Facilitating Conditions	3.052	0.002	H0: Facilitating Conditions do not influence the Intention to Use.	Supported
Perceived Ease of Use	0.171	0.864	H0: Perceived Ease of Use does not influence Intention to Use.	Supported
Perceived Playfulness	0.268	0.789	H0: Perceived Playfulness does not influence Intention to Use.	Supported
Perceived Usefulness	2.038	0.042	H0: Perceived Usefulness does not influence Intention to Use.	Supported
Social Influence	2.656	0.008	H0: Social Influence does not affect Intention to Use.	Not supported

IX. DISCUSSION AND CONCLUSION

This study was primarily investigating factors influencing millennials' perceptions about M-learning in higher education in developing countries. The research model involved factors drawn from TAM and UTAUT: Perceived Usefulness, Perceived Ease of Use, Facilitating Conditions, Social Influence, Perceived Playfulness, and Intention to Use.

Unlike Qashou [14] and Ameen *et al.* [18]'s studies, social influence was the only construct that acted as a predictor of M-learning among respondents surveyed in this research. Additionally, Social Influence was observed to moderately impact the Intention to use M-learning in this survey. Based on the geographical location and contextual environment in which this research study was carried out, it could be inferred the presence of Social Influence is a prime factor motivating the usage intention of M-learning by Millennials in developing countries. This could be explained by the fact communities in developing countries, specifically in the sub-Sahara, are socially centric. In these communities, people's perceptions are interdependent with individualism giving way to socialism.

The significance of social influence echoes Kaliisa *et al.* [26]'s finding of major differences in how M-learning is perceived in Ugandan and Australian universities. This means the provisioning of M-learning solutions should consider the social context. Just like Hao *et al.* [27] insisted on considering cultural differences in the adoption of M-learning based on their comparative study among three universities in different locations.

Limitations to this study include the theoretical framework used. A different theory would yield different results. Future research should consider combining different theories to capture more perspectives on the phenomenon. A comparison of the perceptions of the demand and supply side of M-learning which includes learners, educators, and institutions; could also be investigated for further validation of Social Influence on M-learning adoption in a developing country.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Chama D. Ramchurn conducted the research and analyzed the data; Chama D. Ramchurn and S M. Mulaji wrote the paper; Sumarie Roodt supervised the research; all authors approved the final version.

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