Arab World English Journal
INTERNATIONAL PEER REVIEWED JOURNAL ISSN: 2229-9327
مجلة اللغة الانكليزية في العالم العربي

Arab World English Journal (AWEJ) **Special Issue on CALL Number 5. July 2019** Pp.76 - 97
DOI: https://dx.doi.org/10.24093/awej/call5.7

The Determinants of Use and Acceptance of Mobile Assisted Language Learning: The Case of EFL Students in Morocco

Nabil Morchid
Faculty of Letters and Human Sciences
Ibn Tofail University, Kenitra, Morocco

Abstract

The intent of this paper is to research the factors that determine students' acceptance of mobile assisted language learning (MALL) in Morocco. This study emphasizes the inclusive character of the Unified Theory of Acceptance and Use of Technology (UTAUT). After careful assessment of the multiple relationships within UTAUT, a modified version of the theory was hypothesized then researched for the impact it has on the English as Foreign Language (EFL) context in Morocco. The technology acceptance model in this paper emphasized four directions connecting performance expectancy, effort expectancy, teacher feedback and compatibility to behavioral intention, also referred to as the determinants of behavioral intention to use MALL. For the purpose of this study, a technology enhanced environment was created. A total number of 156 EFL common core students were brought to interact on a WhatsApp-based platform by means of text-messaging. The WhatsApp treatment was optimized to synchronize with the institutionalized character of the teaching of English in Moroccan public schools. The questionnaire method was used for data collection. The data were screened for missingness, normality and outliers. Then, multiple reliability and validity tests were performed to substantiate the legitimacy of the dataset. Structural equation modelling (SEM) was used in the assessment of the measurement model and the structural model. The outputs of structural modelling corroborated the hypothesized directions connecting teacher feedback and compatibility to behavioral intention to use MALL while there was lack of support for the relationships linking performance expectancy and effort expectancy to behavioral intention to use MALL.

Key words: educational technology, English as a foreign language, mobile language learning, Morocco, technology acceptance

Cite as: Morchid, N. (2019). The Determinants of Use and Acceptance of Mobile Assisted Language Learning: The Case of EFL Students in Morocco. *Arab World English Journal (AWEJ) Special Issue on CALL* (5),76 – 97. DOI: https://dx.doi.org/10.24093/awej/call5.7

Introduction

The telecommunication market in Morocco is in constant maturation as an increasing number of Moroccans continue to use and adapt to the emerging technology-empowered means of communication. This orientation towards digital mobile data marks the evolution of a society that is conscious of the legitimacy of digital input. Mobile technology is a promising field of interest that is also replete with many uncertainties, among which is the challenge for sustainability. The offerings of mobile technology need be optimized to synchronize with the fundamentals of education.

The educational discourse in Morocco does not priorities an institutionalized incorporation of educational technology. The implementation of MALL is still obstructed by the scarcity of operational frameworks susceptible to standardize and institutionalize the use of mobile technology for educational purposes. Any prospective implementation of mobile technology in the Moroccan educational context is entitled to belong dependently of valid theoretical framework.

The primary objective of this paper is to investigate the determinants of MALL. This study extends the theoretical frameworks of UTAUT to suit the fundamentals of the language learning discourse in Morocco. In particular, a customized UTAUT model was used in researching acceptance of MALL among EFL students. Data were collected from 156 EFL common core students who were subjected to a WhatsApp-based treatment. The data were screened for missingness, normality and outlier and checked for reliability and validity. SEM was used in the assessment of the measurement theory and the structural theory.

The UTAUT model

The UTAUT model is a synthesis of eight theories of technology use and acceptance: the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model (MM), the Theory of Planned Behavior (TPB), a combined (TBP) and (TAM), the Model of PC Utilization (MPCU), the Innovation Diffusion Theory (IDT), and the Social Cognitive Theory (SCT) (Ventakesh et al., 2003). Indeed, UTAUT offers a theoretically-enhanced research framework in the light of which the determinants of technology use and acceptance are researched in varied contexts.

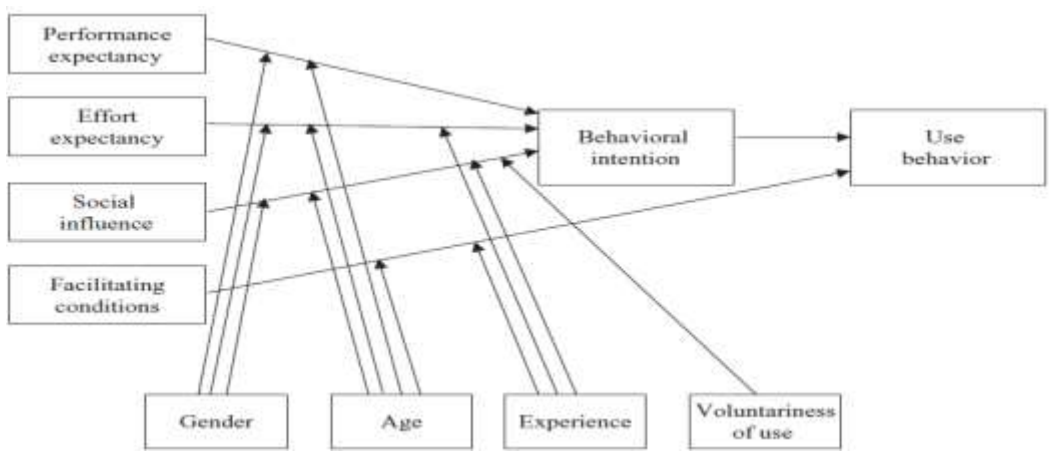

Figure 1. The UTAUT model (Ventakesh et al. 2003, p. 447)

As shown in figure 2, UTAUT is configured to provide for the influence of performance expectancy, effort expectancy, social influence and facilitaing conditions on behavioural intention and use behaviour. Also these connections are moderated by gender, age, experience and voluntariness of use. The fundamental structures of UTAUT are empirically validated and statistically significant.

Most importantly, UTAUT does not only synthesise the research on technology use and acceptance, but it also forwards a creative framework susceptible to identify new patterns of behaviour in different contexts. Many studies used extended versions o UTAUT in researching students' acceptance of mobile mearning. Abu-Al-Aish and Love (2013) modify the initial structures of UTAUT for the purpose of researching the determinants of mobile learning among higher education students. Quality and service together with personal innovativeness are used instead of facilitating conditions. The two constructs are found statistically significant and capable of predicting acceptance of mobile technology. Also in many studies, the UTAUT relationships are not found significant (Barnes & Vidgen, 2009; Cornacchia, Papa, Livi, Nicolo & Bruno, 2008; Jayasingh & EZE, 2009; Pai & Tu, 2011).

Research model

The fundamental structures of UTAUT are not a pure product as they bear the mark and identity of prior research models. Extensibility happens to be a key feature of UTAUT in view of the theory's reliance on a varied range of research orientations in the field of technology use and acceptance. In this vein, Ventakech et al. (2003, p. 471) makes it clear that "future research should focus on identifying constructs that can add to the prediction of intention and behaviour over and above what is already known and understood", and so is the intent of this paper. For the purpose of this study, the internal structures of the UTAUT model are reconfigured and extended to suit the realities of the educational discourse in Morocco. In particular, a customised version of UTAUT is used to research the determinants of language learners' acceptance of Mobile Assisted Language Learning.

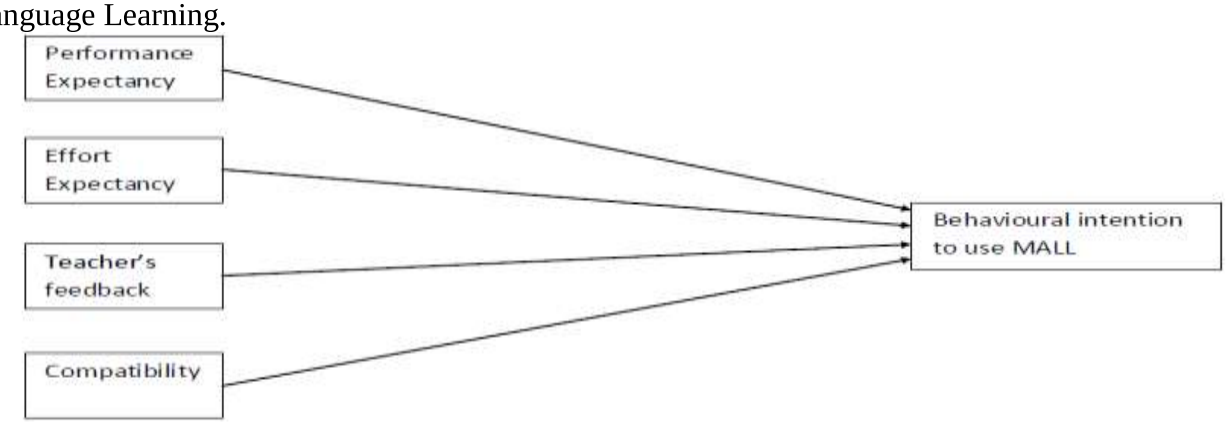

Figure 2. The adopted research model (based on UTAUT by Ventakesh et al., (2003)

As shown in figure 2, the initial structures of UTAUT are modified to synchronize with the intent of this study. Four constructs are researched for the influence they exert on EFL students' behavioral intention to use MALL. In addition to effort expectancy and performance expectancy, two constructs are inserted into original UTAUT: compatibility and teacher's feedback. In this research model, the core determinants of behavioral intention to use MALL are presented as the following:

Performance expectancy is a core determinant of behavioral intention in UTAUT and it is presented as “the degree to which an individual believes that using the system will help him or her to attain gains in job performance” (Fishbein & Ajzen , 1975, p. 447). The performance expectancy construct is theoretically enhanced as it combines the theoretical load of five constructs belonging to prior models and theories of technology use and acceptance, the perceived usefulness construct from TAM, the extrinsic motivation construct from HMIEM, the job fit construct from MPCU, the relative advantage construct from IDT, and the outcome expectations construct from SCT. In this research model, performance expectancy relates to the beliefs learners hold about the susceptibility of mobile learning to boost their performances in language learning contexts.

Effort expectancy is another determinant of intentional and use behavior of technology in the UTAUT model (Ventakesh et al., 2003). The effort expectancy construct arises from the theoretical frameworks of three traditions in the field of technology use and acceptance, the perceived ease of use construct from TAM, the complexity construct from MPCU, and the ease of use construct from IDT. In this modified version of UTAUT, effort expectancy denotes the levels of ease associated with the mobile-based trend in language learning. The accent is placed on learners’ estimations of mobile learning as a less difficult means of learning English.

Teacher feedback is made a core determinant of behavioural intention to use MALL. The teacher feedback construct synchronises with the realities of the educational discourse in general and the language learning context in particular. The legitimacy of teacher feedback as a determining factor in the language learning process could be observed from the lens of a number of studies which are centred on language learners’ responses to teachers’ feedback (Lee,2008; Quinton & Smallbone, 2010). Most importantly, the n teacher feedback construct is not entirely new to the initial structures of UTAUT as it bears resemblances with the source codes within the social influence construct in UTAUT, which is another hybrid determinant in UTAUT in view of its reciprocity with three constructs from prior models and theories of technology use and acceptance, in particular, the subjective norm construct from TRA, the social factors construct from MPCU, and the image construct from IDT. The social influence construct in UTAUT is referred to as the “degree to which an individual perceives that important others believe he or she should use the new system” (Ventakesh et al., 2003, p. 451). Teacher feedback in this research model ensures compatibility with the the social influence construct in UTAUT; still, it concentrates attention on the influence teachers’ feedback has on learners’ inclinations to use MALL.

Compatibility is the fourth determinant of behavioural intention to use MALL in this research model. Compatibility is traced back to the theoretical backgrounds of it is presented as “the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters” (Rogers, 1983, p. 223). The compatibility feature in a newly introduced technology is understood to lower the uncertainties that may obstruct prospective implementation. In this research model, the” compatibility” construct relates to the extent to which the MALL experience synchronizes with learners’ needs and styles of learning.

Hypothesises
The current research model is conceived to emphasize the inclusive character of UTAUT. After critical review of the multiple relationships within the UTAUT model, a series of hypothesizes are formulated to research the patterns of behavioral intention that are true to the mobile-based trend in language learning.
H1: Performance expectancy positively impacts behavioral intention to use MALL.
H2: Teacher's feedback positively impacts behavioral intention to use MALL.
H3: Teacher's feedback positively impacts behavioral intention to use MALL.
H4: Compatibility positively impacts use behavior of MALL.

Population and sampling
The intended population for this research matches the total number of EFL common core students in Morocco. Given the impracticality of research where the entire cases within a population are studied, the researcher must generate a sample that is representative of the target population (Neuman, 2014). The logic of convenience sampling synchronises with the context of this research. The participants in this research correspond to the total number of 156 students who were previously grouped into four intact common core students. The characteristics of the research sample are shown in the figure 3.

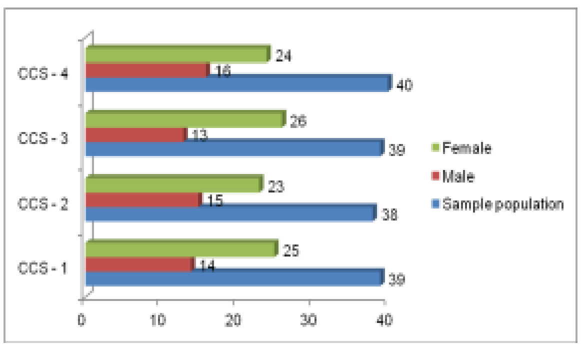

Figure 3. Sample population distribution by gender

The aggregate value of the participants as a collective group is more convenient to this study than the distinct characteristics of students if they are observed separately. This study is carried out with four groups of EFL common core science students who were previously set into four classes. The principles by which students are grouped into classes are statistically considerate of the ratios of age and gender together with the number of students in each class. The students in each class belong as a social group in which each member has equal chances to impact and benefit their community members.

Research site
This research project was carried out with the total number of 156 EFL students belonging to four common core science classes in AlQuds High School in kenitra, Morocco from September 28th, 2017 to January 04th, 2018. The research site of this study affords high levels of reciprocity with the educational landscape in Morocco. It adequately reflects the realities of public schooling in Morocco. The Moroccan Ministry of National Education ensures uniform standards for public school infrastructure. The government commits to provide the fundamentals of institutionalised

education in terms of security, hygiene, water and electricity supply together with operational classrooms for instruction. The margins for innovation are very limited. This is basically due to the administrative hierarchy by way of which all schools in the public sector must harmonise and standardise their infrastructure together with the quality of their education services. Also, the uniform character of institutionalised education in Morocco applies on the same level in both urban and rural areas. For this same reason, public schools in Morocco happen to attract a student population of the same socioeconomic status, basically those who cannot afford the costs of private schools.

Data collection method

The questionnaire method was used for data collection. The intent of this study is to research the factors that influence EFL students' behavioural intention to use MALL. The questionnaire method was needed for the collection of quantitative data that measure the relationships between the constructs under investigation. It should be noted that the questionnaire in this research originated from the fundamental structures of the UTAUT model by Ventakesh et al. (2003) with a few modifications that provided for the inclusion of teacher feedback and compatibility as determinants of behavioural intention to use MALL. In particular, a structured questionnaire with a five-level Likert-scale type was used to enable the statistical analysis of the obtained data. The respondents' knowledge of the English language was thought to be a problem for the full understanding of the contents on the questionnaire. Accordingly, the researcher translated the questionnaire into Arabic.

The WhatsApp treatment

The WhatsApp based treatment in this study was carried out during the first semester of the 2017-2018 school year with a total number of 156 students belonging to four common core science classes, of which 98 are females and 58 are males. Prior to the intervention, all the students were briefed on the intended use of WhatsApp for learning English together with the underlying objectives of the experimentation, which were in harmony with the 2005 Pedagogical Guidelines. The teacher made sure all students could afford to send and receive WhatsApp messages from a portable device. Then, students were given instructions on how to use the WhatsApp platform to submit and receive feedback about their homework assignments. It should be noted that the WhatsApp-based homework did not exclude traditional pen-and-paper homework. The EFL time for common core science students includes three hours per week. The teacher and students met three times a week for three classes of one hour. In the first two classes, students received paper-and-pen homework. It was in the third class which was also the last class of the week that students obtained the WhatsApp-based home assignment. The WhatsApp treatment was set for the closing class of each week to give students sufficient time for the completion of their tasks, knowing that a few students did not have permanent access to mobile devices with Internet connection as they had to be home to honour their duties. Teacher's feedback was achieved in two ways. The teacher shared on the WhatsApp group personalised statements by way of recognition for all the contributors' efforts regardless of the quality of their outputs. The second form of feedback was in class; also, it was content oriented. The teacher noted on the board distinct examples of students' contributions to the WhatsApp group and called for whole-class appreciations of the displayed assignments. In so doing, students would monitor their own improvement in the light of the targeted standards.

Data screening

Prior to data analysis, data screening was carried out to inspect the data for potential inaccuracies, susceptible to interfere with the data analysis procedures. In particular, the data were screened for missingness, normality and outliers.

Missing data

Missing data constitute a sensitive issue when dealing with numeric data (Schlomer & Bauman, 2015). The respondents fail to complete a questionnaire or any instrument for data collection for a number of reasons, ranging from lack of motivation to inherent mediocrity in the instrument of data collection. Given the impossibility to ensure total reciprocity between value variables and their response items, researchers are confronted with the need to reproduce the validity of their dataset. Neuman (2014) identifies three types of missing data: missing completely at random (MCAR), missing at random (MAR) and not missing at random. MCAR remains the least consequential type of missing data. In the case of MCAR, the odds for nonresponse belong independently of any other variables in the data set. Cases presented with missing data can be discarded without causing any statistical bias. In MAR, a case of non-response is automated by other discernible variables in the dataset. For example, in true-experimental design all the participants belonging to the treatment group fail to provide a response for a distinct value variable in relation to the treatment. This case of non-response is conditioned by external variables. NMAR is the most consequential form of missing data. For example, in a questionnaire survey, the respondents fail to provide an answer for a value variable on personality traits because they are too introvert to do it. In this case, missingness is the function of the value variable. Given the impossibility to control the probability for non-response, researchers are bound to choose among a number of missing data methods to restore validity to the statistical analyses in their study (Neuman, 2014). Basically, two approaches are adopted in dealing with missing data: deletion Vs Imputation. Deletion methods simply omit the data with missing value variables while imputation methods depend on statistical protocols to substitute the missing data.

In this study, of 156 questionnaires, 155 were duly completed while one questionnaire was presented with a no-response item for the gender variable. This pattern of missing data was diagnosed as a MCAR because it belonged independently of the other variables in the questionnaire. Also, it was easy to supply the response for the missing variable with maximum likelihood. The questionnaire with missing data was collected from common core science 4, in which there were 24 females and 16 males. After computing the number of questionnaires for that group, 24 questionnaires were found with a female designation for the gender variable while only 15 Questionnaires were presented with a “male” response. Eventually, it was concluded that the missing response item for the value variable on gender corresponded to “male”.

Normality

Normality is the process by which the distribution of data is checked for the purpose of corroborating the validity of dataset (Ghasemi & Zahediasl, 2012). Any assumption about the normal distribution of data needs to convert into finite statistical analyses. The current study deployed a numeric method for assessing normality. The values of kurtosis and skewness were computed. . Skewness interrogates the horizontal proportion of data while kurtosis is a vertical estimation of data. The normality test in this research was carried out by dividing the values of skewness and kiurtosis by their respective standard errors for the purpose of obtaining a z-score for both Kurtosis and skewness. In this vein, Kim (2013) specifies that the z-scores for skewness and kurtosis are fixed at minus or plus 3.29 in sample sizes of 50 to 300.

Table 1. *Results for the statistical estimation of skewness and kurtos*

Variable	Mean	Skewness	Std. Error of Skewness	Skewness z-value	Kurtosis	Std. Error of Kurtosis	Kurtosis z-value
Performance Expectancy							
PE1	4 ,48	-, 500	,194	**-2,577**	,299	,386	**0,774**
PE2	3,83	-,635	,194	**-3,273**	,454	,386	**1,176**
PE3	4,06	-,622	,194	**-3,206**	,297	,386	**0,772**
PE4	3,96	-,362	, 194	**-1,865**	-,463	,386	**-1,199**
Effort Expectancy							
EE1	4,43	-,533	,194	**-2,747**	-,610	,386	**1,580**
EE2	4,29	-,416	,194	**-2,144**	-,782	,386	**-2,025**
EE3	4,38	-,629	,194	**-3,242**	-,673	,386	**-1,743**
EE4	4,37	-,587	,194	**-3,02**	-,670	,386	**-1,735**
Teacher Feedback							
TF1	4,37	-,591	,194	**-3,046**	-,695	,386	**-1,800**
TF2	4,35	-,553	,194	**-2,850**	-,712	,386	**-1,844**
Compatibility							
C1	4,16	-,630	,194	**-3,247**	-,010	,386	**0,025**
C2	4,11	-,623	,194	**-3,211**	,145	,386	**0,375**
C3	4 ,06	-,591	,194	**-3,046**	-,206	,386	**0,533**
Behavioural Intention							
BI1	4,32	-,552	,194	**-2,690**	-,862	,386	**-2,233**
BI2	4,33	-569	,194	**-2,932**	-,856	,386	**-2,217**
BI3	4,30	-,557	,194	**-2,871**	-1,018	,386	**-2,637**

With the acceptable range of skewness and kurtosis being fixed at minus or plus 3.29, all the indicator values were within the acceptable degrees of freedom. Eventually, there was empirical evidence of the normal distribution of data.

Outliers

Outliers interfere with the overall accuracy of data. They appear in the form of anomalous observation points in the distribution of data (Hawkins, 1980). Outliers are suggestive of extreme response patterns in the dataset and they convert into erroneous statistical analyses. In particular, outliers subdivide into: univariate outliers and multivariate outliers. Univariate outliers cause disconformities in a single variable while multivariate outliers operate on different structures to cause instances of deviation that negatively affect the dataset. In this study, Tukey's method, also referred to as the boxplot method, was used for the detection of univariate outliers (Tukey, 1977;

Rocke & Woodruff, 1996; Hoagling & Iglewicz, 1987). The following steps were followed throughout the application of Tukey's method:

- Step 1: Using IBM Statistics SPSS version 25, the researcher subjected the independent variables to descriptive statistics for the purpose of displaying the percentiles in the data.
- Step 2: The researcher identified the lower quartile (Q1) which corresponded to the 25th percentile together with the upper quartile (Q3) which corresponded to the 75th percentile.
- Step 3: the difference between the upper quartile and the lower quartile was calculated and multiplied by the *k* factor that equals 2.2 (Hoagling & Iglewicz, 1987).
- Step 4: The sum from the above formula was added to the upper and lower quartiles for the purpose of obtaining the acceptable limits for extreme values at both ends of the data distribution.
- Step 5: All variables with extreme values that exceeded the obtained interval limits were labelled as univariate outliers.

Table 2 provides an overview of the statistical analysis used for detecting univariate outliers by which the absence of univariate outliers was corroborated.

Table 2. *Assessment of univariate outliers*

Variable	Q1	Q3	K-distance	Minimum limit	Maximum limit	Outlier
Performance Expectancy						
PE1	4	5	2,2	1,8	7,2	**0**
PE2	3	4	2,2	0,8	6,2	**0**
PE3	4	5	2,2	1,8	7,2	**0**
PE4	3	5	4,2	0,8	7,2	**0**
Effort Expectancy						
EE1	4	5	2,2	1,8	7,2	**0**
EE2	4	5	2,2	1,8	7,2	**0**
EE3	4	5	2,2	1,8	7,2	**0**
EE4	4	5	,2,2	1,8	7,2	**0**
Teacher Feedback						
TF1	4	5	2,2	1,8	7,2	**0**
TF2	4	5	2,2	1,8	7,2	**0**
Compatibility						
C1	4	5	2,2	1,8	7,2	**0**
C2	4	5	2,2	1,8	7,2	**0**
C3	4	5	2,2	1,8	7,2	**0**
Behavioural Intention						
BI1	4	5	2,2	1,8	7,2	**0**
BI2	4	5	2,2	1,8	7,2	**0**
BI3	4	5	2,2	1,8	7,2	**0**

The Mahalanobis distance was computed for detecting multivariate outliers (Tabarchnick & Fidell, 2001; Filzmoser, 2004). The Mahalanobis method deploys statistical analyses to identify anomalous observation points throughout the research data. In particular, the method calculates the statistical distance separating the data points for the purpose of identifying extreme values that are visually detached from the centre of the data. In this study, with the help of IBM Statistics SPSS version 25, the Mahalanobis distance for all the independent variables was computed using linear regression estimates. Then, the value variables for the Mahalanobis distance were inspected for the Chi Square distribution. Specifically, the values obtained for the Mahalanobis distance were divided by the number of the research variables, also referred to as degrees of freedom. All cases with values less than 0,001 had to be labelled as multivariate outliers. The outputs of the statistical analyses of the Mahalanobis distance demonstrated the absence of multivariate outliers. The frequencies for the Mahalanobis distance are presented in table 2.

Table 3. *Frequencies of the Mahalanobis distance for the study variables.*

		Mahalanobis Distance	MD_Probability
N	Valid	156	156
	Missing	0	0
Mean		14,9038462	,56806034
Median		14,1619421	,58665653
Mode		3,15286[a]	,001257[a]
Minimum		3,15286	,001257
Maximum		38,56292	,999764
Sum		2325,00000	88,617413

Reliability

Reliability is an important dimension from where to substantiate the legitimacy of scale measurement. Sekaran (2003) posits that “the reliability of a measure indicates the extent to which it is without bias (error free) and hence ensures consistent measurement across time and across the various items in the instrument”(p.203). Reliability informs on the quality of the instrument and its ability to generate satisfactory results.

In this study, Cronbach’s coefficient alpha and item-total correlation were used as ameasures of reliability. The alpha coefficient is a legitimate index of reliability for scales with multiple items and so is the scale measurement in this study (Zikmund, Babin, Carr & Griffin, 2013). On a scale of zero to one, where one means inexistent inter-item consistency and one means absolute inter-item consistency, the acceptable score for a an alpha value is 0,7 (Nunnally, 1978). Item-total correlation is another statistical analysis by which the aggregate value of a scale is computed for its correlation with individual items (Hair et al., 2006). By investigating the levels of correlation in each construct, we get to know the level homogeneity in the measurement scales. In this regard, scores for item-total correlation that are above 0, 3 are suggestive of good inter-item consistency (Cristobal et al., 2007). The values obtained for Cronbach’s coefficient alpha and item-total correlation are displayed in table 3.

In parallel with Cronbach's coefficient alpha, item-total correlation was computed to investigate the consistency of the measures.

Table 4. *Results for Cronbach's coefficient alpha and item-total correlation*

Constructs	**Number of items**	**Chronbach's alpha**	**Item-total correlation**			
Performance expectancy	4	0,705	PE1	PE2	PE3	PE4
			0,320	0,549	0,588	0,526
Effort expectancy	4	0,730	EE1	EE2	EE3	EE4
			0,376	0,490	0,675	0,554
Teacher feedback	2	0,923	TF1	TF2		
			0,857	0,857		
Compatibility	3	0,910	C1	C2	C3	
			0,702	0,909	0,864	
Behavioural intention	3	0,844	BI1	BI2	BI3	
			0,676	0,778	0,678	

As shown above, all the alphas were up to a level that is clearly above 0,7. Also, there was evidence of inter-item consistency. The two reliability tests substantiated the consistency of the measures.

Validity

In the context of measurement, validity lends itself to different paths of logic. In this study, both content validity and construct validity were considered to assess the accuracy of the measures (Zikmund et al., 2013).

Content validity

Content validity designates the levels of reciprocity between a measure and the construct under investigation (Sekaran, 2003). The obligation of a measure to contain the theoretical load of a single concept is vital to the overall validity of the measurement device. The measurement device in this study was based on the questionnaire developed by Ventakesh et al. (2003). The constructs being investigated together with their operational definitions and scales were developed from previously tested research models. Also, the validity of the questionnaire was further checked by means of a focus group method. Together with the researcher, a panel of three doctoral candidates took part in the assessment of the measurement device. The purpose of the focus group method was to identify inaccuracies in the questionnaire, among which the lack of agreement between the scale items and the target items. In a later stage, the content validity of the questionnaire was checked by means of a pilot study. In particular, the Arabic version of the questionnaire was personally administered to a group of thirty-one secondary baccalaureate students in order to assess the clarity of the measurement items. The outputs of the focus group and the pilot study brought minor changes to the Arabic translation of the questionnaire.

Construct validity

Construct validity informs about the levels of agreement between the outputs of a measurement tool and the theoretical framework on which the measurement tool is set (Sekaran, 2003). In this study, factor analysis (FA) was carried out in the assessment of the validity of measurement. FA is a multivariate technique that specifies the relationships among variables (Hair et al., 2006). In particular, FA analysis lends itself to two statistical paths of analysis. One is exploratory while the other is confirmatory. In this study, the assessment of construct validity is carried out by both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

Exploratory factor analysis

Exploratory factor analysis (EFA) specifies the relationships among variables without referring to previously established structures or theories (Loewen & Gonulal, 2015). With the help of IBM Statistics SPSS version 25, all the measurement scales in this research model were subjected to principal component analysis with direct oblique rotation for the purpose of computing the correlation matrix together with KMO and Bartlett’s test for the scales under investigation.

Table 5. *Correlation coefficient matrix for the study variables*

Measurement scales	**Items**				
Performance Expectancy		**PE1**	**PE2**	**PE3**	**PE4**
	PE1	1,000	0,239	0,323	0,233
	PE2	0,239	1,000	0,323	0, 469
	PE3	0,323	0,494	1,000	0,467
	PE4	0,223	0,469	0,467	1,000
Effort Expectancy		**EE1**	**EE2**	**EE3**	**EE4**
	EE1	1,000	0,329	0, 328	0,259
	EE2	0,329	1,000	0,483	0,336
	EE3	0,328	0,483	1,000	0,662
	EE4	0,259	0,336	0,662	1,000
Teacher feedback		**TF1**	**TF2**		
	TF1	1,000	0,857		
	TF2	0,857	1,000		
Compatibility		**C1**	**C2**	**C3**	
	C1	1,000	0,717	0,666	
	C2	0,717	1,000	0,934	
	C3	0,666	0,934	1,000	
Behavioural Intention		**BI1**	**BI2**	**BI3**	
	BI1	1,000	0,687	0,558	
	BI2	0,687	1,0000	0,687	
	BI3	0,558	0,687	1,000	

In general terms, a negative coefficient value gives evidence of collinearity while a coefficient value that is above 1 is suggestive of multicollinearity. In the case of collineartiy, the items are rejected because they are unrelated to one another and they cannot measure the same construct. Also, multicolllinearity reports excessive correlation between one or more items in a measurement scale. Measurement items that are identical cannot be retained because they happen to measure the same thing the correlation matrix for the measurement scales produced satisfactory results. There was no evidence of collinearity or multicollinearity in the dataset. All the correlation

ISSN: 2229-9327

coefficients were positive and below 1,000. The measurement scales used in this study accounted for statistically valid degrees of correlation.

Table 6. *KMO and Bartlett's Test for the study constructs*

Measurement scales	KMO and Bartlett's Test		
Performance Expectancy	Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**,726**
	Bartlett's Test of Sphericity	Approx. Chi-Square	**114,619**
		df	**6**
		Sig.	**,000**
Effort Expectancy	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,671
	Bartlett's Test of Sphericity	Approx. Chi-Square	**153,473**
		Df	**6**
		Sig.	**,000**
Teacher Feedbak	Kaiser-Meyer-Olkin Measure of Sampling Adequacy**.**		**,500**
	Bartlett's Test of Sphericity	Approx. Chi-Square	**203,643**
		Df	**1**
		Sig.	**,000**
Compatibility	Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**, 671**
	Bartlett's Test of Sphericity	Approx. Chi-Square	**425,877**
		Df	**3**
		Sig.	**,000**
Behavioural Intention	Kaiser-Meyer-Olkin Measure of Sampling Adequacy		,702
	Bartlett's Test of Sphericity	Approx. Chi-Square	199,510
		Df	3
		Sig.	,000

The KMO test and Barlett's Test of Spherecity were performed to further assess compatibility of the data with factor analysis. The KMO test is presented as a measure of sampling adequacy (Hair et al., 2006). It reveals the levels of covariance among the items that combine into a measurement scale. the minimum acceptable value for KMO is 0, 5 (Kaiser & Rice, 1974). As shown in table 5, the outputs of the KMO test did not cross the demarcation line for sampling adequacy. With the exception of performance expectancy whose KMO was fairly acceptable, all the measurement scales were presented with KMO values that are greater than 0, 5. In parallel, Barlett's Test of Spherecity was performed to further assess the covariance of the study items in the correlation matrix (Tobias & Carlson, 1969). Barlett's Test of Spherecity displays the degrees of homogeneity between the study items in order to determine the compatibility of the data with factor analysis. For instance, in a data set where the covariance between items is symmetric, factor analysis cannot be performed because the data is statistically insensitive to factor loading. Ebentually, for Barlett's test to be significant, it must be above 0,001. Table 5 displays the test's chi-square values, which were all considerably superior to the critical limits for Spherecity.

Confirmatory factor analysis

CFA interrogates the reciprocity between a research model and the source theory by which the model is conceived; also, CFC is used to substantiate the legitimacy and practicality of the measurement theory (Hair et al., 2006). Most importantly, CFA is a valid index of convergent validity and discriminant validity, which are the core constituents of construct validity. In this study, CFA was used for the estimation of convergent validity and discriminant validity.

Convergent validity

Convergent validity assesses the degrees of correlation among variables that are intended to measure the same construct. Indeed, convergent validity is a prerequisite for attaining construct validity (Sekaran, 2003; Zikmund et al., 2013). Average Variance Extracted (AVE) was calculated for sustaining convergent validity. Indeed, AVE is valid estimate of convergent validity as it determines the levels of variance in a distinct construct by estimating the standards errors obtained for the same construct. AVE deploys factorial loadings to corroborate the accuracy of the measurement model where the latent variables in each construct must belong together, manifesting acceptable amounts of variance. In this study, the values for AVE were manually calculated by dividing the sum of the squared factor loading by the degrees of freedom in each construct. It should be noted that an acceptable value for AVE equals 0.5 while higher values give more evidence of convergent validity (Hair et al., 2006).

Table 7. *AVE and composite reliability for the study variables*

Construct	Average Variance Extracted	Composite Reliability
Performance Expectancy	0,498	0,796
Effort Expectancy	0,510	0,795
Teacher Feedback	0,889	0,941
Compatibility	0,792	0,919
Behavioural Intention	0,704	0,876

As shown in table 7, with the exception of performance expectancy, all the constructs were presented with AVE values that were above 0.5. The AVE for performance expectancy is 0.498. It is only 0.002 below the bottom line for AVE. Here, it is worth mentioning that an AVE value of 0.4 is accepted when it combines composite reliability that exceeds 0.6. That was the case for performance expectancy, which has a composite reliability that equals 0.796.

Discriminant validity

Discriminant validity interrogates the organic unity by which a construct could be distinguished and valued for its unique contributions to the measurement model where it belongs. The items in a measurement model must load highly on their respective constructs. Their degrees of correlation must exceed any possible correlations with any other constructs other than theirs. In this research, discriminant validity was assessed by comparing the values for AVE with the squared root estimates of correlation among the study constructs (Hair et al., 2006).

Table 8. *Confirmatory-based estimation of discriminant validity*

Construct	1	2	3	4	5
1 Performance Expectancy	**0,498**				
2 Effort Expectancy	0,208	**0,510**			
3 Teacher Feedback	0,146	0,139	**0,889**		
4 Compatibility	0,048	0,086	0,085	**0,792**	
5 Behavioural Intention	0,051	-0,007	0,166	0,384	**0,704**

The values in bold in the main diagonal are the values of AVE. The other entries are the inter-item correlations.

As shown in table 8, the AVE values exceeded the average inter-item correlation for all the study constructs. Hence, there was evidence of discriminant validity. All the items related highly to their measurement scales, featuring distinct attributes that accentuated the unique character of the constructs under investigation.

Assessment of the measurement model

A measurement theory differs from a structural theory (Hair et al., 2006). A measurement model, also referred to as measurement theory or a causal theory, determines the scope of correlation and covariance between the measurement items and the factors they load on. A measurement theory is set to assess the reliability and validity of the measurement scales, and this is where EFA and CFA are most needed. The assessment of the measurement theory in this research is carried out by using the goodness-of-fit test (*ibid*). The statistical analyses used in this research are displayed below:

- Degree of freedom (*df*) test
- Chi-square (CMIN/*df*) test
- Comparative fit index (CFI)
- The goodness-of-fit index (GFI)

ISSN: 2229-9327

- Tucker-Lewis index (TLI)
- Incremental-fit index (IFI)
- Root Mean Square Error of Approximation (RMSEA)

Using AMOS, a measurement model was drawn to determine the relationships between the latent variables and the observed variables together with the covariance of the constructs under investigation. The measurement theory in this research is graphically represented in figure 4. Also, the outputs of the measurement model are optimised to illustrate the goodness of fit indices.

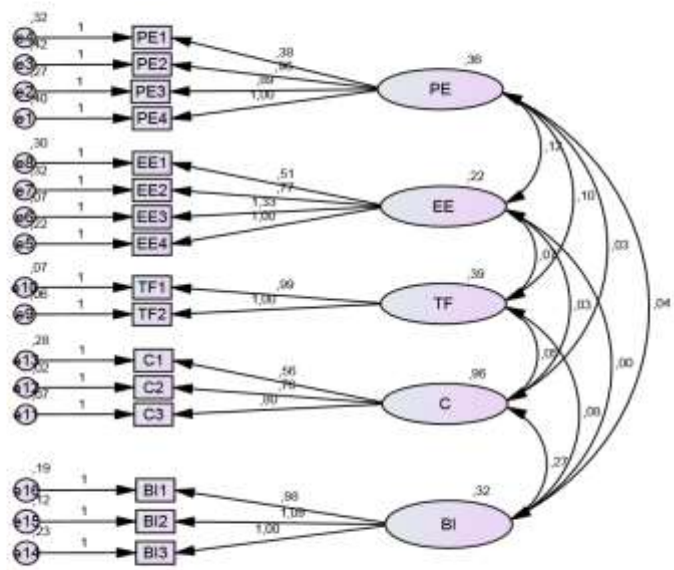

Figure 4. The measurement model

Table 9: *Goodness-of-fit results*

Goodness of fit indices	Measurement results	Requirement
df	94	> 0
df/ X^2	1,56	< 3
CFI	0,95	> 0.90
GFI	0,90	> 0.90
IFI	0,95	> 0.90
TLI	0,94	> 0.90
RMSEA	0,06	< 0.08

As noted in table 6, all the goodness of fit indices are satisfactory. The value for the *df*/ X^2 is reasonable and it corroborates the kurtosis estimates of normality displayed earlier in this study in the data screening section. Indeed, the *df*/ X^2 does not only sustain the goodness-of-fit of the measurement theory, but it also substantiates the normal distribution of the data. In parallel, The CFI value indicates an acceptable range of model fit. CFI measures higher than 0.95 support the legitimacy of the data in relation to the hypothesised model. The GFI value in this model equals the bottom line of reasonable model fit and it emphasises the consistency of the measurement model with the covariance matrix. TLI measures the model fit against the null hypothesis; also, it reports on the degrees of correlation between variables. The TLI measure in model is situated above 0.90, which is suggestive of a satisfactory correlation average between the study variables. IFI is presented as a continuum for assessing the model fit, in which 0 designates total absence of fit while 1 designates maximum estimation of fit. The IFI value in this model demonstrates high-level fitting attributes as it reaches a value of 0.94. RMSEA is a goodness of fit measure that interrogates the parameters of the measurement model against the covariance of the population. The RMSEA in this model falls below 0.08, which is below the upper limit of good fit.

The structural model

A structural model belongs dependently of a previously validated theory. While a measurement theory tests the relationships between the measurement items and the factors they load on, a structural model probes into the causal relationships between the dependent variables and the independent ones. In a structural model, a different kind of analysis is carried out. Path analysis is definitely the most important particularity of structural modelling. It deploys different levels of regression analysis to reveal all itineraries of causation in a structural model. In parallel, structural modelling enables a different kind of validity that is embedded in the nomological connections between the constructs under investigation (Anderson & Gzebing, 1988). It interrogates the feasibility of the hypothesised associations among the constructs of study. The nomological validity of the structural model in this study was evaluated by inspecting the standardised path coefficients. . For the standardised path coefficients to be accurate, they must have a p-value that is less than 0.05 together with a critical ratio of more than 2. The p-value is a reverse estimation of the structural model. It tests the accuracy of the model against the null hypothesis. P-value increases in parallel with the potential inaccuracies in that might interfere with the assumed relationships in the structural model. The t-ration further corroborates the statistical incoherencies in the model.

Table 10. *Structural estimation of the research model*

H	Paths		Estimates (β)	S.E	C.R (T-value)	P	Hypothesis testing
H1	**BI**	**PE**	**,069**	**,086**	**,802**	**,423**	**Not supported**
H2	**BI**	**EE**	**,106**	**,896**	**1,106**	**,269**	**Not supported**
H3	**BI**	**TF**	**,152**	**,074**	**2,040**	**,041**	**Supported**
H4	**BI**	**C**	**,334**	**,059**	**5,624**	*******	**supported**

In the light of the structural estimation of the model, H3 and H4 were supported and there was lack of support for H1 and H2.The outputs of structural modelling revealed that the direction from performance expectancy to behavioural intention was not statistically significant. The significance level for the nomological connection between the two constructs was exceeded (T/CR= 0.82; p= 0.42). Simultaneously, the effort expectancy dimension failed to predict BI (T/CR= 1.10; p= 0.26). On the other hand, the hypothesised connections in H2 and H3 were statistically significant. The path from teacher feedback to behavioural intention sustained statistical support for H1. Also, compatibility was found to have a direct impact on behavioural intention.

ISSN: 2229-9327

Discussion

The current research model emphasises the inclusive character of the UTAUT model. As noted in the research design chapter, the UTAUT model offers a theoretically enhanced framework by which the determinants of technology acceptance could be researched in different contexts. After careful assessment of the multiple relationships within UTAUT, a modified version of the model was hypothesised then validated to suit the educational discourse in general and the EFL context in particular. The technology acceptance model in this research emphasises four directions connecting performance expectancy, effort expectancy, teacher feedback and compatibility to behavioural intention, also referred to as the determinants of behavioural intention to use MALL.

Performance expectancy

The relationship between performance expectancy and behavioural intention is not exclusive to the current research model. It is an established tradition in the technology use and acceptance field of research. In this study, the hypothesised relationship between performance expectancy and behavioural intention is not supported (T/CR= 0.82; p= 0.42). Also, it is inconsistent with original UTAUT where performance expectancy successfully predicts behavioural intention. The lack of support for performance expectancy and behavioural intention agency has been witnessed in many modified and unmodified applications of the UTAUT model (Barnes & Vidgen, 2009; Cornacchia, Papa, Livi, Nicolo & Bruno, 2008; Jayasingh & EZE, 2009; Pai & Tu, 2011). The lack of correlation between the two constructs does not signal a statistical inaccuracy or any other incoherencies in the structural model. Instead, it emphasises the evolving character of the UTAUT model, which is the consequence of the increasing number of technologies that are introduced and used in different environments. The poor linkage between performance expectancy and behavioural intention is the function of both the technology being assessed and the users. The fact is that we cannot expect all forms of technology to have the same effect on a uniform population of users. This would be a simplistic approach to technology use and acceptance. The same technology could activate divergent itineraries of acceptance because of many factors that are intrinsic and extrinsic to the technology in question. The intrinsic factors relate to capabilities of the technology while the extrinsic factors designate the users' perceptions of the technology. The offerings of a distinct technology might be perceived differently by users who have different backgrounds and who depend on the technology for different purposes as well. The technology acceptance model in this research is designed to synchronise with the fundamentals of the teaching of English as a foreign language in Moroccan public high schools. An explanation for the poor linkage between performance expectancy and behavioural intention must emphasise the institutionalised character of the technology treatment. Knowing that there is no institutionalised incorporation of technology in Moroccan public schools, students may not have had enough experience with educational technology to be sure about the impact it has on academic activities.

Effort expectancy

The outputs of structural modelling revealed poor linkage between effort expectancy and behavioural intention (T/CR= 1.10; p= 0.26). The lack of support for effort expectancy as a determinant of behavioural intention is not exclusive to this research model. In many implementations of UTAUT, the relationship between effort expectancy and behavioural intention does not meet the requirements for a statistically significant equation (Holzmann, Schwarz, & Audretsch, 2018; Thomas, Singh & Gaffar, 2013; ŠUmak, HeričKo, & PušNik, 2011; Bekkering

& Hutchison, 2009). All these studies are centred on an educational technology or system. They all depart from the theoretical basis of UTAUT to produce personalised technology acceptance models that are simultaneously statistically significant and true to the context of implementation. The lack of support for effort expectancy in these models does not fully represent the theoretical landscape for educational technology in general and mobile learning in particular. Contradictory findings are indispensable resources for the upgrade of the existing knowledge on technology use and acceptance. The technological trend in education is much wider. An increasing number of studies are conducted for the purpose of activating new perspectives from where to conceptualise a valid integration of technology in education.

Teacher feedback

In this technology acceptance model, teacher feedback is core determinant of MALL. The effect of teacher feedback on behavioural intention to use MALL is this research model's contribution to the theoretical basis of UTAUT. It is evident that the teacher feedback construct suits the context of this research. It is optimised to synchronise with the realities of the educational discourse. The legitimacy of teacher feedback as a predictor of behavioural intention to use WhatsApp-based language learning is well established in the literature on language learning. In many studies, teachers' feedback is exposed and researched for the positive effect it has on students' performances (Lee, 2008; Quinton & Smallbone, 2010). Also, there is evidence for the legitimacy of teacher feedback in the technology use and acceptance field of research. Teacher feedback relates to the "social influence" construct in UTAUT, which is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Ventakesh et al., 2003, p. 451). Both constructs emphasise the influence of others on use behaviour. Teacher feedback is well suited to the context of language learning because it delimits the wide scope of social influences by means of exclusive emphasis on students' perceptions of the feedback from teachers. In this study, the effect of teacher feedback on behavioural intention is statistically significant (T/CR= 2,040; p=, 041). The fact is that the e-learning context has particularities which must be considered in any conceptual model for technology use and acceptance. The significance of teacher feedback as a predictor of behavioural intention to use MALL is well observed from the lens of the Diffusion of Innovation Theory (Rogers, 1983). Use and acceptance of a technology require the users to go through a five-stage innovation decision process: the knowledge stage, the persuasion stage, the decision stage, the implementation stage and the confirmation stage. In the knowledge stage, the user mentally recognises the capabilities of the innovation. The persuasion stage designates the feedback the individual has about the merits of the innovation. In the decision phase, the user explicitly rejects or endorses the use of the innovation. The implementation stage concretises the behavioural use of the technology. In the confirmation stage, the user seeks endorsement and reinforcement for prospective use of the innovation. In the context of this research, the WhatsApp-based treatment is an innovation that requires the students to go through the innovation decision process. Throughout the whole process, teacher's feedback is essential and consequential because it facilitates the transition from one stage to the other. The feedback of the teacher is well positioned to expose the merits of technology-enhanced language learning. Also, the intervention of the teacher in the adoption process helps clear the uncertainties associated with a user-unfriendly innovation. The odds for adoption increase in parallel with the teacher' ability to give incentives and reinforce the use of the technology. Indeed, there is statistically significant linkage between teacher feedback and behavioural intention that is also true to the realities of the educational discourse.

Compatibility

The conceptual model in this research gives evidence of the positive impact of compatibility on behavioural intention (T/CR= 5,62; p= 0.00). Compatibility is a statistically significant predictor of behavioural intention to use mobile learning. The attributes of the WhatsApp treatment are found to be supportive of students' perception of the utility of mobile technology in language learning. The particularities of mobile learning are well suited to the meanings students attach to language learning. Obviously, students' beliefs and cultural values do not conflict with the educational incorporation of mobile learning for language learning purposes. Also, students' perception of mobile learning is endorsed because of the latter's ability to meet their needs. In the educational context, the needs of students constitute a controlling factor for endorsement and adoption. This is the reason why maximum attention needs to given to the planning aspects of MALL. Prior to the implementation of technology, students should be aware of the attributes of the target technology together with the rationale for its use. This was the case for this research. Prior to the WhatsApp-based treatment, all the participants were briefed on the utility of the technology and the different protocols of implementation.

Conclusion

The conceptual model in this research connects to the fundamental structures of UTAUT to produce a theoretically enhanced framework for understanding the determinants of MALL. Four factors were researched for the influence they have on behavioural intention to use WhatsApp-based language learning. The effects of teacher feedback and compatibility on behavioural intention were statistically significant while there was lack of support for the hypothesised direction linking performance expectancy and effort expectancy to behavioural intention. The outputs of the current research model are consistent with prior implementations of UTAUT. They successfully emphasise the fast evolving character of the technology use and acceptance field of research.

About the Author:

Nabil Morchid, is a PhD candidate. His doctoral thesis is on acceptance and use of mobile assisted language learning. He also conducts research in gender studies. He published an article on female role associations in Moroccan print advertising. He is currently working as an assistant professor of English at the Faculty of Letters and Human Sciences, Ibn Tofail University.
https://orcid.org/0000-0002-3430-2483

References

Abu-Al-Aish, A., & Love, S. (2013). Factors influencing students' acceptance of m-learning: An investigation in higher education. *The International Review of Research in Open and Distributed Learning*, *14*(5).

Barnes, S., & Vidgen, R. T. (2009). An evaluation of user acceptance of a corporate intranet. *In 17th European Conference on Information Systems, ECIS 2009.*

Cornacchia, M., Papa, F., Livi, S., Sapio, B., Nicolò, E., & Bruno, G. (2008). FACTORS

Cristobal, E., Flavián, C., & Guinaliu, M. (2007). Perceived e-service quality (PeSQ) Measurement validation and effects on consumer satisfaction and web site loyalty. *Managing service quality: An international journal*, *17*(3), 317-340.

Filzmoser, P. (2004). *A multivariate outlier detection method*. na.

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, and behavior: An introduction to theory and research (p. 447). *Reading, Mass.: Addison Wessley*.

Gerbing, D. W., & Anderson, J. C. (1988). An updated paradigm for scale development incorporating unidimensionality and its assessment. *Journal of marketing research*, *25*(2), 186-192.

Ghasemi, A., & Zahediasl, S. (2012). Normality tests for statistical analysis: a guide for non-statisticians. *International journal of endocrinology and metabolism*, *10*(2), 486.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). Multivariate data analysis sixth edition pearson education. *New Jersey*, 42-43.

Hawkins, D. M. (1980). *Identification of outliers* (Vol. 11). London: Chapman and Hall.

Hoaglin, D. C., & Iglewicz, B. (1987). Fine-tuning some resistant rules for outlier labeling. *Journal of the American Statistical Association*, *82*(400), 1147-1149.

Holzmann, P., Schwarz, E. J., & Audretsch, D. B. (2018). Understanding the determinants of novel technology adoption among teachers: the case of 3D printing. *The Journal of Technology Transfer*, 1-17.

Jayasingh, S., & Eze, U. C. (2009, June). Exploring the factors affecting the acceptance of mobile coupons in Malaysia. *In 2009 Eighth International Conference on Mobile Business* (pp. 329-334). IEEE.

Kaiser, H. F., & Rice, J. (1974). Little jiffy, mark IV. *Educational and psychological measurement*, *34*(1), 111-117.

Kim, H. Y. (2013). Statistical notes for clinical researchers: assessing normal distribution (2) using skewness and kurtosis. *Restorative dentistry & endodontics*, *38*(1), 52-54.

Lee, I. (2008). Understanding teachers' written feedback practices in Hong Kong secondary classrooms. *Journal of second language writing*, *17*(2), 69-85.

Loewen, S., & Gonulal, T. (2015). Exploratory factor analysis and principal components analysis. *In Advancing quantitative methods in second language research* (pp. 182-212). Routledge.

Markee, N. (1992). The diffusion of innovation in language teaching. *Annual Review of Applied Linguistics*, *13*, 229-243.

Meter, D. J., & Bauman, S. (2015). When sharing is a bad idea: the effects of online social network engagement and sharing passwords with friends on cyberbullying involvement. *Cyberpsychology, Behavior, and Social Networking*, *18*(8), 437-442.

Mosteller, F., & Tukey, J. W. (1977). Data analysis and regression: a second course in statistics. *Addison-Wesley Series in Behavioral Science: Quantitative Methods*.

Neuman, W. L., & Robson, K. (2014). *Basics of social research*. Toronto: Pearson Canada.

Nunnally, J. (1978). *Psychometric methods*. New York, NY: McGraw-Hill.

Pai, J. C., & Tu, F. M. (2011). The acceptance and use of customer relationship management (CRM) systems: An empirical study of distribution service industry in Taiwan. *Expert Systems with Applications*, *38*(1), 579-584.

Quinton, S., & Smallbone, T. (2010). Feeding forward: using feedback to promote student reflection and learning–a teaching model. *Innovations in Education and Teaching International*, *47*(1), 125-135.

Rocke, D. M., & Woodruff, D. L. (1996). Identification of outliers in multivariate data. *Journal of the American Statistical Association*, *91*(435), 1047-1061.

Rogers, E. M. (2010). Diffusion of innovations (3rd ed.) (p. 223). New York: Free Press.

Sekaran, U. (2006). *Research Methods for Business, A Skill Building Approach* (p. 203). John Willey & Sons.

Šumak, B., Heričko, M., Pušnik, M., & Polančič, G. (2011). Factors affecting acceptance and use of Moodle: An empirical study based on TAM. *Informatica*, *35*(1).

Tabachnick, B. G., & Fidell, L. S. (2001). Using multivariate statistics (Vol. 5). *Nedham Heights, MA: Allyn & Bacon*.

Thomas, T., Singh, L., & Gaffar, K. (2013). The utility of the UTAUT model in explaining mobile learning adoption in higher education in Guyana. *International Journal of Education and Development using ICT*, *9*(3).

Tobias, S., & Carlson, J. E. (1969). Brief report: Bartlett's test of sphericity and chance findings in factor analysis. *Multivariate Behavioral Research*, *4*(3), 375-377.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view (pp. 447/451). *MIS quarterly*, 425-478.

Tukey, J. W. (1977). Some thoughts on clinical trials, especially problems of multiplicity. *Science*, *198*(4318), 679-684.

Wangpipatwong, S., Chutimaskul, W., & Papasratorn, B. (2008). Understanding Citizen's Continuance Intention to Use e-Government Website: a Composite View of Technology Acceptance Model and Computer Self-Efficacy. *Electronic Journal of e-Government*, *6*(1).

Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2013). *Business research methods* (pp. 306-307). Cengage Learning.