

# An Exploratory Study in Nursing Education: Factors Influencing Nursing Students' Acceptance of Mobile Learning

R. Abdulrahman, A. Eardley, A. Soliman

## I. INTRODUCTION

**I**N academic environments, the acceptance and adoption of technologies is an important factor in determining the success of m-learning technology. Thus, technology acceptance becomes an active area of research where several models and theories have been proposed to understand the drivers of technology adoption [4]. One of the most prominent models is the UTAUT model. Therefore, the objective of this study was to investigate the factors, as well as the different experiences provided by mobile devices together with student's readiness as a moderating construct in the acceptance of m-learning system based on the UTAUT proposed by [1].

## II. RESEARCH MODEL

Reference [1] provided empirical evidence to show that IT use behaviour was correctly interpreted by the UTAUT, and encouraged others to continue validating and testing their model. Accordingly, we adopted UTAUTM as a primary theoretical framework to examine nursing students' acceptance of m-learning use. However, since there are differences in context between m-learning and traditional IT, the UTAUT's fundamental constructs do not entirely reflect the specific influences of m-learning context factors that may affect student acceptance. After considering the m-learning context and user factors, we incorporated two additional constructs into the UTAUT in order to account for m-learning acceptance: II and QoS. To avoid any incorrect interpretations, this study used behavioural intention (BI) as a dependent variable in the early stage of m-learning acceptance research. Thus, few constructs found in UTAUTM, including facilitating conditions, age, gender, and use behaviour were ignored in this study. Due to that fact that all participants are female, their age typically ranks between 18-23 years old, and they all attend the same nursing course. This is typical of a cohort of nursing students in Saudi Arabia as it is a requirement of the study on this type of course. The research model tested in this study is shown in Fig. 1.

The questions of these constructs were derived from previous studies [1]-[3]. The questions were adapted with modifications to make them relevant to the context of m-learning in a nursing institute environment. We also hypothesised that mobile devices experience differences and voluntariness of use that were equivalent to the student's readiness of use would moderate the influence of these

**Abstract**—The proliferation in the development of mobile learning (m-learning) has played a vital role in the rapidly growing electronic learning market. This relatively new technology can help to encourage the development of in learning and to aid knowledge transfer a number of areas, by familiarizing students with innovative information and communications technologies (ICT). M-learning plays a substantial role in the deployment of learning methods for nursing students by using the Internet and portable devices to access learning resources 'anytime and anywhere'. However, acceptance of m-learning by students is critical to the successful use of m-learning systems. Thus, there is a need to study the factors that influence student's intention to use m-learning. This paper addresses this issue. It outlines the outcomes of a study that evaluates the unified theory of acceptance and use of technology (UTAUT) model as applied to the subject of user acceptance in relation to m-learning activity in nurse education. The model integrates the significant components across eight prominent user acceptance models. Therefore, a standard measure is introduced with core determinants of user behavioural intention. The research model extends the UTAUT in the context of m-learning acceptance by modifying and adding individual innovativeness (II) and quality of service (QoS) to the original structure of UTAUT. The paper goes on to add the factors of previous experience (of using mobile devices in similar applications) and the nursing students' readiness (to use the technology) to influence their behavioural intentions to use m-learning. This study uses a technique called 'convenience sampling' which involves student volunteers as participants in order to collect numerical data. A quantitative method of data collection was selected and involves an online survey using a questionnaire form. This form contains 33 questions to measure the six constructs, using a 5-point Likert scale. A total of 42 respondents participated, all from the Nursing Institute at the Armed Forces Hospital in Saudi Arabia. The gathered data were then tested using a research model that employs the structural equation modelling (SEM), including confirmatory factor analysis (CFA). The results of the CFA show that the UTAUT model has the ability to predict student behavioural intention and to adapt m-learning activity to the specific learning activities. It also demonstrates satisfactory, dependable and valid scales of the model constructs. This suggests further analysis to confirm the model as a valuable instrument in order to evaluate the user acceptance of m-learning activity.

**Keywords**—Mobile learning, nursing institute, unified theory of acceptance and use of technology model.

Abdulrahman, R, Eardley, A, and Solima, A are with Staffordshire University, Faculty of Computing, Engineering and Science, UK (e-mail: a002824b@student.staffs.ac.uk, w.a.eardley@staffs.ac.uk, a.soliman@staffs.ac.uk).

determinants on BI to use m-learning activity. These five constructs and the two moderating constructs are delivered and defined in Table I.

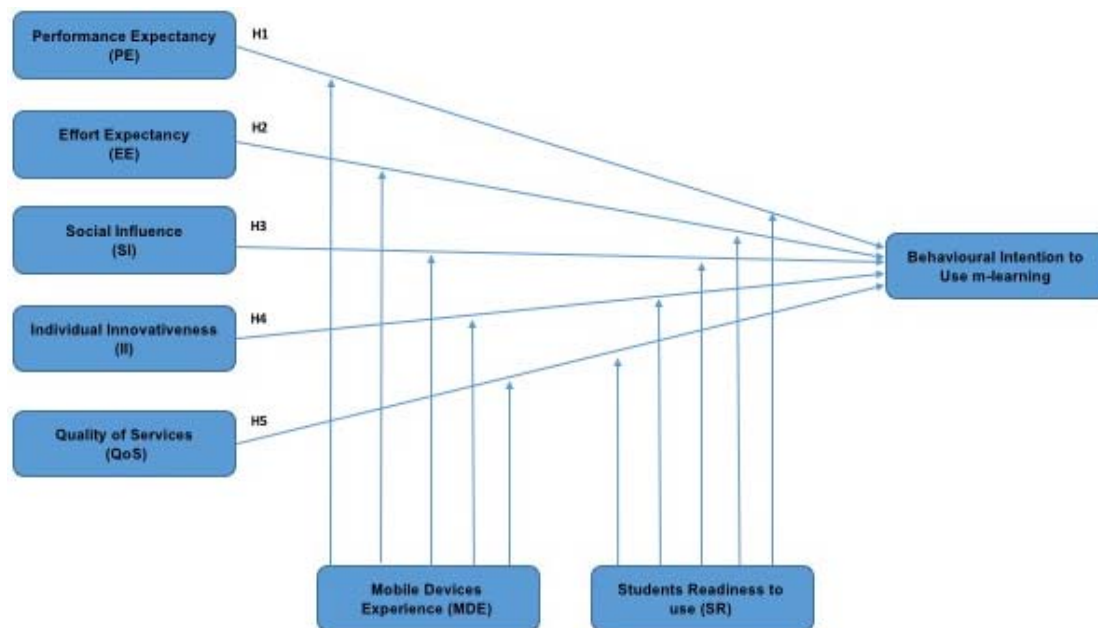


Fig. 1 Research model

TABLE I  
 RESEARCH MODEL CONSTRUCTS

The Construct	Definition
Performance Expectancy (PE)	The degree to which an individual believes that using a certain system will help him or her to attain gains and would improve job performance.
Effort Expectancy (EE)	The degree of ease associated with the use of the system.
Social Influence (SI)	The degree to which an individual perceives the importance placed by others on whether he or she should use the new system.
II	The degree to which an individual is willing to try out any new information technology.
QoS	The degree of user satisfaction in the services being offered
Voluntariness of use (Readiness of use)	The degree to which use of the innovation is perceived as being voluntary. In this study it is equal to the readiness of the students' use of m-learning.
Mobile devices experiences (MDE)	The degree to which use of the mobile devices user experience is perceived.

### III. RESEARCH MODEL AND HYPOTHESES

This survey has attempted to explore the factors influencing the student behavioural intention to use M-learning activity. The survey is testing the following hypothesis:

- **H1:** PE will have a positive influence on behavioral intentions (BI) to use m-learning.
- **H2:** EE will have a positive effect on behavioural intention to use m-learning.
- **H3:** SI has a positive effect on behavioural intention to use m-learning.
- **H4:** II has a positive effect on behavioural intention to use m-learning.
- **H5:** QoS has a positive effect on behavioural intention to use m-learning.

### IV. THE PILOT STUDY

The questionnaire was pilot tested with 6 students who enrolled in the nursing institute in the Armed Forces Hospital in Saudi Arabia. This was in order to evaluate its constructs, reliability and validity.

Reliability means the degree to which measures are free from error and reflect results consistently. The internal consistency reliability (ICR) was assessed and calculated using Cronbach's Alpha for each constructs as shown in Table II. All constructs had an ICR higher than 0.70. High ICR indicates that the elements used to measure that constructs are adequately representing the construct and generate almost similar scores [4] The result certified the researcher to proceed to the main survey.

TABLE II  
 INTERNAL CONSISTENCY RELIABILITY (ICR) MEASURED BY CRONBACH'S ALPHA

Constructs	No of Items	Cronbach's Alpha
PE	5	.873
EE	4	.807
SI	10	.859
II	3	.827
QoS	6	.763
BI	5	.876
ALL	33	.786

### V. RESEARCH METHODOLOGY

This study used a convenience sample technique to collect the data [2]. The quantitative phase of this study focuses on empirically retesting the UTAUT model in a different setting from recently gathered data. The objective of the study is the

assessment of nursing institute acceptance to use m-learning activity.

#### A. Research Instruments

The questionnaire was modified from the UTAUT study of [1]. It contained 33 items measuring five constructs. The items were derived from different research bands and were adapted to accommodate the questionnaires for this study. These items represent dependents and independents variables employed in this study. The questionnaire consisted of three sections

- **1<sup>st</sup> Section:** The participant's demographic background.
- **2<sup>nd</sup> Section:** Learning and mobile devices experience, frequency of using mobile devices, and m-learning knowledge.
- **3<sup>rd</sup> Section** contains five subsection questions that include study of the following factors: PE, EE, SI, II and QoS. A five-point Likert scale ranging from 1-Strongly Disagree to 5- Strongly Agree was used and students were asked to measure each sentence from their point of view regarding its importance in the context of m-learning.

#### B. Characteristics of Participants

The questionnaire was distributed to 42 nursing students' in the nursing institute at the Armed Forces Hospital Al-hada (NIAFH-A) in Saudi Arabia. They are from different academic levels. A total number of 42 responses were obtained, for an overall rate of 100%. The study certified that the most students are 18-20 years old (59.52%) as shown in Fig. 2 that is why we have decided to ignore the age variables in the research model as a moderating variable. Moreover, as the majority of students fall within the same age cohort and are all female, the impacts of gender also were not tested.

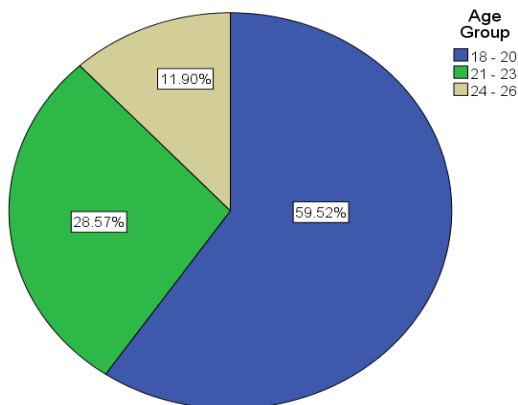


Fig. 2 Age group

## VI. DATA ANALYSIS AND RESULT

The results of the survey can be discussed in different areas: Construct validity, reliability, and correlation. Reference [5] recommended multiple validation strategies for the information system (IS) research. For this study, coefficient factor analysis was used to define the convergent and discriminant construct validity. Cronbach's Alpha was used to assess the internal consistency reliability. The inter-correlation was also employed to explain the construct reliability. Lastly,

the regression analysis technique investigated the relationship between variables.

#### A. Assessment of Construct Validity and Reliability

Construct validity is a distribution of effectiveness or measurement between constructs. The concern on the construct validity is that instrument elements selected for a given construct are a reasonable operationalization of the construct [6]. For this study, the descriptive statistics of each main construct and element are presented in Table III.

TABLE III  
DESCRIPTIVE STATISTICS

Variables	Means	Standard Deviation (S.D)
PE	2.56	.815
EE	2.36	.705
SI	2.84	.638
II	2.14	.786
QoS	1.84	.593
BI	2.46	.749

The reliability is a measurement within a construct. For this analysis, to examine whether one construct is calculated separately from that of other constructs, the Cronbach's Alpha method and Inter-Correlation Matrix are used. Each construct in Table IV shows a high level of reliability coefficient or internal consistency. The numbers of the Cronbach's Alpha in total is .786 confirming the results of reliability analysis of the research model. Furthermore, the correlation between variables illustrated in Table V clarified the self-determining relationship between variables. All off-diagonal elements are close to zero, representing strong independence of each construct. The results of inter-correlation matrix provide more confirmation to verify the reliability of the UTAUT scales.

TABLE IV  
INTERNAL FACTORS RELIABILITY BY CRONBACH'S ALPHA TECHNIQUE

Constructs	No of Items	Cronbach's Alpha
PE	5	.873
EE	4	.807
SI	10	.859
II	3	.827
QoS	6	.763
BI	5	.876
ALL	33	.786

TABLE V  
INTER-CORRELATION MATRIX

	PE	EE	SI	II	QoS	BI
PE	1.000	.609**	.657**	.053	.373*	.563**
EE	.609**	1.000	.533**	.164	.374*	.560**
SI	.657**	.533**	1.000	.290	.182	.648**
II	.053	.164	.290	1.000	.090	.199
QoS	.373*	.374*	.182	.090	1.000	.505**
BI	.563**	.560**	.648**	.199	.505**	1.000

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

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

#### B. Assessment of Correlation

Based on the initial construct validity and reliability analysis, all five constructs were thought to be potentially

important determinants of the behavioral intention to use the m-learning activity. The R-Square value for the model of this study is approximately .40, which is relatively high to determine the strength of linear relationship between the independent variables and dependent variables BI. The data from Table VI indicate that the coefficients for all constructs are statistically significant ( $p$  value  $\leq .01$ ). Likewise, SI is found to have the greatest impact on BI ( $\beta = .648$ ). Ultimately, the data indicated that II is not significant to the BI assessment. The coefficient for II ( $\beta = .199$ ) is statistically significant, compared to other four (PE, EE, SI, and QoS) constructs.

In summary, the result from the experiment can be interpreted to mean that only PE, EE, SI, and QoS are significant factors to determine the students' acceptance on using m-learning.

TABLE VI  
REGRESSION COEFFICIENTS FOR PREDICTORS

Constructs	Standardized Coefficients	Significant (P Value)
	Beta	
PE & BI	.563	.000
EE & BI	.560	.000
SI & BI	.648	.000
II & BI	.199	.207
QoS & BI	.505	.001

Dependent Variables (PE, EE, SI, II, and QoS)  
Predictors: (Constant), BI

## VII. DATA ANALYSIS TECHNIQUES AND OBTAINED RESULT

The data analysis techniques involved two steps: 1) the measurement model and 2) structural model and testing hypotheses [7].

### A. Measurement Model

Before running the hypothesized model, it is necessary to establish reliability and validity of the constructs in the model. First of all, Cronbach's alpha is computed for all constructs using SPSS 22. The minimum Cronbach's alpha found is 0.763 and it is for QoS. This is above 0.7, so it is good. Rest constructs, as shown in Table IV, have Cronbach's alpha greater than 0.8, which is more than enough.

BI has highest value of Cronbach's alpha, equals to 0.876 and it cannot be further improved. PE also has Cronbach's alpha value of 0.873. This can be improved to 0.92 by dropping 1 of the item but it is not preferable because we will lose information for the structural modelling which would be higher than the benefit of improving reliability. The Cronbach's alpha for EE is 0.807, which cannot be further improved.

The Cronbach's alpha for SI is 0.859, which can be improved by dropping SI7, but it is not preferable again because Cronbach's alpha is already high enough. Similarly, Cronbach's alpha of II can be increased from 0.827 to 0.906 but it is not preferable.

The data are reliable for proceeding with CFA model. CFA model will help in establishing validity of the items in the questionnaire. CFA model is run using SPSS Amos. CFA

model assumes positive variance for all error terms in the model. In the first run, error variance of item II2 is found to be negative, therefore II2 is dropped. Threshold value for modification indices is set to 4 before running CFA in SPSS Amos. Items or covariance between errors of same construct with highest modification indices are modified first. If an item is troubling, then it can be dropped from the model. Then, these errors are allowed to co-vary by adding covariance between them in SPSS. We can also drop error term if it has negative variance without dropping relevant item. This algorithmic process is performed until the model is good. This process ultimately ended up with dropping of 2 error terms and several items and adding of 2 covariance paths in the model.

In CFA, one of the loading is set to 1 and remaining loadings are computed with reference to fixed loading item. The first covariance is added between errors of BI2 and BI3. The second covariance is added between errors of SI3 and SI9. Variances of error of II3 and QoS4 were negative, therefore error terms were deleted. BI is the only construct, whose items are not dropped. 6 items of SI, 4 of QoS, 2 of PE, 1 of II and 1 of EE were dropped to achieve the goodness of the model. The chi square value of goodness of fit (Chi Square=151.6, DF=137) shows that model is good as its  $p$  value is reasonably high.

From factor loading matrix of CFA model, we can compute Composite Reliability (CR) and Average Variance Extracted (AVE). CR and AVE establish reliability and validity of measurement constructs respectively. Table VII shows the reliability and validity of the constructs.

TABLE VII  
RELIABILITY AND CONSTRUCT VALIDITY

Construct	Number of items	CR	AVE
PE	3	0.89	0.733
II	2	0.76	0.63
SI	4	0.79	0.50
EE	2	0.55	0.41
QoS	2	0.66	0.55
BI	5	0.87	0.58

TABLE VIII  
CONSTRUCTS' COVARIANCE MATRIX

	PE	II	SI	EE	QoS	BI
PE	0.741					
II	0.132	0.173				
SI	0.527	0.389	0.156			
EE	0.651	0.237	0.557	0.089		
QoS	0.536	0.001	0.324	0.673	0.855	
BI	0.746	0.236	0.589	0.683	0.656	0.481

Reliability estimates from the good model are also needed to be calculated. For this purpose, CR for all construct is computed from loadings of CFA model. All values shown in Table VII are greater than 0.6 except EE. The CR for EE is 0.55, which is although low but acceptable in social sciences. The other component of construct validity is discriminant validity, which refers to the fact that items of different construct must have low correlation while items of same

construct must have high correlation. CFA model is used to reproduce the covariance between constructs as shown in Table VIII.

The discriminant validity is not well established for some constructs but we can proceed for structural model because construct can be theoretically correlated. PE and QoS have very high variance, 0.741 and 0.855, and low covariance with other constructs less than 0.741 for PE except with BI, less than 0.855 for QoS, which establish their discriminant validity. EE has very low variance 0.089 as compared to its covariance with other constructs (at-least greater than 0.2. Therefore, for EE discriminant validity is doubtful. But we can

still proceed with structural model since its convergent validity is already established and it might be correlated with other constructs. Exogenous constructs might be correlated together and that might be a reason for failing to establish adequate discriminant validity.

*B. Structural Model and Hypothesis Testing*

Initially, model is tested using all the items in the questionnaire. The model with standardized estimates is shown in Fig. 3. Error terms are indicated by small circles represented by “e” with a number to differentiate. Path estimates are shown middle of the arrows.

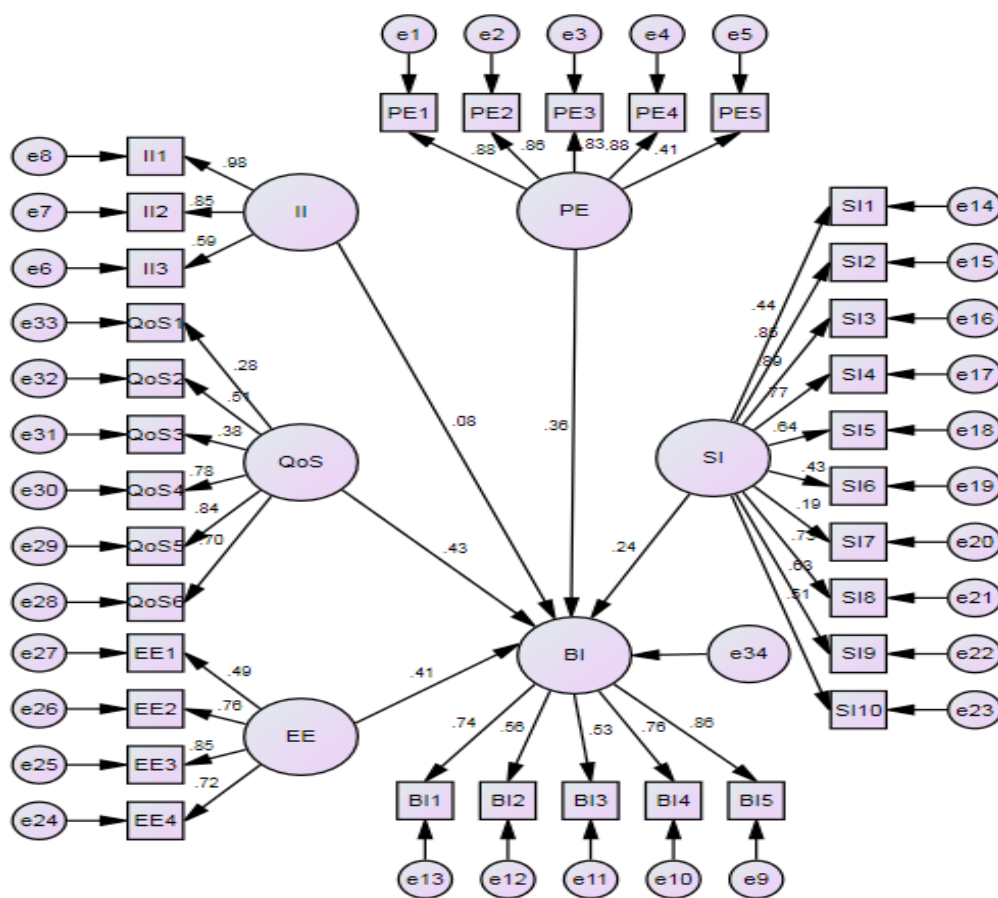


Fig. 3 Initial model with Standardized Estimates

The fit of the model is very bad (Chi Square 1070.6, DF=490) as indicated by p-value which is smaller than 0.001. Therefore, slight improvement cannot make the model good. Thus, items dropped in measurement model are abandoned for estimating structural model.

The structural model is estimated using the items retained in the measurement model. These items are good to estimate the structural model. In the estimation of structural model, we need to drop some more items. The constructs II and EE are completely dropped from model to achieve goodness of the model. QoS is measured by only QoS3 in structural model. SI1 is also dropped to make the model good. Finally, the covariance between PE and SI is added as suggested by

modification indices as shown in Fig. 4. The model is finally good as shown in Table IX.

TABLE IX  
 MODEL FIT INDICES

Fit Indices	Criterion	P-Value
Chi Sq /DF	≤3	1.1
RMR	≤0.08	0.066
IFI	≥0.9	0.984
TLI	≥0.9	0.977
CFI	≥0.9	0.983
RMSEA	≤0.1	0.049

All fit indices in Table IX are meeting the goodness of fit

criteria. So this model is a good fit to the data. Fit indices penalizing small samples are not included in Table IX because the sample size of this study is small. The Chi Square/DF ratio and RMR are reasonably smaller than the criterion value. IFI, TLI and CFI are all well greater than 0.9 and close to 1, indicating the model goodness. Finally, RMSEA is less than 0.05, indicating a close fit. Although having RMSEA less than 0.1 indicates fitness of the model but having less than 0.05 indicates a close fit.

There are some more indices to check the model goodness but their absolute values are not meaningful unless compared with saturated models. The Akaike Information Criterion (AIC), ECVI and MECVI indices are shown in Table X.

The values of AIC, ECVI and MECVI indices are smaller than their corresponding saturated models, indicating the

goodness of model fit. In Fig. 4, structural model with standardized estimates are shown. The Path between item and construct show loading value while paths between behavioral intention and its predictors are regression paths. Every item and BI has an error term indicated by circle. There are two covariance in the model to make it good. One is between the two constructs; PE and SI. The other is between errors of item BI2 and BI3.

TABLE X  
 AIC, ECVI AND MECVI INDICATORS

Model	AIC	ECVI	MECVI
Default model	110.88	2.7	3.3
Saturated model	156	3.8	5.6

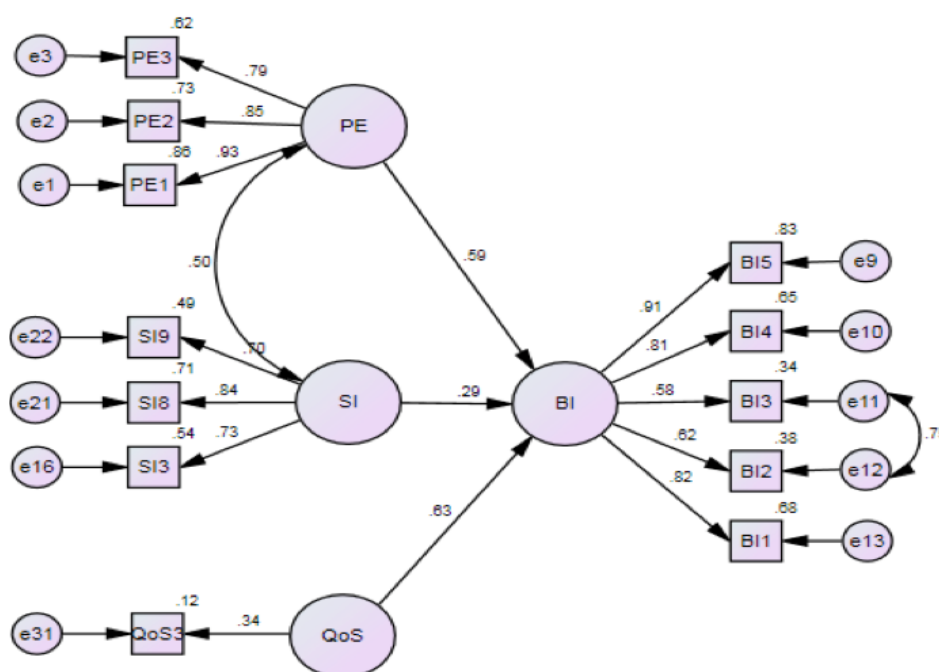


Fig. 4 Final structural model

TABLE XI  
 ESTIMATES OF ITEMS' LOADINGS

Path	Un-SE	Standard Error (S.E)	value	Standardized Estimate
BI5 <- BI	1			0.911
BI4 <- BI	0.973	0.145	***	0.806
BI3 <- BI	0.834	0.204	***	0.58
BI2 <- BI	0.956	0.216	***	0.616
BI1 <- BI	0.991	0.142	***	0.824
QoS3 <- QoS	1			0.341
PE2 <- PE	0.993	0.134	***	0.852
PE3 <- PE	0.947	0.146	***	0.785
PE1 <- PE	1			0.925
SI8 <- SI	1.128	0.256	***	0.843
SI9 <- SI	0.965	0.241	***	0.697
SI3 <- SI	1			0.733

Note: \*\*\* indicates that P value is smaller than 0.001

All the estimates in Fig. 4 are significant at-least at 0.1 level

of significance. The significance for each path is shown in Table XI.

All coefficients are significant at-least at 0.01 level because all p-values are less than 0.01 and some loading values are significant at even higher level of 0.001 level. The standardized loading QoS3 is low but we can proceed with the model because this path was fixed to estimate the model. After this, lowest loading of any item on the corresponding construct is 0.58. This is BI3 having a standardized loading of 0.58. This item is not deleted since model is already very good and remaining items are having at least 0.6 standardized loading. As shown in Table XI, there are 2 BIs (BI4 and BI1) with standardized loading greater than 0.8 and 1 BI (BI5) with standardized loading greater than 0.9. The standardized loading values of PE and SI are at least 0.7. So no further deletion on the basis of loading is needed. Hence the model is now set to test the hypothesis.

Hypotheses H2 and H4 are already rejected in the initial stage of model building. Hence we are left with following three predictors of BI to use m-learning. Hypothesis H1 is related to PE. The coefficient of PE is significant at 0.001 level of significance since P-value of this coefficient is less than 0.001. The standardized coefficient is 0.59, which is greater than 0.5. Hence the strength of relationship is moderate. So hypothesis H1 is accepted. Hypothesis H3 is also accepted but at 0.1 level of significance because the p value of coefficient of SI is less than 0.1 (0.068). The standardized coefficient value of SI is 0.286, which is smaller than 0.5. So the impact of SI on BI is weak. Finally, hypothesis H5 is also accepted at 0.1 level of significance but the impact is moderate. The standardized coefficient of QoS is 0.635, which is of moderate strength. In the final model, note that PE and SI are correlated with each other. The correlation is significant at 0.05 level of significance.

### C. The Influence of the Moderators

Two potential moderators that may influence the relationship between BI and its predictors in m-learning are Mobile Device Experience (MDE) and Student Readiness (SR). Two categorical index variables are formed for each moderator as shown in Table XII.

TABLE XII  
 HYPOTHESIS TESTING RESULT

Moderator	Category	Frequency
MDE	Less Experienced Users	16
	More Experienced Users	25
SR	Low Readiness	25
	High Readiness	17

Based on number of years of experience of using different types of portable devices, students are categorized into less experienced and more experienced. If years of experience of using different types of portable devices is less than 8 years, then the user will be categorized as less experienced student and if sum is greater than 8, then it will be categorized as more experienced. Similarly, the SR are also categorized into low and high based on their responses to 7 items of readiness. 7 items of SR are converted into single index variable SR. If student responds with "Yes" to 4 or more items, then student will be classified in high readiness group, else in low readiness group.

#### 1) Moderation by MDE

Data are divided into 2 groups based on MDE and analysis is then run in SPSS Amos. Estimates of the model are shown in Table XIII.

TABLE XIII  
 MDE MODERATOR

	Less Experienced Users			More Experienced Users		
	Un-SE	P	SE	Un-SE	P	SE
H1	0.239	0.419	0.354	0.574	***	0.6
H3	0.251	0.615	0.241	0.462	0.002	0.46
H5	1.067	0.033	0.831	3.427	0.599	0.382

PE is significant for the more experienced students at 0.001 level of significance but it is insignificant for less experienced. This shows that MDE interacts significantly with PE. SI is significant at 0.01 level for more experienced group but not for less experienced group. This indicates that MBE interacts significantly with SI to influence BI to use m-learning. QoS is important for less experienced users only and not for more experienced users. It is significant predictor at 0.05 level for less experienced people but not significant for more experienced users. Hence MBE significantly moderates the relationship between QoS and BI to use m-learning.

#### 2) Moderation by SR

Time related data are divided into 2 groups based on SR. If student responds with "Yes" to 4 or more items, then student will be classified in high readiness group, else in low readiness group. Structural model is run in SPSS Amos. Estimates of the model are shown in Table XIV.

TABLE XIV  
 SR MODERATOR

	Low Readiness			High Readiness		
	Un-SE	P	SE	Un-SE	P	SE
H1	0.26	0.042	0.42	0.448	0.013	0.408
H3	0.103	0.295	0.205	1.063	0.071	0.507
H5	0.948	0.01	0.853	8.383	0.643	0.713

PE is significant for the both low and high readiness groups. However, un-standardized coefficient of PE is more than 1.5 times higher for high readiness group as compared to low readiness group. The difference is only 0.12, which is not big. Hence PE affects the BI in similar way across low and high readiness groups, so it does not provide significant relationship between PE and BI. SI is significant at 0.1 level for high readiness group and not so important for low readiness group. This indicates that SR interacts significantly with SI and creates interactive effect on influence BI to use m-learning. QoS is important for low readiness group only. It is significant predictor at 0.05 level for low readiness group. Hence, SR in m-learning acts as moderator between QoS and BI in the adoption of m-learning.

### VIII. DISCUSSION

The objective of this study is to empirically test some established factors of adoption of m-learning in nursing students and to test two moderators influencing the UTAUT Model. MDE is one such moderator that was tested in past and have been found to influence the UTAUT Model [8]. The new moderator added in this study is SR that moderates some of the constructs in UTAUT Model.

Secondly, II is found to be insignificant predictor of adoption of m-learning. This shows that use of m-learning does not depend on personal skills to use it. This might be due to the reason that technology has made the m-learning easy. The m-learning has now become easy to use and procedures are now easier than in past. That could be the reason of inconsistency with previous studies [8]. A study [3] concludes that innovativeness is a significant predictor of not only

behavioral intention but also perceived ease of use and perceived usefulness. Perceived ease of use and perceived usefulness are nearly equivalent to EE and PE of the model tested in this study.

High correlation of innovativeness with EE and PE might have made innovativeness insignificant in our study. This could be resolved by increasing sample size.

Finally, QoS is also a significant predictor of m-learning adoption [1], [8]. If service provider improves quality, then this service provider is likely to charge higher price and depending upon university financial position, university may choose higher quality m-learning even it costs more. Ease of use is an important aspect of quality. That makes the II insignificant because m-learning is designed in a way that it is easy to use and there is no requirement of innovativeness on the part of user. If there is no requirement of innovativeness, then II will no more be significant in the model.

MDE is playing a moderator role in the model. PE is not significant for less experienced users but is highly significant for more experienced users. This suggests that experienced users can take the advantage of PE by increasing their PE. SI is not significant in case of less experienced users. But it is highly significant in case of experienced users. This concludes that experienced people take suggestions of knowledgeable people seriously and implement them. While less experienced users do experiment and do not seek serious advice from knowledgeable people. Less experienced users do not bother the SI but experienced people take SI. QoS is found important for less experienced students. The quality has the component of ease of use. That is the reason that QoS is significant for less experienced students and is insignificant for experienced students. Experienced people would not mind the deficiencies and their experience will compensate the low quality. That is why quality is not important as much for more experienced students as for less experienced students.

SR is also playing a limited moderator role. It does not influence the relationship between PE and Behavioural Intention (BI). PE is equally important determinant for low and high readiness groups. SI is significant for high readiness group but not for low readiness group. People in high readiness group will certainly want to take advice before they take decision while people with low readiness are in evaluation stage of adopting m-learning. That is why they take less serious the advice from other people. But if a person who is ready to use m-learning will take advice, his or her intention to use m-learning are likely to be influenced. In case of high readiness, advice will be more recent from the reference of purchase of time of m-learning. But students with low readiness are still in evaluating stage, and although they will take advice but at the time of purchase decision, more time will have been passed. The advices they took might be outdated and they will not take them seriously.

Finally, QoS is important for low readiness students but not that much important for high readiness students. This may be because high readiness group has sorted the brand which they intend to purchase and low readiness group is in evaluation stage where they are comparing different service provider of

m-learning.

## IX. CONCLUSION

Initially, we clarified that the purpose of this study was to find out what factors will mostly affect a student's acceptance of new technology within education such as m-learning. We decided that the basis of the study was going to revolve around the UTAUT. Five hypotheses were made and stated. These became the theoretical model of the study. The empirical model that was made to test the theoretical model was in the form of questionnaires that were distributed to various respondents. The results were collected and analysed.

From the studies undertaken, it is reasonable to say that m-learning should be aimed at those who are known to have high performances expectancies. It was also found that the student's EE of the m-learning technology was not a major factor to be considered because students will most definitely have different amounts of experience in this area, meaning that students with more experience will have a lower EE. SI was defined a strong factor to consider for designers and distributors of m-learning applications. This is because students are very susceptible to influence from those who they deem to be of better knowledge. Although II is an important factor, it will not largely affect the outcomes as most students are of younger age groups such as 18-23 years old, an age during which, most individuals in this period are becoming more and more accepting towards the adaptation of new technology. Finally, QoS was bound to be a strong factor to be considered, as individuals are drastically more willing to partake in certain activities, such as m-learning, when and if the QoS is outstanding.

Even though this study has some challenges and limitations in sampling selection of participants, such as gender, course and cultural background, it provides a significant result on which to base a proposed m-learning framework that will be carried out using a case study and validation process. The factor analysis explains the factors that influence the deployment of the m-learning activity. The overall findings reveal an important implication for policy makers and educational practitioners for designing successful m-learning systems.

## REFERENCES

- [1] Venkatesh, V. et al., 2003. User acceptance of information technology: towards a unified view. *MIS Quarterly*, 27(3), p.425-478.
- [2] Creswell, J.W., 2012. *Qualitative inquiry and research design: Choosing among five approaches*. Sage publications.
- [3] Liu, Y., Li, H. and Carlsson, C., 2010. Factors driving the adoption of m-learning: An empirical study. *Computers and Education*, 55(3), p.1211-1219. Available at: <http://dx.doi.org/10.1016/j.compedu.2010.05.018>. (Accessed 21 April 2016).
- [4] Yu, T.K., Lu, L.C. and Liu, T.F., 2010. Exploring factors that influence knowledge sharing behavior via weblogs. *Computers in Human Behavior*, 26(1), pp.32-41.
- [5] Straub, D., Boudreau, M.C. and Gefen, D., 2004. Validation guidelines for IS positivist research. *The Communications of the Association for Information Systems*, 13(1), p.63.
- [6] Cronbach, L.J. and Meehl, P.E., 1955. Construct validity in psychological tests. *Psychological bulletin*, 52(4), p.281.



- [7] Zarpou, T., Saprikis, V. and Vlachopoulou, M., 2012. Examining behavioral intention toward mobile services: An empirical investigation in Greece. *Mobile opportunities and applications for E-service innovations*, 37.
- [8] Abu-Al-Aish, A., 2014. Toward mobile learning deployment in higher education. Available at: <http://v-scheiner.brunel.ac.uk/handle/2438/7998>. (Accessed 16 June 2016).