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Validation of Non-Linear Relationships-Based UTAUT Model on Higher Distance Education Students' Acceptance of WhatsApp for Supporting Learning

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Abstract

This study examined relationships among the exogenous constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) model to identify those that significantly predict others. Questionnaires were used to collect data from 273 distance education students pursuing various diploma, bachelor's degree and post-graduate diploma programs at the Cape Coast study center of the Institute for Distance and e-Learning (IDeL) of the University of Education, Winneba in Ghana. Proportional stratified random sampling technique was employed to obtain the sample of students. The data were analyzed using Partial Least Squares – Structural Equation Modeling (PLS-SEM). The results indicated that in acceptance of WhatsApp for supporting higher distance learning, effort expectancy and social influence predict performance expectancy; mobile self-efficacy and facilitating conditions predict effort expectancy; and facilitating conditions predict social influence. Also, mobile self-efficacy was found to significantly predict behavioral intention. We recommend that prior to introduction of a new technology such as WhatsApp for supporting learning, necessary resources and training should be provided by educational administrators and faculty to the students. This would make the students perceive that they can use the technology effectively to bring about gains in their learning; and subsequently accept the technology.

Keywords: *technology acceptance, WhatsApp for learning, WhatsApp in distance education, structural equation modeling, exogenous variables.*

Introduction

Teaching and learning in educational institutions at all levels have undergone a changing trend from face-to-face modes of delivery to different degrees of blended and distance education modes. This trend of evolution in education is greatly influenced by emerging disruptive technologies. Educationists and researchers all over the world seek new ways of supporting students' learning with emerging technologies. One ubiquitous technology that is accessible to higher distance education students in various parts of the world, especially in Ghana, is WhatsApp messenger mobile application. Some researchers such as [1], [2], [3], [4] and [5] have found educational benefits of using WhatsApp to support learning in higher education contexts.

As in the case of many new technologies, successful implementation of WhatsApp as a learning support tool requires acceptance from students who are the pivot of the teaching and learning processes. It is therefore pertinent for faculty and educational administrators to understand factors that could influence students to adopt WhatsApp as learning support tool before deciding on implementation. Several models and theories have been developed over the years which attempt to explain technology acceptance. One such models is Unified Theory of Acceptance and Use of Technology (UTAUT) [6]. This model explains that intention to adopt a new technology is determined by performance expectancy, effort expectancy and social influence. Also, actual use of a technology is determined by behavioral intention and facilitating conditions. The variables that predict others are referred to as exogenous variables, whereas the predicted variables are endogenous variables.

The UTAUT model involved only relationships (referred to as linear relationships) between the exogenous variables and endogenous variables. However, [7] proposed non-linear relationships among some exogenous variables of the original UTAUT model. As a result, they proposed a modified linear and non-linear relationships-based UTAUT model that included non-linear relationships. Although before this current study, many studies had been conducted to validate the original UTUAT model proposed by [6], no other studies had been conducted to validate the linear and non-linear relationships-based UTAUT model that [7] proposed in different contexts.

The current study sought to validate the linear and non-linear relationships-based UTAUT model proposed by [7]. The findings of this study will hopefully contribute to the understanding of the linear and non-linear relationships among exogenous and endogenous constructs of the UTAUT model in the context of adoption of WhatsApp for supporting learning in higher distance education. The same knowledge will form a basis for understanding adoption of other technologies as well.

Research Objectives

1. To determine which of the exogenous constructs in the UTAUT model have significant non-linear relationships regarding Distance Education students' behavioral intention to use WhatsApp for learning purposes.
2. To determine whether mobile self-efficacy predicts behavioral intention in the non-linear relationship-based UTAUT model with respect to acceptance of WhatsApp chat by distance education students for supporting learning.

Model Development and Hypotheses Formulation

The original formulators of the UTAUT model [6] proposed and validated existence of direct linear predictive relationships between the independent and dependent constructs. These relationships were further validated and confirmed by subsequent researches over the past years. A new development regarding the predictive relationships among the UTAUT constructs is the possible existence of non-linear predictive relationships among the exogenous constructs of the UTAUT model. [7] proposed the existence of these non-linear relationships based on existing literature. The results of their study confirmed significance of some these non-linear relationships. This section reviews the bases for the proposition of existence of non-linear relationships among the UTAUT exogenous constructs.

Effort Expectancy and Performance Expectancy

The proposition of non-linear relationship between effort expectancy and performance expectancy is based on the Technology Acceptance Model developed by [8]. This model identifies two major belief constructs that are crucial in predicting the attitude of a potential user toward acceptance of a computer technology. These are perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which a potential user of a given technology believes that using the technology would result in improvement in the performance of his or her job. Perceived ease of use also refers to how a potential user of a technology believes that he or she could use the technology without physical or mental effort.

The construct perceived ease of use is postulated to have a predictive effect on perceived usefulness. [8] hypothesized a significant direct effect of perceived ease of use on perceived usefulness. This hypothesis was based on the reason that if the use of a given technology is easier for the users, they are more likely to have improvement in their job accomplishments. Thus, as productivity increases with easy use of a technology, the technology is perceived to be more useful for the designated job.

The constructs perceived ease of use and perceived usefulness in technology acceptance model are the root constructs from which the constructs effort expectancy and performance expectancy of the UTAUT model respectively were derived [6]. By virtue of the derivative of the UTAUT constructs from the technology acceptance model constructs, it is logical to expect the predictive relationship between perceived ease of use and perceived usefulness to replicate between effort expectancy and performance expectancy as well. This relationship was hypothesized and tested by [7] and their result indicated that effort expectancy determined performance expectancy. Their finding was consistent with [8]. In view of existing literature, this study seeks to validate this relationship by testing the null hypothesis that:

H_{01}: Effort Expectancy does not predict Performance Expectancy

Mobile Self-Efficacy and Effort Expectancy

Self-efficacy is a social psychology concept defined as "judgements of how well one can execute courses of action required to deal with prospective situations" [9]. Before attempting to perform any action such as use of a technology, every individual has an inner perception of his or her ability or otherwise to perform the action. According to Badura, measurement of self-efficacy of an individual should be fashioned to the domain of psychological functioning under consideration [9]. Thus, in the domain of computer technology usage, computer self-efficacy can be considered; whereas mobile self-efficacy can be considered in the domain of mobile or smart phone technology usage.

In technology acceptance model, [10] proposed that perceived ease of use of a technology is determined by control, intrinsic motivation and emotion. The anchoring construct referred to as control consists of two kinds of beliefs – internal control and external control. Venkatesh conceptualized internal control as computer self-efficacy and external control as facilitating conditions. Thus, he established that at early stages of a computer technology usage, perceived ease of use of the computer technology is determined by both computer self-efficacy and facilitating conditions among others.

In the context of this study, the technology used was WhatsApp messenger which is a mobile phone application. Thus, the construct computer self-efficacy hypothesized by [10] as a determinant of perceived ease of use of a computer technology could be likened to mobile self-efficacy in the context of this study. In order to validate the predictive relationship between mobile self-efficacy and effort expectancy (perceived ease of use), a null hypothesis is tested that:

H_{02}: Mobile self-efficacy does not predict Effort Expectancy.

Social Influence and Performance Expectancy

The construct social influence in the UTAUT model is a derivative of subjective norm in Technology Acceptance Model 2 [6], [11]. These terms connote the idea that the acceptance of a new technology by an individual is influenced by how he or she believes others will view him or her as a result of using the technology. If the perceived view of important others is positive, a prospective user is more likely to adopt the new technology whereas vice versa is also likely.

Performance expectancy is also derived from other constructs such as perceived usefulness in technology acceptance model, among others [6], [11]. It refers to the belief an individual has that using a technology would result in improvement in job accomplishments.

Attempts to identify predictive relationship between social influence and performance expectancy were arguably pioneered by [12]. They hypothesized a positive direct effect of subjective norm on perceived usefulness in the formulate of Technology Acceptance Model 2. Their results confirmed the hypothesis, significantly moderated by experience. The predictive relationship between social influence and performance expectancy was subsequently tested by [7] using the UTAUT model. Contrary to Venkatesh and Davis, the results obtained by [7] showed non-significant relationship between the constructs social influence and performance expectancy. This study sought to validate this relationship by testing the null hypothesis that:

H_{03}: Social Influence does not predict Performance Expectancy.

Facilitating Conditions and Performance Expectancy

Facilitating conditions were hypothesized by [7] to be a direct determinant of performance expectancy. The basis of their assertion was that availability of resources and favorable conditions for utilization of a new technology would make prospective users develop favorable attitude towards adoption of the technology and its usefulness. Thus, when prospective users perceive that organizational or institutional provisions are available to support the use of a new technology, the user are more likely to also perceive the technology as one that would require little or no effort in its utilization, and subsequently more likely to yield gains in job performance. However, the results obtained by [7] from testing the hypothesis was contrary to their assertion. The predictive relationship between facilitating conditions and performance expectancy was not significant at the acceptable significant level ($p<.05$). This study therefore sought to validate this relationship by testing the null hypothesis that:

H_{04}: Facilitating Conditions do not predict Performance Expectancy

Facilitating Conditions and Effort Expectancy

The relationship between facilitating conditions and effort expectancy was hypothesized by [10]. According to the author, facilitating conditions (referred to as external control beliefs) in the technology acceptance model positively determines ease of use perception (effort expectancy in UTAUT) about a new technology. The hypothesized effect of facilitating conditions on perceived ease of use was said to be more paramount particularly at the early stages of user experience with a new technology. Venkatesh tested the hypothesis using data collected from three different organizations over three months period and the data supported the hypothesis. The predictive relationship between facilitating conditions and effort expectancy was later tested by [7] using the UTAUT model and reported that facilitating conditions had a direct positive effect on effort expectancy of distance education tutors on Learning Management System usage. In order to validate this relationship in the context of this study, a null hypothesis was tested that:

H_{05}: Facilitating Conditions do not predict Effort Expectancy.

Facilitating Conditions and Social Influence

In technology adoption, the construct facilitating conditions is perceived to have a potential of influencing the impact of social influence on target users of a novel technology in an organization. This assertion was held by [7]. In their view, the availability of conducive environment for the utilization of a new technology serve as motivation for important referents to encourage potential users or adopters of the technology to accept same. Thus, facilitating conditions likely has the potential to enhance the effect of social influence. Based on this premise, [7] tested the hypothesis that "facilitating conditions will predict social influence" on the adoption of Learning Management System by distance education tutors. Their results supported this assertion. This study further sought to validate the UTAUT model on this postulation by testing the null hypothesis that:

H_{06}: Facilitating Conditions do not predict Social Influence.

Mobile Self-Efficacy and Behavioral Intention

Mobile self-efficacy refers to the belief an individual has in his or her own ability to use mobile communication technologies such as mobile phone, tablet pc, etc. to perform some task [13]. This construct originated from the social cognitive theory of [14]. Bandura introduced the concept of self-efficacy as one's belief in his or her own ability to successfully carry out a certain task.

Self-efficacy is more significant at the initial stages of one's attempt to perform a novel activity. In educational application of mobile technologies, it is logical to expect that people who strongly believe in themselves that they have the ability to use mobile devices and applications would readily accept to utilize the technology in their studies, all other things being equal.

Similar to mobile self-efficacy in the use of mobile technologies is computer self-efficacy in the use of computers and their related technologies. Computer self-efficacy was hypothesized by [6] to have none-significant influence on behavioral intention to accept computer technology. The findings of their study supported their hypothesis, hence self-efficacy was excluded from the original UTAUT model.

Mobile self-efficacy is not a construct in the original UTAUT model, neither has it been theorized in any extended version of the UTAUT model as a direct determinant of behavioral intention in existing literature. It is however postulated in this study that in the adoption of WhatsApp messaging application for distance learning, mobile self-efficacy could play a significant role in predicting behavioral intention of the students to adopt the technology. In order to validate the UTAUT model on the predictive relationship between mobile self-efficacy and behavioral intention, this study tested a null hypothesis that:

H_{07}: Mobile Self-Efficacy does not predict Behavioral Intention.

Based on the preceding hypotheses, the researchers proposed a conceptual model to guide this study. The model named Mobile Self-Efficacy and Non-linear Relationships-based Unified Theory of Acceptance and Use of Technology (MSENR-UTAUT) model is illustrated in Figure 1.

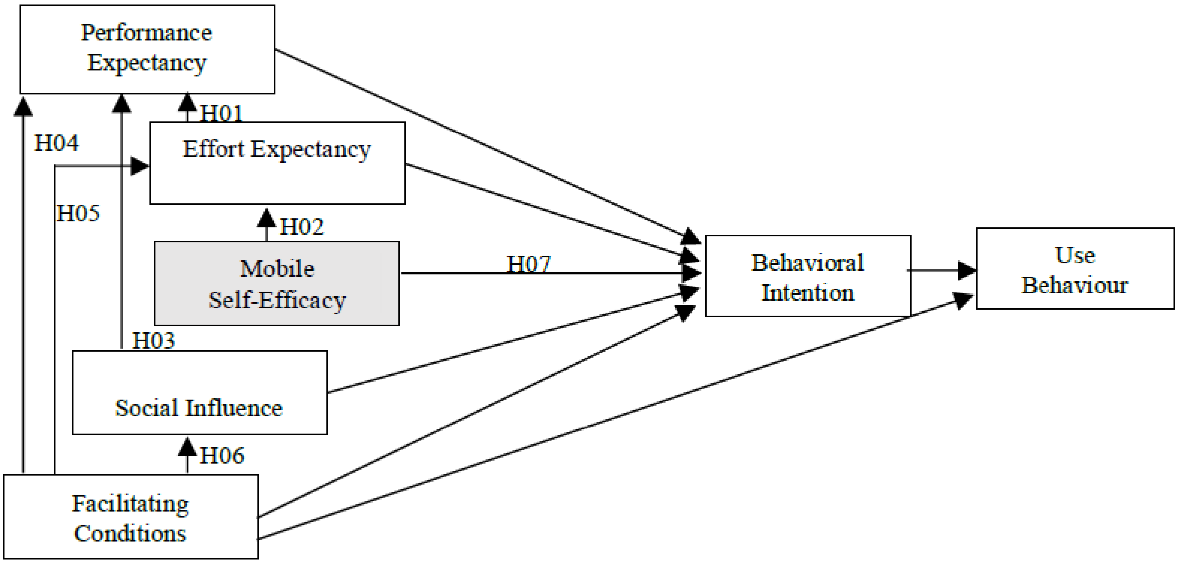

Figure 1. MSENR-UTAUT Model

Source: Adapted from [7]

Materials and Methods

This study employed correlational research design in which structured questionnaires were used to collect primary data from a sample of distance education students. Proportional stratified random sampling technique was employed. The sample consisted of 273 distance education students selected from the Cape Coast study center of the Institute for Distance and e-Learning (IDeL) of the University of Education, Winneba in Ghana. These were pursuing various programs at the diploma, bachelor's degree and post-graduate diploma levels by distance. The sample size was determined based on [15].

Two sections constituted the structure of the questionnaires used for the study. The first section contained 24 statements that measured seven latent constructs required for the study. The constructs are effort expectancy, performance expectancy, social influence, facilitating conditions and mobile self-efficacy, behavioral intention and use behavior. Each statement was accompanied by five-point Likert type scale ranging from strongly disagree as 1 to strongly agree for 5. These solicited students' extent of disagreement or agreement respectively regarding the construct statements. The construct indicator statements were adopted from [6], [16] and [17] and modified to befit the context of the current study. The second part of the questionnaire contained eight items that obtained socio-demographic data about the participants.

The researchers administered the questionnaires by themselves on February 15, February 22, and February 29, 2020. The data analysis involved both descriptive and inferential statistics. SPSS version 25 was used to perform the descriptive statistics which involved frequency counts, percentages, mean and standard deviation. Also, SmartPLS version 3.2.7 [18] was used to perform regression analysis of path coefficients in Partial Least Squares-Structural Equation Modeling (PLS-SEM). All hypotheses were tested at a significance level of 0.05.

Results

Background characteristics of the respondents the participants consisted of 133 (49%) females and 140 (51%) males. Their ages ranged from 20 to 48 years (M = 30.4, SD = 5.03). Age was non-normally distributed, with skewness of 1.32 (SE = 0.15) and kurtosis of 2.02 (SE = 0.29). Distribution of the participants according to academic levels enrolled were 89(33%) Diploma students, 118 (43%) Post-Diploma Bachelor degree students and 66 (24%) Post-Graduate

Diploma students. Other characteristics of the participants are presented in Table 1.

Table 1. Background characteristics of participants

Programme Enrolled	**No. of Students**	**Percentage**
Basic Education	111	40.7
Early Childhood Education	62	22.7
English Language Education	8	2.9
Social Studies Education	12	4.4
Mathematics Education	5	1.8
Accounting	13	4.8
Management	13	4.8
Human Resource Management	16	5.9
1 Year Education	29	10.6
Science Education	4	1.5
Total	273	100
Ownership of WhatsApp-supported Mobile Phone		
No	4	1.5
Yes	269	98.5
Total	273	100.0
Whether students used WhatsApp		
No	1	0.4
Yes	272	99.6
Total	273	100.0
Years of WhatsApp Usage		
less than 1 year	9	3.3
1-3 years	59	21.6
4-6 years	85	31.1
more than 6 years	119	43.6
n/a	1	0.4
Total	273	100.0

Table 1 shows variety of characteristics of the participants. It indicates the programs of study that the participants enrolled in as well as respective numbers and percentages of students in those programs. Also, number of participants who owned WhatsApp-supported mobile phones is indicated as 269 (98.5%) as against 4(1.5%) who did not own any. This shows that WhatsApp-supported mobile phones are common among undergraduate and post-graduate distance education students at the Cape Coast study center of the University of Education, Winneba. Another characteristic of the participants is that 272 (99.6%) indicated that they had been using WhatsApp, with the exception of one person who indicated that he/she had not been using WhatsApp at the time of the study. Lastly, years of WhatsApp usage experience is presented. This indicates that 119 (43.6%) of the participants had been using WhatsApp for more than 6 years whiles 144 (52%) had experience of WhatsApp usage between one and six years inclusive. Only one student indicated no experience in the use of WhatsApp. These characteristics of the participants indicate that they had necessary resources and experience that would equip them to accept and use WhatsApp chat to support their distance learning.

Assessment of the Measurement Model

The reflective measurement models of the research model were assessed by testing the individual indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and item cross loadings as recommended by [19]. Item indicator reliability was assessed using outer loadings of individual measurement items. Internal consistency reliability was assessed using rho_A and composite reliability. Also, convergent validity was assessed using Average Variance Extracted. Finally, discriminant validity was assessed using Heterotrait-Monotrait Ratio (HTMT).

The PLS Algorithm was ran in SmartPLS version 3.2.7 [18] in order to accomplish aforementioned assessments of the measurement model. The outer loadings, reliability and validity estimates of the PLS algorithm are presented in Table 2.

Table 2. Outer loadings, Construct Reliability and Validity of Measurement Model

Construct	Item	Loading	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BI	BI1	0.943	0.926	0.947	0.857
	BI2	0.944			
	BI3	0.888			
EE	EE1	0.872	0.908	0.932	0.773
	EE2	0.919			
	EE3	0.907			
	EE4	0.815			
FC	FC1	0.812	0.874	0.912	0.722
	FC2	0.898			
	FC3	0.829			
	FC4	0.858			
MSE	MSE1	0.885	0.900	0.862	0.677
	MSE2	0.762			
	MSE3	0.818			
PE	PE1	0.779	0.907	0.916	0.732
	PE2	0.943			
	PE3	0.785			
	PE4	0.903			
SI	SI1	0.801	0.736	0.848	0.650
	SI2	0.840			
	SI3	0.777			
UB	UB1	0.930	0.883	0.907	0.767
	UB2	0.955			
	UB3	0.723			

EE, PE, MSE, SI, FC and BI denote effort expectancy, performance expectancy, mobile self-efficacy, social influence, facilitating conditions and behavioral intention respecively.

Table 2 shows that outer loadings of the items in the measurement model ranged from 0.723 (UB3) to 0.955 (UB2). All the outer loadings were greater than 0.708 which is the minimum value recommended by [19] for measurement items to have significant convergent validity. Also, Table 2 reports on internal consistency reliability of the measurement model using composite reliability. This is recommended by [19] as being more robust than the use of Cronbach's alpha. The values of composite reliability ranged from 0.848 (SI) to 0.947 (BI) which were all greater than 0.7 as recommended by [19]. Hence, the composite reliability values indicate that the measurement mode had significant internal consistency reliability. Finally, assessment of convergent validity of the measurement model is reported in Table 2 using Average Variance Extracted (AVE). The minimum recommended value for AVE is 0.5 [19]. Evidently, Table 2 indicates that the AVE values of the model ranged from 0.650 (SI) to 0.857 (BI) which were all greater than the minimum recommended value. The measurement model therefore passed the convergent validity test as well.

The measurement model was again assessed for discriminant validity using Heterotrait-Monontrait (HTMT) ratio as recommended by [20]. The HTMT ratios estimated through the PLS algorithm for the measurement model are presented in Table 3.

Table 3. HTMT Results

	BI	EE	FC	MSE	PE	SI	UB
BI							
EE	0.561						
FC	0.720	0.711					
MSE	0.357	0.764	0.662				
PE	0.658	0.485	0.467	0.220			
SI	0.781	0.457	0.553	0.440	0.704		
UB	0.604	0.617	0.523	0.508	0.411	0.316	

EE, PE, MSE, SI, FC and BI denote effort expectancy, performance expectancy, mobile self-efficacy, social influence, facilitating conditions and behavioral intention respecively

Table 3 shows that HTMT ratios of the constructs in the measurement model ranged from 0.22 to 0.78. All the ratios of HTMT are less than the upper limit value of 0.85 recommended by [20] for a model to have discriminant validity. Thus, the measurement model in this study passed the test for discriminant validity.

Assessment of the Structural Model

Assessment of the structural model is the second stage in the analysis of PLS-SEM. This stage involves tests for collinearity, significance and relevance of path coefficients in the structural model, level of R2 values, effect sizes of f2, predictive relevance (Q2) and q2 effect sizes.

Test for Collinearity

The collinearity of a structural model is assessed using Variance Inflation Factors (VIF) automatically generated by the SmartPLS software during PLS algorithm procedure. The results of inner VIF of the structural model are presented in Table 4.

Table 4. Collinearity (VIF) Statistics

	BI	EE	FC	MSE	PE	SI	UB
BI							1.718
EE	2.503				1.701		
FC	1.994	1.545			1.828	1	1.718
MSE	2.253	1.545					
PE	1.752						
SI	1.665				1.277		
UB							

EE, PE, MSE, SI, FC and BI denote effort expectancy, performance expectancy, mobile self-efficacy, social influence, facilitating conditions and behavioral intention respecively.

As shown in Table 4, each of the values of VIF of the structural model is less than 3.3 which is the maximum recommended value for which the model does not contain common method bias and pathological collinearity [21], [22]. Thus, the VIF values are confirmation that the structural model did not contain common method bias. Significance and relevance of path coefficients.

The bootstrapping procedure in SmartPLS was ran to generate values for assessment of the significance of relationships in the structural model. The bootstrapping procedure involved 5000 subsamples, two-tailed test type and significance level of 0.05 as recommended by [19]. Figure 2 shows a screenshot of the output from the bootstrapping procedure.

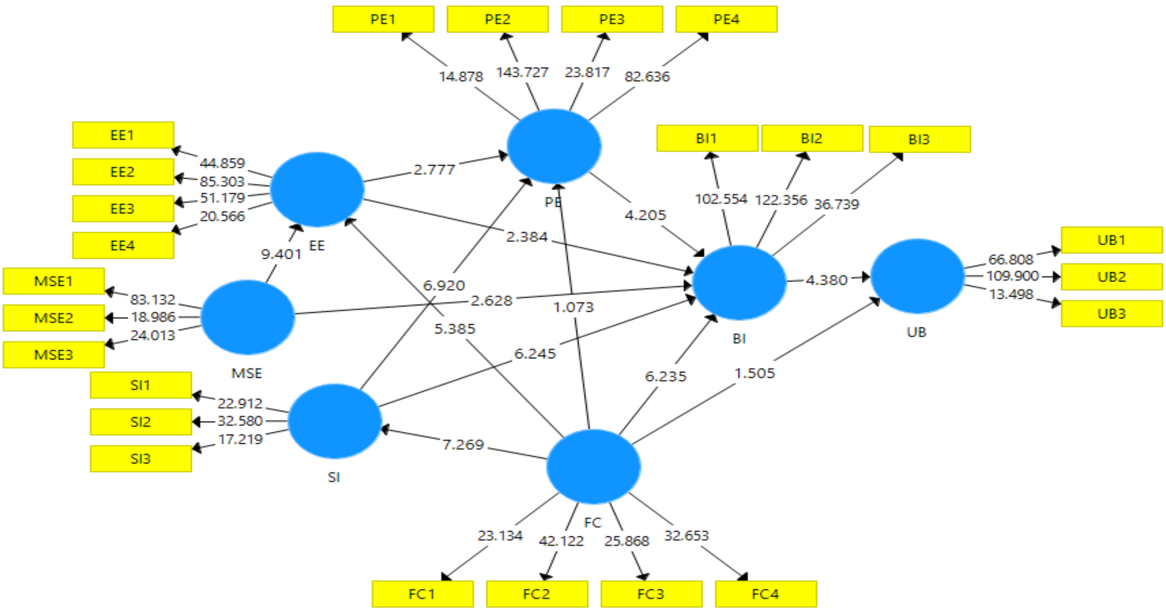

Figure 2. Output of Path Analysis from Bootstrapping procedure

The results obtained from the bootstrapping procedure regarding the hypothesized relationships are presented in Table 5.

Table 5. Results of Path Analysis and Hypothesis testing

Hypo-thesis	**Relationship**	**Std. Beta**	**Std. Error**	**t-value**	**p value**	**f 2**	**Confidence interval**	
							2.5%	**97.5%**
H_{01}	EE -> PE	0.212	0.077	2.777	0.005	0.044	0.058	0.361
H_{02}	MSE -> EE	0.483	0.052	9.401	0.000	0.341	0.374	0.577
H_{03}	SI -> PE	0.454	0.065	6.920	0.000	0.258	0.321	0.578
H_{04}	FC -> PE	0.079	0.074	1.073	0.283	0.006	-0.062	0.228
H_{05}	FC -> EE	0.345	0.064	5.385	0.000	0.173	0.222	0.473
H_{06}	FC -> SI	0.452	0.062	7.269	0.000	0.254	0.323	0.569
H_{07}	MSE -> BI	-0.155	0.060	2.628	0.009	0.030	-0.272	-0.036

EE, PE, MSE, SI, FC and BI denote effort expectancy, performance expectancy, mobile self-efficacy, social influence, facilitating conditions and behavioral intention respectively.

With regards to non-linear relationships hypothesized in the model, the results in Table 5 revealed that five out of the six relationships were significant with the exception of one. Performance Expectancy was significantly predicted by Effort Expectancy ($\beta = 0.212$, $p < 0.01$) and Social Influence ($\beta = 0.454$, $p < 0.01$). Conparison of the f^2 effect sizes of the two predictors indicates that Social Influence proved to be a stronger predictor of Performance Expectancy than Effort Expectancy. This is because the f^2 effect size of social influence (0.258) is greater on performnance expectancy than that of effort expectancy (0.044). However, the prediction of Performance Expectancy by Facilitating Conditions ($\beta = 0.079$, $p > 0.05$) was not significant.

Effort Expectancy was significantly predicted by Mobile Self-Efficacy ($\beta = 0.483$, $p < 0.01$) and Facilitating Conditions ($\beta = 0.345$, $p < 0.01$). Though both predictors had strong positive relationships with Effort Expectancy, the prediction by Mobile Self-Efficacy was stronger than that of Facilitating Conditions as shown by their f 2 effect sizes. In fact, mobile self-efficacy had the greatest effect size than all else in the model.

The last non-linear relationship reported on in Table 5 is the prediction of social influence by facilitating conditions. The results indicated that there was a significant relationship between Social Influence and Facilitating Conditions (β = 0.450, $p < 0.01$). Thus, facilitating conditions significantly predict social influence.

Finally, the only linear relationship hypothesized was that between mobile self-efficacy and behavioral intention. The results in Table 5 further show that mobile self-efficacy (β = -0.155, $p < 0.01$) is a significant predictor of behavioral intention, with their relationship being negative.

Coefficients of determination (R2 values)

Coefficient of determination is a measure of the predictive accuracy of structural model. It shows the estimated combined effect of exogenous variables on each of their related endogenous variable(s). The coefficient of determination estimates the amount of variance in an endogenous variable that is explained by the model. The values of R2 are in the range of 0 and 1 inclusive. The closeness of the value of R2 to 1 indicates the strength of predictive accuracy, and vice versa. The coefficients of determination for the structural model are presented in Table 6.

Table 6. Coefficients of Dermination of endogenous constructs

	R Squared	R Squared Adjusted
BI	0.634	0.627
EE	0.554	0.550
PE	0.382	0.376
SI	0.203	0.200
UB	0.309	0.304

EE, PE, MSE, SI, FC and BI denote effort expectancy, performance expectancy, mobile self-efficacy, social influence, facilitating conditions and behavioral intention respectively.

As shown in Table 6, the model explained about 63% of the variance in behavioral intention and 30% in use behavior. Among the non-linear relationships in the model, effort expectancy had the highest value of R2 (55%). This is evidently the result of the strongest effect size of mobile self-efficacy on the effort expectancy.

Discussion

The finding of significant prediction of performance expectancy by effort expectancy is consistent with [8], and [7]. Davis found that perceived ease of use (effort expectancy) significantly determines perceived usefulness (performance expectancy) in Technology Acceptance Model. Similarly, [7] hypothesized and empirically tested this relationship, and their result indicated existence of significant relationship between effort expectancy and performance expectancy within the UTAUT model. Thus, when potential users perceive the use of a new technology to be effortless, they tend to hope that they could use the technology efficiently to maximize their work performance.

Mobile self-efficacy was found as a significant predictor of effort expectancy. This could be explained that an individual's belief in the extent of his or her own ability to use mobile communication technologies influences how much effort the person perceives the use of a given mobile technology would require. Thus, if an individual believes that he or she has the ability to use mobile devices effectively, he or she would naturally expect that using a new mobile technology would require just a little or no effort from him or her. This finding is consistent with [10]. [10] maintained that at early stages of using a computer technology, a potential user's computer self-efficacy (similar to mobile self-efficacy) determines his or her perceived ease of use (similar to effort expectancy). Thus, the finding of the current study logically fits in existing body of knowledge.

The study also found that social influence significantly predicts performance expectancy. This relationship could be explained that if an individual feels other people who are important to him or her think he or she should use a technology, that individual will eventually have a belief that using the technology will probably bring improvement in job performance. The converse is also true. This finding is consistent with [12] .These authors found in Technology Acceptance Model 2 that subjective norm (similar to social influence) significantly determined perceived usefulness (similar to performance expectancy). Nevertheless, [7] found a contradiction. Their results showed non-significant relationship between social influence and performance expectancy. The contradiction in the finding of this current study to that of [7] could be attributed to the fact that influence of important others is stronger on the participants of the current study because they are students; however, the participants of [7] were tutors and more independent. Hence, the tutors did not care much about the thoughts of important others.

The study found no significant relationship between facilitating conditions and performance expectancy. This finding is consistent with the result reported by [7]. Though their study focused on acceptance of Learning Management System by distance education tutors, they obtained a similar result. The explanation for this finding could be that at an early stage when a new technology is introduced to prospective users, availability of enabling conditions would not necessarily imply the users would perceive use of the technology to result in gains in job performance.

The study also revealed that facilitating conditions significantly determine effort expectancy. This finding is consistent with previous studies [10], [7]. Venkatesh tested the relationship between external control beliefs (similar to facilitating conditions) and perceived ease of use (similar to effort expectancy) using Technology Acceptance Model and found a significant and positive effect of external control beliefs on perceived ease of use. Likewise, [7] used the UTAUT model to test the non-linear relationship between facilitating conditions and effort expectancy, and they concluded that facilitating conditions significantly predict effort expectancy. The significant relationship between facilitating conditions and effort expectancy could be explained that when prospective users of a new technology perceive that the resources and conditions that will make the use of the technology are available, they tend to believe that using the technology will be effortless. Conversely, when a prospective user perceives that necessary resources and conditions for convenient use of a new technology are not available, the user will have the tendency to believe that using the technology will require more effort or even be difficult for him or her.

Again, facilitating conditions were found to significantly predict social influence in this current study. This finding is consistent with that of [7] in their study involving usage of Learning Management System by distance education tutors of a Ghanaian university. This relationship could be explained that during introduction of a new technology to potential users, when conducive environment and resources are available to support utilization of the technology, people who are important to the potential users would have the tendency to encourage the latter to adopt the technology. Hence, the more important others perceive availability of resources and conducive environment to support use of a new technology, the more they encourage potential users to adopt the technology.

The negative significant prediction of behavioral intention by mobile self-efficacy is quite an interesting finding in this study. It is an indication that distance education students who have stronger belief in their own ability to use mobile devices (higher mobile self-efficacy) have lower intention (i.e. are less likely) to accept WhatsApp technology for use in supporting their learning aside from scheduled face-to-face lecture sessions. Conversely, distance education students who have weaker belief in their own ability to use mobile devices (lower mobile self-efficacy) have higher intention (are more likely) to accept WhatsApp technology for use in supporting their learning.

The finding in this study that mobile self-efficacy is a significant negative predictor of behavioral intention is consistent with the findings of some previous studies [10], [6]. In a study to establish determinants of perceived ease of use (effort expectancy) in TAM3, [10] maintained that computer self-efficacy was an indirect predictor of behavioral intention fully mediated by perceived ease of use. That view implies that in the absence of mediating effect of effort expectancy, self-efficacy would not determine behavioral intentions; thus, significance of mobile self-efficacy in predicting behavioral intention is as a result of mediating effect of effort expectancy. Similarly, [6] postulated and empirically confirmed in the UTAUT model that self-efficacy does not have direct significant effect on behavioral intentions. The current study has contributed to the existing knowledge that in the adoption of WhatsApp chat for supporting distance learning, mobile self-efficacy is a significant determinant of behavioral intention of distance education students.

Conclusion

The main aim of the study was to validate non-linear relationships among exogenous constructs of the UTAUT model regarding acceptance of WhatsApp for supporting learning by higher distance education students. Also, a new construct; mobile self-efficacy; was assessed for its significance in predicting behavioral intention. The partial least squares structural equation modeling was used to test hypotheses. The results showed that effort expectancy and social influence are significant predictors of performance expectancy, mobile self-efficacy and facilitating conditions are significant predictors of effort expectancy, and facilitating conditions determine social influence. Mobile self-efficacy was also found to significantly predict behavioral intention for use of WhatsApp as a learning support tool.

Implications for Theory

The findings of the study have theoretical implications. They affirm existence of non-linear relationships among exogenous constructs of the UTAUT model. These non-linear relationships affirmed can be applied to better understand studies involving acceptance of technologies in variety of domains. Furthermore, this study has discovered that in studies involving adoption of mobile technologies, mobile self-efficacy is a significant factor. Therefore, the researchers recommend that in studies involving adoption of mobile technologies, the UTAUT model should be extended to include mobile self-efficacy.

Implications for Practice

The findings of the study have practical implications for faculty and administrators of distance education institutions. The finding that effort expectancy and facilitating conditions predict performance expectancy could be used as the basis to provide necessary resources and training that would make the target learners perceive the use of a novel technology to be easier. This would influence the potential users to perceive that they will be able to use the technology efficiently to maximize their job performance and subsequently be willing to accept the technology.

Limitations of the Study

The study excluded the moderating variables of the original UTAUT model. This eliminated understanding of how interactions between the exogenous and endogenous variables are influenced be the moderating variables.

Recommendations for future research

The researchers recommend that future researches on adoption of WhatsApp for supporting distance learning should include moderating variables such as gender, age and experience. This will hopefully help to understand how the moderators influence the relationships between the exogenous and endogenous variables, and hence extend existing knowledge on this subject.

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