

Article

Structural Determinants of Mobile Learning Acceptance among Undergraduates in Higher Educational Institutions

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Abstract: Mobile learning has become a critical aspect of online learning in the post-pandemic era. As a result, practitioners and policymakers have paid increasing attention to mobile learning acceptance among various stakeholders. However, there is a vacuity of literature on mobile learning acceptance in developing countries, particularly in the African context. This study sought to examine the determinants of mobile learning acceptance among undergraduates in higher educational institutions using a structural equation modelling approach. Data were collected through a web survey distributed to 415 undergraduate students in Namibia. The majority of the UTAUT relationships were confirmed, although some were not supported. The results revealed a strong positive relationship between performance expectancy and hedonic motivation. Hence, hedonic motivation mediates the relationship between performance expectancy and behavioural intention to use mobile learning in Namibia. The results of this study may help to inform mobile learning implementation efforts, particularly in the post-pandemic period.

Keywords: higher education; mobile learning; Namibia; technology acceptance; UTAUT



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1. Introduction

Smart phones have become an integral part of 21st century society, permeating and fundamentally transforming various facets of the modern society such as agriculture [1], mobile money transactions [2], and education [3]. The influence of mobile phones on modern society is unsurprising, given that 96% of the global population lives within reach of a mobile network [4,5]. In the developing world in particular, some studies [6,7] have reported mobile phone adoption rates of over 100%, thereby creating an “always connected” society [8].

A key development that arose due to the proliferation of mobile phones is the discipline of mobile learning. While mobile learning is often regarded as a natural evolution of e-learning [9], the deep penetration of mobile devices has led to the recognition and growing importance of mobile learning as a distinct discipline that is independent of e-learning [5]. In the domain of education, mobile learning has broadened prospects of skills acquisition through both formal and informal learning channels [7]. If harnessed properly, mobile phones can help to support empowerment and growth, as well as enhance students' attitudes and general academic achievements [10]. Mobile devices in education were given further prominence by the onset of the COVID-19 pandemic, particularly the social distancing regulations that necessitated the closure of institutions of learning. Studies such as that conducted by Katsumata et al. [11] in Japan indicate a significant increase in mobile phone use during the COVID-19 pandemic. As in other disciplines, the ICTs in education became the topic du jour, leading to a proliferation of literature from various contexts around the world enthusing over the discipline.

Namibia is one of the leading economies in Africa in terms of GDP per capita, ranked within the top 10 richest countries in the 54-member continent [12]. Mobile phone adoption in Namibia is among the highest in the African continent, with a subscription rate of around 112%. According to Peters et al. [12], up to 98% of Namibian university students own mobile phones. Even though the high mobile phone subscription presents a major opportunity for mobile learning, research on mobile learning is still at an embryonic stage. Whilst “ICTs in education” is hardly a new discipline, the myriad of challenges that impeded the appropriation of education technologies at the peak of the COVID-19 pandemic suggests that there is a lot that scholars and practitioners do not know. Furthermore, relative to the developed world, there is still a paucity of mobile learning literature in the developing world [13], including Namibia. Consequently, anchored upon the UTAUT framework, this study seeks to explore the structural determinants that influence Namibian undergraduate university students’ intention to adopt mobile learning. As aptly noted by Al-Emran et al. [14], because the development and deployment of mobile learning systems is costly, time consuming and challenging, scholars constantly seek to identify the determinants that influence their acceptance and subsequent usefulness.

The rest of this paper is structured as follows: a review of the extant literature on mobile learning acceptance is undertaken, primarily through the lens of the UTAUT framework. This is followed by a discussion of the conceptual framework hypothesis development, and various aspects of the research methodology. After that, a presentation of results is provided, and a discussion of both theoretical and practical implications of the results. Finally, the conclusions, limitations of the study and avenue for future research are provided.

2. Related Works

2.1. Mobile Learning

Fombona et al. [15] regard mobile learning as a new way of transmitting information and transforming it into knowledge. At the core of mobile learning are portable digital devices which eliminate traditional constraints of time, space and geopolitics, among others. The relatively cheap cost of mobile phones (when compared to desktop computers) and the ubiquity of mobile phones means that the demand for mobile learning is likely to increase [3]. Therefore, the increase in mobile learning necessitates a better understanding of the various factors that influence mobile learning acceptance in various contexts.

2.2. Factors Influencing Mobile Learning Acceptance

Scholars have demonstrated that ICTs provide innumerable benefits to the education sector, particularly in the knowledge economy. Nevertheless, the benefits can only be realised if there is acceptance among students and education stakeholders alike [13]. Similarly, Almaiah and Alismaiel [16] posit that the successful implementation of mobile learning requires overcoming problems associated with students’ acceptance of such systems. Such problems emerge because mobile learning acceptance is not a simple unidirectional intentional process, but one that is influenced by the participation of all stakeholders and requisite logistics [4]. Due to the importance of user acceptance, there has been a proliferation of user acceptance models in the broader IT/IS literature.

Many scholars have attempted to identify the determinants that influence the adoption of IT/IS systems (of which mobile learning is one such system) under different conditions and contexts. Such determinants are usually banded together to develop a model that could effectively predict the usage and acceptance of IT/IS such as mobile learning [14]. Some of the more prominent models include the Technology Acceptance Model (TAM), diffusion of innovation, the theory of planned behaviour, as well as the Unified Theory of Acceptance and Use of Technology (UTAUT) model. Having considered the various technology acceptance models, we chose the UTAUT model as the theoretical basis of this study, as it is a synthesis of several user acceptance models. By doing so, we sought to draw on the different strengths of each model. Although UTAUT was developed almost two decades ago by Venkatesh et al. [17], it remains a seminal framework used in various

mobile learning studies. In the following sub-sections, we briefly expound on the various determinants that make up the original UTAUT model.

2.2.1. Performance Expectancy

Performance Expectancy (PE) is defined as “the degree to which an individual believes that using the system will help him or her to attain gains in job performance” [17] p. 447. Arpaci [18] likens PE to the “relative advantage” construct in Rogers’s diffusion of innovation theory. In their study, Sitar-Taut and Mican [4] found that the most powerful relationship was between PE and Hedonic Motivation (HM). PE was found to be the strongest determinant of mobile learning adoption behaviour in Canada [18].

2.2.2. Effort Expectancy

Effort Expectancy (EE) is a crucial predictor of technology acceptance [19]. Venkatesh et al. [17] define EE as “the degree of ease associated with the use of the system” p. 450. Thus, in the context of mobile learning, EE is concerned with the ease with which students can appropriate mobile devices for learning purposes. In the original UTAUT model, EE is presented as having an influence on system acceptance. In the context of mobile learning, previous studies have reported varying conclusions on the influence of EE on mobile learning acceptance. In a study conducted among Thai tertiary students, Thongsri et al. [3] found that EE did not have a significant effect on Behavioural Intention (BI) to use mobile learning. Similar findings are reflected in Pan and Gao’s [20] study conducted among nursing students in China. Thongsri et al. [3] reason that the insignificant influence of EE on intentions could be attributed to the nascence of mobile learning in Thailand. Nevertheless, their findings contrast with the findings of other scholars such as Mtebe and Raisamo [21], whose multi-country study in East Africa found that EE had a positive influence on students’ intention to use mobile learning.

2.2.3. Social Influence

Social Influence (SI) pertains to the degree to which an individual’s behaviour is influenced by the perceptions of important others in their lives. People in collectivistic societies are particularly inclined to decide in cognizance of the society rather than themselves [18]. In a study that compared mobile learning adoption behaviour between Canada (an individualistic country) and Turkey (a collectivistic country), Arpaci [18] found that there is a strong link between extant culture and students’ mobile learning adoption behaviour. Arpaci’s [18] findings indicate that SI has a more significant influence on students’ BI to adopt mobile learning in collectivistic cultures than individualistic countries. The strong influence of social factors was established in other collectivistic societies such as Saudi Arabia [22]. That is because “students in collectivist cultures . . . are more introvert and depend on group effort” [18] p. 708. We theorise that in Namibia, which is considered a highly collectivistic country [23], SI is likely to exert a significant influence on students’ intention to adopt mobile learning.

2.2.4. Facilitating Conditions

Facilitating Conditions (FCs) refer to a system user’s perception of the degree to which the organisational and infrastructural inducements that support the uptake of the mobile learning system exist. Whilst the other three constructs of the UTAUT model are directly associated with BI to use a given system, FCs are associated with actual system usage [24]. According to Arpaci [18], FCs have a strong influence on mobile learning adoption in developed countries, due to the relatively better availability of infrastructure. Considering the well-documented challenges such as poor network connectivity, distractions in the family environment, costs and lack of requisite policies in Namibia [25], FCs may be a critical construct that requires further attention.

2.3. Hedonic Motivation

HM is regarded the degree of pleasure or fun with the usage of a particular system of technology [4]. Sitar-Taut and Mican [4] expound on HM in the context of mobile learning, presenting it as “the enthusiastic, playful and joyful attitude given by the use of mobile devices in an educational context” [4] p. 1003. Scholars such as Fagan [26] have called for the investigation of the role of HM in mobile learning acceptance. It is in recognition of such a call that we extended the UTAUT model to incorporate the hedonic construct as an exogenous mediating factor. According to Chao [19], it is an increasingly common practice among scholars to add external variables to the UTAUT model to increase its ability to predict the acceptance of IT/IS systems.

2.4. Behavioural Intention

BI refers to a system user’s intention to engage in a particular action or activity, or commitment to engaging in a certain behaviour [4]. In assessing students’ acceptance of mobile learning, BI is regarded as the most important predictor of acceptance [27]. The key thesis of the UTAUT model is that BI is a product of several factors [28]. In the UTAUT model, the four constructs that directly predict a user’s BI to adopt a given technology are PE, EE, SI and FC.

2.5. Conceptual Framework and Hypothesis Development

This research’s conceptual model illustrated in Figure 1 is a modification of the original UTAUT model. The purpose of this modification was to examine the mediating influence of HM on the interplay between exogenous latent variables and endogenous latent variables in the original model. The model relies on the four independent constructs of the UTAUT model and incorporates “hedonic motivation” as a mediating exogenous variable. In the model, HM is explained by the constructs of the UTAUT2 model. In our model, we adopted the position of [29] in eliminating the moderators of age, gender and experience, which are part of the original UTAUT model. The elimination of the three variables allowed for a simplification, and building models which could be used in any context [29].

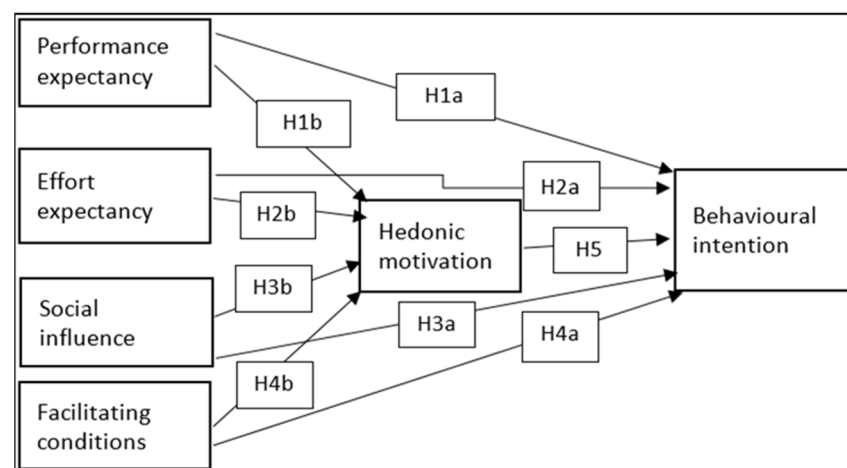


Figure 1. Research conceptual model.

The model specification in Figure 1 shows that performance expectancy, effort expectancy, social influence and facilitating conditions are the exogenous latent variables investigated in this study. Hedonic motivation is the mediating variable observed in the study. Behavioural intention to use smartphones for mobile learning, on the other hand, is the endogenous latent variable investigated in this research. The items measuring each latent variable are illustrated with boxes in the structural model illustrated in Figure 2. To subject the conceptual model presented in Figure 1 to empirical analysis, we hypothesised as follows:

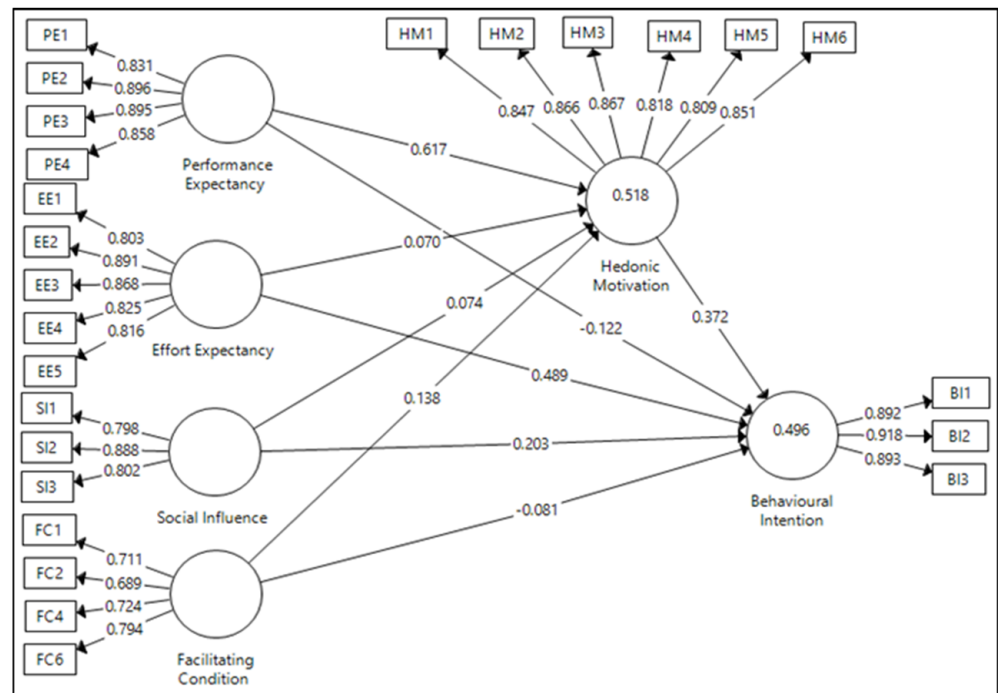


Figure 2. Structural determinants of mobile learning acceptance.

H1a. Performance expectancy exerts a significant effect on behavioural intention to use a smartphone for mobile learning.

H1b. Performance expectancy has a direct effect on hedonic motivation.

H2a. Effort expectancy has a direct effect on behavioural intention to use a smartphone for mobile learning.

H2b. Effort expectancy has a direct effect on hedonic motivation.

H3a. Social influence has a direct effect on undergraduates' behavioural intention to use a smartphone for mobile learning.

H3b. Social influence has a direct effect on hedonic motivation.

H4a. Facilitating conditions have a significant effect on behavioural intention to use a smartphone for mobile learning.

H4b. Facilitating conditions have a significant effect on hedonic motivation.

H5. Hedonic motivation has a direct effect on behavioural intention to use a smartphone for mobile learning.

H6a. Hedonic motivation mediates the relationship between performance expectancy and behavioural intention to use a smartphone for mobile learning.

H6b. Hedonic motivation mediates the relationship between effort expectancy and behavioural intention to use a smartphone for mobile learning.

H6c. Hedonic motivation mediates the relationship between social influence and behavioural intention to use a smartphone for mobile learning.

H6d. Hedonic motivation mediates the relationship between facilitating conditions and behavioural intention to use a smartphone for mobile learning.

3. Materials and Methods

This study employed a quantitative approach following a cross-sectional survey design. A structured questionnaire [30] was adapted in order to engage respondents about the acceptance of mobile learning in higher educational institutions in Namibia. The study was conducted in selected state-owned higher educational institutions in Namibia.

3.1. Research Procedure and Participants

The target population for this study were undergraduates across various faculties in the participating higher educational institutions in Namibia. The estimated population of undergraduate students in the institutions was 22,153. A convenience sampling technique was adopted based on the need to comply with the ethical guidelines in social science research, which stipulate that no respondent should be forced to participate in a survey. The convenience sampling technique helps in ensuring that only respondents who were interested in participating in the study were provided the survey link to respond to the questionnaire. Thus, respondents were contacted via email and WhatsApp with the help of their course instructors. The link to complete the online survey and the survey introduction containing the consent form were provided to respondents via email, e-learning platform and WhatsApp. The inclusion criterion used to select participants was that students needed to be enrolled in an undergraduate degree and/or diploma program in the participating higher educational institutions in Namibia. With reminders at regular intervals, a total of 415 respondents completed the online survey in four months. The demographic profile of respondents indicates that there were 220 (52.9%) females, 183 males (44.3%), while the remaining 12 (2.9%) preferred not to declare their gender. In terms of age distribution among respondents, 255 (61.4%) belonged to the age group of 18–22 years, 67 (16.2%) were 23–27 years, 44 (10.5%) were within the age group of 28–32 years, and 49 (11.9%) were 33 years old or older. The classification of respondents by race shows that 376 (90.5%) were black Africans, 29 (7.1%) were coloured, 6 (1.4%) were white Caucasians and 4 respondents preferred not to declare their race. The majority, that is, 300 (72.4%) of our respondents, were full-time students, 46 (11%) were part-time students and 69 (16.7%) chose other modes of study.

3.2. Research Instruments

A structured questionnaire was adapted to gather information on the acceptance of mobile learning among the undergraduate students in the participating higher educational institutions in Namibia. In total, the questionnaire contains 34 items, of which 6 items were instrumental in gathering demographic information about the respondents. The remaining 28 items measured the key constructs (6) on mobile learning acceptance among the undergraduate students using a 5-point (“1—strongly disagree” to “5—strongly agree”) Likert type rating scale. The first construct contains 3 items measuring BI to adopt mobile learning among the undergraduates, which were adapted from Abdulameer and Zwain [31] and Sitar-Tăut [9]. The second construct that measures EE with 5 items was adapted from Hoi [32] and Sitar-Tăut [9]. FCs [9,32–34] were the third construct in this study using 6 items adapted from the previous studies on mobile learning acceptance. The fourth construct also contains 6 items adapted to measure HM [9,32,33]. PE is the fifth construct containing 4 items adapted [9,33] in this study. The sixth construct contains 4 items adapted from previous studies [9,35] to measure SI in the current study. The survey containing all items measuring mobile learning acceptance among the undergraduate students in Namibia was made accessible to the respondents using Google Forms.

3.3. Ethical Considerations

The ethical considerations in social science research were adhered to in this study. The confidentiality and anonymity of respondents and the participating higher educational institutions were ensured. An ethical clearance certificate was obtained from the partici-

pating institutions before administering the research instrument. The informed written consent of the participants was solicited on the cover page of the online survey.

3.4. Data Analysis

The quantitative data collected in this study were analysed using descriptive and inferential statistics. For preliminary analyses, the data were downloaded and saved as a CSV (comma-delimited) file. The CSV file was imported into SmartPLS version 3.3.9 [36] for descriptive statistical analyses (mean scores and standard deviation), psychometric property of the research instrument and inferential statistics such as partial least squares structural equation modelling [37] for path analysis, shown in Figure 2. The psychometric property of the research instrument and/or measurement model in this study was assessed using the Cronbach's alpha coefficient, Composite Reliability (CR), Average Variance Extracted (AVE), square root of AVE, and Fornell–Larcker criterion to establish the reliability and validity of the research instrument.

4. Results

The measurement model was assessed using Exploratory and Confirmatory Factor Analyses (EFA and CFA), reported in Tables 1 and 2. The validity of latent variables (constructs) in this study was ascertained statistically using convergent and discriminant validity. During EFA and CFA, to ensure convergent and discriminant validity, the following items were expunged consecutively: SI4, FC3 and FC5. Tables 1 and 2 show the factor loadings for the six latent variables as well as the reliability and validity of the scales measuring mobile learning acceptance in higher educational institutions in Namibia.

Table 1. Reliability and convergent validity of the reflective latent variables.

Latent Variable	Indicator	Loading	VIF	Mean	SD	Cronbach's Alpha	CR	AVE
Behavioural Intention	BI1	0.892	2.378	0.377	0.013	0.884	0.928	0.812
	BI2	0.918	3.017	0.356	0.010			
	BI3	0.893	2.395	0.378	0.011			
Effort Expectancy	EE1	0.803	2.613	0.186	0.018	0.897	0.924	0.708
	EE2	0.891	3.301	0.262	0.016			
	EE3	0.868	3.753	0.230	0.017			
	EE4	0.825	2.238	0.280	0.024			
	EE5	0.816	2.211	0.229	0.021			
Facilitating Condition	FC1	0.711	1.465	0.276	0.045	0.719	0.821	0.534
	FC2	0.689	1.361	0.280	0.054			
	FC4	0.724	1.383	0.317	0.055			
Hedonic Motivation	FC6	0.794	1.281	0.476	0.057	0.919	0.936	0.711
	HM1	0.847	3.542	0.230	0.010			
	HM2	0.866	3.757	0.231	0.010			
	HM3	0.867	3.107	0.186	0.008			
	HM4	0.818	3.231	0.165	0.008			
	HM5	0.809	3.187	0.166	0.007			
Performance Expectancy	HM6	0.851	2.603	0.206	0.008	0.893	0.926	0.758
	PE1	0.831	2.064	0.294	0.012			
	PE2	0.896	2.871	0.292	0.009			
	PE3	0.895	3.078	0.260	0.011			
Social Influence	PE4	0.858	2.410	0.305	0.011	0.776	0.869	0.690
	SI1	0.798	1.647	0.330	0.053			
	SI2	0.888	1.843	0.472	0.042			
	SI3	0.802	1.470	0.393	0.042			

Note: SD = standard deviation, CR = composite reliability, AVE = average variance extracted.

Table 2. Discriminant validity of latent variables and collinearity evaluation of predictors.

Discriminant Validity of Latent Variables by Fornell–Larcker’s Criterion						
Latent Variable	BI	EE	FC	HM	PE	SI
Behavioural Intention(BI)	0.901					
Effort Expectancy(EE)	0.608	0.841				
Facilitating Condition(FC)	0.091	0.164	0.731			
Hedonic Motivation(HM)	0.423	0.284	0.398	0.843		
Performance Expectancy(PE)	0.259	0.274	0.407	0.700	0.870	
Social Influence(SI)	0.396	0.299	−0.030	0.152	0.098	0.830

Note: Diagonals in bold are the square roots of AVE.

Discriminant Validity Evaluation for the Reflective Variables by HTMT Criterion						
Latent Variable	BI	EE	FC	HM	PE	SI
Effort Expectancy (EE)	0.676					
Facilitating Condition (FC)	0.112	0.269				
Hedonic Motivation (HM)	0.456	0.294	0.457			
Performance Expectancy (PE)	0.289	0.297	0.496	0.760		
Social Influence (SI)	0.474	0.336	0.145	0.162	0.120	

Collinearity Evaluation between the Predictor Constructs by Inner VIF Values		
Latent Variable	BI	HM
Effort Expectancy (EE)	1.195	1.185
Facilitating Condition (FC)	1.254	1.214
Hedonic Motivation (HD)	2.075	–
Performance Expectancy (PE)	2.060	1.269
Social Influence (SI)	1.121	1.109

Source: Survey.

As indicated in Table 1, the factor loadings for reflective latent variables ranged from 0.689 to 0.918. The evaluation of these loadings revealed that all factors loaded considerably well, which also impacted the Average Variance Extracted (AVE) values. The AVE values in Table 1 ranged from 0.534 to 0.812. The value of AVE must be greater than 0.5 to establish convergent validity [38]. Statistically, the AVE values reported in this study are greater than the threshold of 0.5. Therefore, convergent validity of the key constructs investigated in this study was established using AVE and confirmed judging from composite reliability coefficients ranging from 0.821 to 0.936. The Cronbach’s alpha coefficients of the latent variables ranged from 0.719 to 0.919, which ascertained the internal consistency of the measurement scales used in this study. Empirically, the scales used in measuring all latent variables in this study were reliable due to the fact that their Cronbach’s alpha coefficients were greater than 0.7 [39]. Discriminant validity for the reflective latent variables investigated in this study is reported in Table 2.

The discriminant validity of the latent variables was statistically ascertained by comparing the square roots of AVE values to the inter-construct correlations. The square roots of AVE for each latent variable must be greater than inter-construct correlations to establish discriminant validity [38,40]. The HTMT on the other hand measures similarity between predictor variables, which means that if the ratio is less than one, discriminant validity is established in the study [41]. Table 2 indicates that all HTMT ratios are less than the cut-off value of one (1). Therefore, the results reported in Table 2 showed that the discriminant validity of the key constructs investigated in this study was established. Judging from the empirical evidence presented in Tables 1 and 2, one can conclude that the measurement scales adapted to measure mobile learning acceptance in Namibian higher educational institutions are valid and reliable. The multi-collinearity evaluation of predictor variables was examined using Variance Inflation Factor (VIF) scores for all construct combinations reported in Table 2. The VIF values ranged from 1.109 to 2.075, which indicated that no multi-collinearity issues were found among the predictor variables, since the VIF values

are less than 3.3 [42]. The results of the partial least square structural equation modelling and/or path analysis conducted in this study are illustrated in Figure 2.

The empirical evidence presented in Figure 2 reveals that PE exerts a significant positive effect on HM ($r = 0.617, p < 0.001, n = 415$), but an adverse effect on BI ($r = -0.122, p < 0.05, n = 415$). Hence, PE exerts significant direct effects on both HM and BI among undergraduate students in the higher educational institutions in Namibia. EE has a significant direct effect on BI ($r = 0.489, p < 0.001, n = 415$). On the contrary, the latent variable (effort expectancy) has no significant direct effects on HM ($r = 0.070, p > 0.05, n = 415$). Hence, one can infer that HM has no significant mediating influence on the interplay between EE and BI to accept mobile learning among the undergraduate students in Namibia.

Statistically, SI has a significant direct effect on BI ($r = 0.203, p < 0.001, n = 415$), but no significant direct effect was established on the link between SI and HM ($r = 0.074, p > 0.05, n = 415$). Therefore, HM has no significant mediating influence on the relationship between SI and BI to adopt mobile learning among the undergraduate students in Namibia. Empirical evidence suggests that FCs have no significant direct effect on BI ($r = -0.081, p > 0.05, n = 415$) to accept mobile learning in higher educational institutions in Namibia. However, FCs exert a significant direct effect on HM ($r = 0.138, p < 0.01, n = 415$). The implication of these results is that HM mediates the relationship between FCs and BI to adopt mobile learning by undergraduates in Namibia. Among the four (4) exogenous variables investigated, only PE and FCs provided significant effects on HM ($R^2 = 0.518, p < 0.001, n = 415$). This means that PE and FCs explained 51.8% of the variance in HM. HM as a mediating variable exerts a significant direct effect on BI ($r = 0.372, p < 0.001, n = 415$). The direct and indirect effects of the independent exogenous variables and the mediating influence of HM are reported in Table 3.

Table 3. Direct and indirect effects of key latent variables.

Hyp.	Direct Effect	M	SD	Coeff.	T Stat	p Values	Decision
H1a	Performance Expectancy →Behavioural Intention	−0.121	0.055	−0.122	2.220	0.027	Supported
H1b	Performance Expectancy →Hedonic Motivation	0.614	0.046	0.617	13.564	0.000	Supported
H2a	Effort Expectancy →Behavioural Intention	0.488	0.052	0.489	9.330	0.000	Supported
H2b	Effort Expectancy →Hedonic Motivation	0.073	0.039	0.070	1.779	0.076	Not supported
H3a	Social Influence →Behavioural Intention	0.202	0.042	0.203	4.848	0.000	Supported
H3b	Social Influence →Hedonic Motivation	0.077	0.044	0.074	1.671	0.095	Not supported
H4a	Facilitating Conditions →Behavioural Intention	−0.080	0.055	−0.081	1.470	0.142	Not supported
H4b	Facilitating Conditions →Hedonic Motivation	0.140	0.045	0.138	3.054	0.002	Supported
H5	Hedonic Motivation →Behavioural Intention	0.370	0.065	0.372	5.697	0.000	Supported
H6	Specific Indirect Effects (Mediation)	M	SD	Coeff.	T Stat	p Values	Decision
H6a	Performance Expectancy →Hedonic Motivation →Behavioural Intention	0.228	0.045	0.229	5.069	0.000	Supported
H6b	Effort Expectancy →Hedonic Motivation → Behavioural Intention	0.027	0.016	0.026	1.630	0.103	Not supported
H6c	Social Influence → Hedonic Motivation → Behavioural Intention	0.029	0.018	0.028	1.550	0.121	Not supported
H6d	Facilitating Conditions →Hedonic Motivation →Behavioural Intention	0.051	0.017	0.051	2.956	0.003	Supported

Source: Survey.

Judging from the beta loadings and their corresponding level of significance, there is no doubt that PE, EE, SI and HM explained 49.6% of the variance in BI ($R^2 = 0.496, p < 0.001, n = 415$). The indirect specific effects presented in Table 3 reveal that HM mediates the

relationship between PE and BI ($r = 0.229, p < 0.001, n = 415$) to adopt mobile learning by the undergraduates in Namibia. Meanwhile, the relationship between FCs and BI was fully mediated by HM ($r = 0.051, p < 0.01, n = 415$). The decisions reached on the research hypotheses formulated in this study are reported in Table 3.

5. Discussion

The primary objective of this research was to identify the structural determinants that influence undergraduates' adoption of mobile learning in higher education. The results of this cross-sectional survey of 415 undergraduate Namibian students have implications for theory, practice and future mobile learning research.

5.1. Theoretical Implications

Whilst scholars [3,19,20] found a significant positive relationship between PE and BI, our findings show that PE has an adverse effect on BI, which perhaps could be attributed to the fact that this study was undertaken in the time of the COVID-19 pandemic. The implication is that lower levels of PE are associated with higher levels of BI in times of crisis. Our results contradict the original theoretical foundation of the UTAUT framework, which holds that higher levels of PE are associated with higher levels of BI. The wide adoption of mobile learning was under non-volitional circumstances due to the prevailing social distancing regulations enacted by the Namibian government. We can deduce that the acceptance of mobile learning during a crisis or in non-volitional situations has little to do with PE of mobile learning technologies.

Furthermore, PE exerts a significant influence on HM, resulting in the strongest relationship among all variables tested in the structural model reported in Figure 2. Our findings echo those of Sitar-Tăut [9], although in our study, PE exerted a stronger influence on HM. On the other hand, Fagan [26] used HM as a predictor of PE, and established a strong relationship between the two variables.

Effort Expectancy (EE) and BI exhibited a significant relationship. Fagan [26] observed that within the education discipline, literature employing the UTAUT framework has reported a positive relationship between EE and BI in several contexts, which was corroborated by our study in Namibia. Nevertheless, in a study conducted among undergraduate students in a developed world context (United States of America), Fagan [26] found the relationship between EE and BI to be insignificant. Fagan [26] reasons that the general feeling that mobile learning was easy to use could be the reason why EE may be regarded as a weak predictor of mobile learning acceptance. Nevertheless, it is important to note that the relationship between EE and BI may also be influenced by the course enrolled for. Al-Adwan et al. [43] found that the influence of EE (which they termed "complexity") on BI of IT students was less influential than on other non-IT courses. They opine that students enrolled for IT-related courses generally possess higher digital literacy skills owing to the nature of their courses. It is generally believed that the more an individual's skills and experience with mobile learning use increase, the more the influence of EE on BI decreases [44]. In relation to our findings, perhaps the novelty of using mobile learning under compulsion could have influenced students' perceptions.

This study found that SI has a significant positive influence on BI. Our findings are consistent with those of Moorthy et al. [45] and Thomas et al. [43], which highlights the importance of peers, parents, educators and other influential people in a student's decision to adopt mobile learning. Nevertheless, the results are contrary to the findings of Thongsri et al. [3], whose study found that SI has no significant effect on BI. The encouragement of students to utilise their mobile learning devices by university and government authorities could have contributed to the influence of SI on BI in our findings. Sitar-Tăut [9] concurs, arguing that SI should be important in a crisis situation such as a pandemic, when social support tends to play a critical role.

Our findings also indicate that FCs have a significant influence on HM. The implication of these findings is that the requisite conditions must have been developed and put in

place in order to promote HM among Namibian undergraduate students, especially in times of crisis. FCs may be in the form of quicker and qualitative support in HEIs [4], and fewer distractions at home, which was identified as a key concern among Namibian students [25]. However, FCs exert no direct significant influence on BI, thus affirming the findings of [45]. Perhaps the non-volitional nature of mobile learning adoption among the undergraduate students could be used to explain why FCs exert no significant effect on BI to use a smartphone for mobile learning.

We also studied the relationship between HM and BI. Our findings revealed a significant relationship between HM and BI in mobile learning, thus echoing the findings of Sitar-Tăut [9], whose study found the relationship between HM and BI to be the most influential of all variables tested. Sitar-Tăut [9] posits that “the higher the fun, joyfulness, and rewarded attitude regarding m-learning use, the higher the related acceptance” p. 375. The significant influence of HM on BI has been established in a number of studies in various contexts such as India [29], Malaysia [45] and the United States of America [26]. Meet et al. [29] posit that due to the increase in digitisation and social media, the contemporary generation values online experiences, and this leads to lives punctuated by fun, interesting and experience-rich lifestyles. Thus, it is pertinent that when implementing mobile learning systems, systems should not only be functional, but integrate the fun and enjoyment aspects as well.

The analysis of specific indirect effects revealed that HM mediates the relationship between PE and BI, as well as the relationship between FCs and BI. Statistically, a full mediation was found on the interplay between FCs and BI to use a smartphone for mobile learning since FCs exert no direct significance effect on BI in the structural model. Our results differ from the empirical evidence provided by Sitar-Tăut [9], who posits that HM does not provide a full mediating effect. Both studies found that HM plays a critical role in the structural model. However, the current study showed that HM neither mediates the relationship between EE and BI, nor that between SI and BI in the post-pandemic period. UTAUT is a well-established and widely used technology adoption model. However, our findings suggest that the application of UTAUT should not be universal but should rather be carried out in cognizance of the prevailing culture in each context. This viewpoint is echoed by scholars such as Thomas et al. [46], who reason that an arbitrary application of the UTAUT model could lead to non-detection of important relationships between variables.

5.2. Practical Implications

The findings reported in our study suggest practical implications for the management of higher educational institutions concerning BI to appropriate smartphones for mobile learning in the post-pandemic period. Specifically, this study found a significant association between PE and HM. This suggests that the performance value of mobile learning systems should be well articulated and communicated to students so as to motivate them to adopt mobile learning. This is critical, given that students have been found to be less inclined to use mobile devices for learning than for hedonic purposes.

Judging from the critical role of HM, higher educational institutions should incorporate gamification or game-based learning (EdApp) into their mobile learning applications to enhance learning experiences among undergraduates in the post-pandemic period. The development of appropriate educational policies to foster the acceptance of mobile learning is critical in stimulating creativity and innovation among undergraduates in the fourth industrial revolution and beyond. Governments need to provide the required support to promote game-based learning strategies. Gamification incorporates fun game-based elements and leads to increased knowledge retention and student performance [47,48] as well as enhanced graduate employability [49] in the fourth industrial revolution.

5.3. Limitations and Future Research

This research is not without its limitations. Firstly, the study was undertaken at two public universities in Namibia. Consequently, the generalisability of the findings needs to

be treated with caution. Future studies may include more tertiary institutions for a holistic perspective of the Namibian environment. Secondly, as with other quantitative studies, the nature of the study did not allow for probing questions, which could have potentially unearthed in-depth knowledge. Future studies could adopt a qualitative approach in order to address this vacuity or a methodologically triangulated approach such as a sequential or concurrent mixed method to obtain depth from two vantage points. Furthermore, future studies may also consider the perspectives of other mobile learning Namibian stakeholders such as systems administrators, academics, senior management and designers of the mobile learning platforms.

6. Conclusions

This study investigated the predictive ability of the UTAUT model to comprehend the BI of Namibian students to adopt mobile learning under non-volitional circumstances such as those brought about by the COVID-19 pandemic. The original UTAUT model was modified by including HM as a mediating variable to explain its influence on the interplay between exogenous latent variables (PE, EE, SI and FCs) and the endogenous latent variable (BI). Whilst affirming the utility of the UTAUT model in predicting BI, our results suggest that context and prevailing circumstances should be carefully considered before any generalisation can be made. This is particularly important for Namibia with its Apartheid past and relatively new public universities that were built after independence. Furthermore, the issue of technological infrastructure and access to a stable internet connection play a major role in mobile learning uptake among the undergraduates in the country. A strong positive relationship was established between PE and HM. Hence, HM mediates the relationship between PE and BI to use mobile learning by undergraduates in Namibia. The results of this study may help to inform mobile learning implementation efforts, particularly in the post-pandemic period. Finally, we believe that our findings could be useful to decision-makers, system designers and mobile learning implementers who endeavor to implement mobile learning systems.

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