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The Utility of the UTAUT: An Application to Mobile Learning Adoption in the Caribbean

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ABSTRACT

This paper focuses on the usefulness of the UTAUT model in explaining behavioural intention to adopt mobile learning in the Caribbean. It employs confirmatory factor analysis with robust maximum likelihood estimation, to evaluate the measures, comparability of the measures and to compare the means of the factors between five university-territory combinations. It estimates a full structural equations model to evaluate the UTAUT relationships with an added effect of facilitating conditions on behavioural intention and it finds little support for effects of effort expectancy and social factors on behavioural intention in the region. However, the impacts of performance expectancy and effort expectancy on behavioural intention are similar across the region. With the UTAUT model underperforming in the region, there is a need for further research to strengthen measurement of the factors and to improve the explained variance by determining measures that are relevant to the regions and which can be included in a modified model.

Keywords: *UTAUT, mobile learning, higher education, technology adoption, measurement, equivalence, invariance*

INTRODUCTION

Technology is changing the way we teach and learn in a fundamental way and it has the potential to help solve some of the problems of 21st century education (Kukulska-Hulme, 2010). Along with rapid development in digital technologies, there is an increase in the uptake in education due to the opportunities for learning to take place anytime and anywhere using multimedia functions (Shih & Mills, 2007), and synchronously or asynchronously (Chang, 2010) through e-learning, m-learning or u-learning (Moreira et. al, 2018). In fact, such technologies have become ubiquitous as ownership has spread at unprecedented rates (ITU, 2016). Mobile technologies and mobile learning in particular, have engaged the interest of educational researchers for several decades (Chang et al., 2018; Chiang et al., 2016) and have received specific attention in relation to higher education, with students as the most popular targets (Chiang et al., 2016).

The UTAUT (Venkatesh et al., 2003) or some variant thereof is very popular in research on mobile learning. Numerous studies have been conducted in different domains and cultural contexts with the overarching aim of explaining behavioural intention to adopt technology (Attuquayefio & Addo, 2014; Williams et al., 2015; Baydas & Yilmaz, 2016; Kamau, 2017). Though the model is well recognised with many indicating that it is robust (for example, Nassuora 2012; Teo, 2011), variable results have been encountered in different cultures and in relation to differences in geography and infrastructure among other contextual variables (for example, Isaias et al., 2017; Mosunmola et al., 2018; Thomas et al., 2013). This underscores the need for conducting context-specific evaluations of the UTAUT model applied to mobile learning.

In this regard, this paper addresses the cross-national equivalence of the relationships in the UTAUT model and in so doing, provides a more nuanced perspective on the model than studies that focus on the existence of the relationships. On the way to addressing cross-national structural invariance of the model, this paper also evaluates the measurement model and compares the means of the factors to determine where there is room for relative improvement, with a view to enhancing mobile learning adoption.

The UTAUT Model

The UTAUT model was developed to explain and predict technology acceptance in general (Venkatesh et al., 2003). It is based on a synthesis of several other models on technology diffusion (Kamau, 2017) and it includes three independent variables which act as determinants of behavioural intention. These are performance expectancy (*degree to which individuals believe that the use of the technologies will result in performance gains*), effort expectancy (*ease of use of technologies*) and social influences (*extent to which the individuals believe that important others believe that they should use the technologies*). A fourth variable - facilitating conditions (*perceived extent to which the organisational and technical infrastructure required exists*) - is a predictor of usage behaviour. In addition, the model includes age, gender, experience and voluntariness of use, which function as moderators of the effects of various predictors (Venkatesh et al., 2003).

The UTAUT model has been applied across many domains including mobile learning (Attuquayefio & Addo, 2014; Williams et al., 2015; Baydas & Yilmaz, 2016; Kamau, 2017) and with respect to mobile learning, the model relationships have largely been confirmed. Indeed, several studies indicate that performance expectancy, effort expectancy and social factors have significant effects on behavioural intention (for example, Al-Adwan et al., 2018; Al-Hujran et al., 2014; Alasmari, 2017; Al-Shahrani, 2016; Arpaci, 2015). Many of these studies were conducted in different countries representing differences in cultures with some studies being cross-cultural in nature (for example, Arpaci, 2015).

Notwithstanding the validity of the model in various contexts, the results of other studies are at variance with general confirmation of the model relationships, especially with respect to effort expectancy and social factors. For example, Mosunmola et al. (2018) and Chaka and Govender (2017) with respect to Nigeria and Isaias et al. (2017) with respect to Portugal, report no effect of social factors on behavioural intention whereas Thomas et al. (2013) report an absence of an effect of effort expectancy in data from Guyana. These results are not necessarily unequivocal since other studies done in the same contexts have reported different results. For example, Briz-Ponce et al. (2017) observe social influence to be an important factor on behavioural intention and attitude towards mobile learning in Portugal whereas Singh et al. (2016) report a significant effect of effort expectancy on behavioural intention to adopt mobile learning in Guyana.
Apart from examining the UTAUT relationships as proposed by Venkatesh et al. (2003), several modified versions of the model have been implemented with additions of both endogenous and exogeneous factors and inclusion of a direct effect of facilitating conditions on behavioural intention (for example, Singh et al., 2016). The model is also often implemented without the interaction terms and without inclusion of age, gender, experience and voluntariness of use as exogenous variables.

In relation to an effect of facilitating conditions, is has been suggested that it will likely become an important determinant of behavioural intention in contexts where there is scarcity of resources (Thomas et al., 2013). In contrast, Arpaci (2015) related the presence or absence of such an effect to cultural differences having found such a relationship in Canada but not in Turkey. A significant effect of facilitating conditions on behavioural intention is also reported by others (for example, Arpaci, 2015; Kang et al., 2015; Mosunmola et al., 2018) and this suggests that it is useful to evaluate the existence of such a direct effect of facilitating condition, if it is not yet known whether it exists in the particular context under study.

One of the issues that might intervene in the discrepancies in results for the effects of the UTAUT factors is the type of modelling done. As an example, Thomas et al. (2013) employed confirmatory factor analysis whereas Singh et al. (2016) employed exploratory analysis using principal components analysis. Another possibility that might coexist with the foregoing is that there is indeed cultural moderation of the results (Al-Adwan et al., 2018; Arpaci, 2015) so that any expectation of universal applicability of the UTAUT model would be unrealistic.

Although the UTAUT model has become well-established as a choice for modelling technology acceptance in general, and mobile learning adoption in particular, there are several issues with its performance. The modifications to the model over time, have led somewhat to several extensions, and that this need arose suggests that researchers believe that important variables and relationships are omitted. In this regard, a study in Guyana found that the model explained approximately 43% of the variance in behavioural intention and approximately 58.3% of the variance when attitude was included as an endogenous factor, along with facilitating conditions as an exogenous predictor of behavioural intention (Thomas et al., 2013). Furthermore, several other studies also report much lower explained variance than the 70% that the model is expected to explain (for example, Dwivedi et al., 2019; Al-Gahtani et al., 2007; Teo, 2011; Wang & Shih 2009). It is worth noting that, Venkatesh, Thong and Xu (2012) proposed an extended UTAUT model which includes hedonic motivation, price value and habit as additional exogenous factors and drops voluntariness of use. This extended UTAUT model additionally includes an effect of facilitating conditions on behavioural intention.

Cross-National Comparisons

Cross-national comparisons and group comparisons in general, assume the absence of bias which implies independence between observed scores and membership of the groups involved in the comparisons (van de Vijver & Leung, 1997). In relation to cross-national comparisons, van de Vijver and Leung (1997) indicate that there are three main types of bias to consider. These are:

(a) *Construct bias* – which means that the constructs measured are different among the groups involved.
(b) *Method bias* – which means that means the items in the instrument function differentially among the groups either due to cultural or other influences that aligned with the groups involved.
(c) *Item bias* – which refers to idiosyncrasies of various items in the instrument used.

Each of these biases can be investigated by evaluating measurement invariance.

Measurement Invariance

Measurement invariance (MI) means that there are no group differentials in the observed scores for a construct, given the true score on the construct (Meredith, 1993; Meredith & Millsap, 1992; Millsap, 1995).

Hence for an attribute W measured by a set of variables X, over populations V, $F(X \mid W,V) = F(X \mid W)$.

MI is therefore achieved when the observed score of an individual is determined by only his/her true score on the construct regardless of the group to which the person belongs (Schmitt & Kuljanin, 2008). A lack of MI is indicative of item bias which is a threat to instrument validity and which impairs group comparability of data (van de Vijver & Tanzer, 2004; Oorta et al., 2009; Chen, 2008). There are several levels of measurement invariance which form a hierarchy. Three levels of MI that are relevant to this article are: configural, metric and scalar invariance. These levels of measurement invariance are addressed in this article using the language of factor analysis.

Configural Invariance

Configural invariance hypothesises that the number of factors (k) is the same in each group, that is,

$$H_k : k_1 = k_2 = \ldots = k_G$$

and that the same set of relationships are specified (Jöreskog, 1971; Horn & McArdle, 1992; Steenkamp & Baumgartner, 1998; Vandenberg & Lance, 2000). If the model with non-salient factor loadings set to zero fits the data well in all groups under study, and all salient factor loadings are significantly and substantially different from zero, and the correlations between factors (if any) in the model are significantly less than unity, configural invariance is achieved (Steenkamp & Baumgartner, 1998). This is an important requirement and it must be established before moving on to more restrictive forms of invariance (Horn & McArdle, 1992). An omnibus test of invariance which test for full equality of covariance matrices across all the groups [15, 42, 36] is recommended as a starting point. If this is achieved, then the data are entirely comparable and there is no need for any other test. It involves the null hypothesis,

$$H_\Sigma : \Sigma_1 = \Sigma_2 = \ldots = \Sigma_G$$

which states that the covariance matrices are the same across the groups. This is very unlikely to be achieved.

Metric Invariance

Metric invariance (weak MI) relates to the sizes of the salient factor loadings and it assumes that configural invariance is achieved. Metric invariance requires configural invariance and it indicates that the respective item loadings are equal across the groups under study (Jöreskog, 1971; Dimitrov, 2010; Vandenberg & Lance, 2000), that is,

$$H_\Lambda : \Lambda^1 = \Lambda^2 = \ldots = \Lambda^G$$

where the Λs represent vectors of regression slopes which represent the rates at which the indicators are influenced by the latent constructs (Dimitrov, 2006). Metric invariance means that the measurement units or the meanings of the constructs are the same across groups (Steinmetz et al., 2009). This level of invariance enables comparisons of structural relationships, inclusive of factor variances and covariances and of comparisons between the effects of external variables on the factors (Dimitrov, 2010).

Scalar Invariance

Scalar (strong) invariance is required for group comparisons of the means of latent variables (Schmitt & Kuljanin, 2008; Vandenberg & Lance, 2000). In addition to invariant measurement units (metric invariance), scalar invariance implies invariant item intercepts (or thresholds) (Steinmetz et al., 2009; Sass, 2011), that is, the null hypothesis,

$$H_{\Lambda ^{2}} : \Lambda^1 = \Lambda^2 = \ldots = \Lambda^G ; {}^{2\,1} = {}^{2\,2} = \ldots = {}^{2\,G} ,$$

where $^{2\,i}$ is the vector of item means in group i, must be accepted to avoid upward or downward biasing of the factor means in any of the groups.

Strict Invariance

Strict invariance also referred to as invariant uniqueness asserts that the measurement errors of the manifest variables are equal. This test involves the hypothesis that the variances of the item error terms are equal across the groups. This would also require achievement of metric and scalar invariance and some have indicated that it should also require invariant factor variances and covariances when the intent is to interpret the results as evidence of invariant item reliability (Vandenberg & Lance, 2000; Schmitt & Kuljanin, 2008; Steinmetz et al., 2009; Steenkamp & Baumgartner, 1998). Strict invariance is unlikely to be achieved in practice (Horn & McArdle, 1992) and it is often not of interest. Such a test has also been described as up to the discretion of the researcher (Vandenberg & Lance, 2000).

Structural Invariance

Structural invariance refers to an absence of bias at the factor level. It includes evaluating the equality of factor variances and covariances inclusive of regression relationships among factors or between factors and external variables. In part, this study focuses on the consistency of the sizes of the UTAUT relationships, which means that structural invariance is important. Structural invariance requires metric invariance, but apart from this, the order of the tests for structural invariance is not crucial (Steenkamp & Baumgartner, 1998).

Invariant Factor Variances

Checking for invariant factor variances involves testing the hypothesis,

$H_{\Lambda\Phi}:\Lambda^1=\Lambda^2=\ldots=\Lambda^G;\Phi_{jj}^1=\Phi_{jj}^2=\ldots=\Phi_{jj}^G$ where $\Phi_{jj}^i; j=1,2,\ldots,m$ are the variances of the factors in group i.

Acceptance of this hypothesis means that the factors are measured with the same precision across the groups.

Invariant Factor Covariances

Equality of factor covariances is evaluated by testing the hypothesis,

$$H_{\Lambda\Phi}:\Lambda^1=\Lambda^2=\ldots=\Lambda^G;\Phi_{jk}^1=\Phi_{jk}^2=\ldots=\Phi_{jk}^G$$

where $\Phi_{jk}^i; j=1,2,\ldots,m; k=1,2,\ldots,(j-1)$ is the variance-covariances between factors in group i.

This implies that the respective factor variances should also be equated among the groups involved in the comparisons. For the purposes of this paper, evaluating the invariance of the factor covariances which can also be the regression relationships among the factors, will allow determination of whether the sizes of the UTAUT relationships are consistent among the groups involved.

Partial Invariance

A final element of measurement invariance that often becomes important in application is partial invariance. Partial invariance is not a new level of measurement invariance. It applies to all levels of measurement and structural invariance and it is relevant when full invariance as per the definitions is not achieved, but some subset of the parameters is equal across the groups. Whenever partial invariance is applied, the non-invariant parameters are not equated and do not contribute to the intended comparisons. Full measurement invariance is often difficult to achieve and, in such cases, partial invariance provides some basis for proceeding with the intended analysis though with some limitation.

DATA AND METHODS

Data

The data for this study were collected from students in a web survey conducted between October 2012 and February 2013 at six university campuses. These are four of the campuses of The University of the West Indies (The UWI) - Cave Hill Barbados, Mona Jamaica, St. Augustine (Trinidad and Tobago) and the Open Campus - the University of Guyana (Guyana) and the University of Technology (Jamaica). The UWI Open Campus pulls students primarily from several territories within the region. In this paper, the Open Campus is regarded as an entity onto itself and the other groups in the data as campus-territory combinations. The data from the two university campuses in Jamaica are therefore pooled to form a single sample for Jamaica.

Table 1: *Measurement of the UTAUT Constructs*

Construct	Code	Item
Performance Expectancy	PE1	Mobile Technologies are useful in education in general.
	PE2	Using mobile technologies enable students to accomplish tasks more quickly.
	PE3	Mobile technologies would improve students' performance.
	PE4	Mobile technologies would increase students' productivity.
Effort Expectancy	EE1	Mobile technologies are easy to use.
	EE2	Finding or using features in mobile technologies is easy.
	EE3	Learning to operate mobile technologies is easy.
Social Factors	SF1	People who influence my behaviour think that I should use mobile technologies.
	SF2	People who are important to me think that I should use mobile technologies for learning.
	SF3	University teachers are supportive of the use of mobile technologies.

Construct	Code	Item
Facilitating Conditions	FC1	I have the resources necessary to use m-Learning.
	FC2	I have the knowledge necessary to use m-Learning.
	FC3	Support from an individual or service is available when problems are encountered with m-Learning technologies.
Behavioural Intention	BI1	I intend to use m-Learning technologies in the next semester.
	BI2	I predict I will use m-Learning technologies in my courses in the next semester.
	BI3	I have a plan to use m-Learning technologies in the near future.

Scale labels: 1 – Strongly disagree, 2 – Disagree, 3 – Neither Agree nor Disagree, 4 – Agree, 5 – Strongly Agree. In the items, m-Learning refers to mobile learning.

The students were invited to participate in the survey via email and a total of 1726 respondents completed it. The respondents are distributed over the university-territory groups as follows: 649 (Barbados), 243 (Guyana), 262 (Jamaica: 150 - UWI Mona; 112 - University of Technology), 333 (Trinidad and Tobago), and 239 (UWI Open Campus). Given the large difference in sample size especially for Barbados, resampling of the data was done to randomly select 243 respondents from each university-territory group (except the Open Campus) with the gender distribution preserved. This selection of 243 was done in light of the sample size for Guyana to balance power among the groups. However, the sample for the Open campus was left at 239. The effective combined sample size for the data used in this paper is therefore 1211.

The five factors in the UTAUT model were measured in the survey with the items indicated in Table 1. These items have been employed and validated in several studies. For this study, the items were modified to focus attention on mobile learning. The items were all scored on five-point fully labelled agree/disagree rating scales with larger numeric values indicating stronger agreement.

Methods

One of the objectives is to perform a multi-group evaluation of the structural parameters of the UTAUT model. We refer to this somewhat loosely as a cross-national evaluation given the description of the groups provided earlier. Multi-group confirmatory factor analysis is employed to evaluate the measurements and a multi-group structural equations modelling is subsequently utilised to evaluate the UTAUT relationships. In all cases, robust maximum likelihood estimation is used and estimation is done using the Mplus software.

For the models estimated, the root mean square error of approximation (RMSEA) less than 0.60, comparative fit index (CFI) greater than or equal to 0.95 and the standardised root means square error residual (SRMR) less than or equal to 0.50 are regarded of indicative of good global fit of the models (Byrne, 1989; Hu & Bentler, 1999) and a majority of these indices are used as the basis for conclusion. In addition, the chi-square statistics are reported along with the change in chi-square for nested models.

The first step of the analysis is that of evaluating the factorial validity of the measurement models. Standardised factor loadings greater than or equal to 0.70 are regarded as ideal and an average variance extracted of at least 0.50 is adequate for factor convergent validity (Fornell & Larcker, 1981). In addition, discriminant validity is established when the factor correlations are lower than the square root of the average variance extracted for the factor under consideration (Fornell & Larcker, 1981).

The second step in the analysis is evaluation of measurement invariance. Configural and metric invariance are required for comparisons of the structural relationships whereas scalar invariance is necessary for comparison of the factor means.

For metric and scalar invariance, changes in RMSEA and CFI that are less than 0.015 and 0.01 respectively and changes in SRMR that are less than 0.03 (metric invariance) and 0.01 (scalar invariance) are indicative of good relative fit (Chen, 2008). These benchmarks are for maximum likelihood estimation but they are used as guides in this paper where robust maximum likelihood estimation is applied. In addition to this approach, the nested models are evaluated using JRule for Mplus (Oberski, 2008; Van der Veld, 2008). JRule (judgment rule) for Mplus is a program that evaluates the modification indices, expected parameter change and the power to detect misspecifications in the model. Such misspecifications can occur even when the global fit indices indicate adequate fit (Saris, Satorra, & Van der Veld, 2009; Van der Veld & Saris, 2011). For this evaluation, high power is set at 0.80 and Type I error at 0.05. The misspecification is set to 0.10 for error covariances and at 0.40 for factor loadings.

The third step in the analysis is evaluation of the structural relationships between behavioural intention to adopt mobile learning and the other latent variables in the model. The equality of the structural parameters between the groups is evaluated and also the percentages of the variance in behavioural intention that are explained by the model.

RESULTS

Validity

The initial confirmatory factor model for the UTUAT constructs for each group, is a good fit for the data (see Table 1). Nevertheless, there were some issues with the loadings for two items. These are the third indicator of social factors (*SF3: University teachers are supportive of the use of mobile technologies*) and the third indicator of facilitating conditions (*FC3: Support from an individual or service is available when problems are encountered with m-Learning technologies*).

Table 1: *Initial Confirmatory Factor Models*

Initial Models	χ^2	*df*	RMSEA	CFI	SRMR
Barbados	153.15	94	0.05	0.97	0.05
Guyana	148.36	94	0.04	0.98	0.05
Jamaica	160.95	94	0.04	0.98	0.05
Open Campus	189.10	94	0.06	0.96	0.06
Trinidad	159.88	94	0.05	0.97	0.05

Table 2: *Factor Loadings*

Item	Barbados	Guyana	Jamaica	Trinidad & Tobago	Open Campus
PE1	0.69	0.66	0.68	0.72	0.61
PE2	0.78	0.68	0.75	0.75	0.77
PE3	0.78	0.86	0.87	0.85	0.89
PE4	0.78	0.88	0.86	0.79	0.91
AVE(PE)	***0.56***	***0.55***	***0.59***	***0.60***	***0.59***
EE1	0.87	0.83	0.85	0.84	0.82
EE2	0.86	0.89	0.90	0.90	0.89
EE3	0.82	0.81	0.86	0.78	0.87
AVE(EE)	***0.72***	***0.71***	***0.76***	***0.71***	***0.74***
SF1	0.90	0.84	0.92	0.90	0.96
SF2	0.88	0.85	0.88	0.93	0.93
AVE(SF)	***0.79***	***0.71***	***0.81***	***0.84***	***0.89***
FC3	0.71	0.57	0.65	0.72	0.72
FC4	0.81	0.79	0.78	0.85	0.82
AVE(FC)	***0.58***	***0.47***	***0.52***	***0.62***	***0.60***
BI1	0.95	0.93	0.97	0.94	0.96
BI2	0.92	0.82	0.90	0.92	0.95
BI3	0.85	0.78	0.74	0.84	0.80
AVE(BI)	***0.82***	***0.72***	***0.77***	***0.81***	***0.82***
Model Fit					
Chi-Squared	107.98	96.75	110.01	102.49	118.48
Degrees of Freedom	69	69	69	69	69
RMSEA	0.04	0.03	0.04	0.04	0.05
CFI	0.98	0.99	0.98	0.99	0.98
SRMR	0.04	0.04	0.04	0.03	0.04

PE – Performance Expectancy, EE – Effort Expectancy, SF – Social Factors, FC – Facilitating Condition, BI – Behavioural Intention.

Table 3: *Factor Discriminant Validity*

	PE	EE	SF	FC	BI	PE	EE	SF	FC	BI
	Barbados					**Guyana**				
PE	**0.75**					**0.74**				
EE	0.32	**0.85**				0.26	**0.84**			
SF	0.40	0.12	**0.89**			0.52	0.23	**0.84**		
FC	0.45	0.51	0.21	**0.76**		0.29	0.41	0.34	**0.69**	
BI	0.62	0.41	0.32	0.55	**0.91**	0.49	0.36	0.39	0.54	**0.85**
	Jamaica					**Trinidad & Tobago**				
PE	**0.77**					**0.77**				
EE	0.33	**0.87**				0.34	**0.84**			
SF	0.42	0.31	**0.90**			0.46	0.31	**0.92**		
FC	0.49	0.38	0.34	**0.72**		0.25	0.32	0.24	**0.79**	
BI	0.48	0.37	0.40	0.50	**0.88**	0.58	0.44	0.40	0.47	**0.90**
	Open Campus									
PE	**0.77**									
EE	0.26	**0.86**								
SF	0.46	0.24	**0.94**							
FC	0.42	0.49	0.27	**0.77**						
BI	0.61	0.31	0.39	0.54	**0.91**					

Off-diagonal elements are factor correlations; diagonal elements are the square roots of the average variance extracted for the respective factors.

PE – Performance Expectancy, EE – Effort Expectancy, SF – Social Factors, FC – Facilitating Condition, BI – Behavioural Intention.

The third social factors indicator had standardised loadings less than 0.48 in all but the Jamaica data (loading = 0.51 in Jamaica) and this loading is spectacularly low, 0.28, in the Guyana group. JRule also detects the absence of a loading of this item on the facilitating conditions or behavioural intention or performance expectancy, depending on the group, as a misspecification, The use of mobile learning by students in the region is generally voluntary and this low loading might mean that encouragement to use them or that promotion of mobile learning does not usually come from university professors in general. The item also fails to discriminate well among the factors in the model and it is dropped from further analysis.

The loading of the third indicator of facilitating conditions is lower than 0.50 in all the groups except Jamaica where it stands at 0.68 with the result that the average variance extracted for the factor lies below 0.50 in each group. The first two indicators of the factor focus on the individual, but the third focuses externally and this might account for the low standardised loading observed. The usefulness of this indicator is limited and it is removed from the model.

Removing the item from the analysis does not resolve all the issues with low item loadings. The facilitating conditions factor, though improved in Guyana (average variance extracted moved from 0.37 to 0.47) still shows low overall convergent validity there (see Table 2). Nevertheless, the revised models are accepted.

For the accepted models, the average variance extracted for each factor except facilitating conditions in Guyana is adequate and this indicates that each of the other factors is recovered well from the data (see Table 2). Notwithstanding the convergent validity issue identified, each factor provides unique information and is a useful inclusion in the model. This is the result of discriminant validity having been achieved for each factor (see Table 3).

Measurement Invariance

Acceptance of the models means that configural invariance is achieved. The models have the same factorial form with respect to the number of factors and with respect to the salient loadings and absence thereof. However, it is still necessary to estimate the models simultaneously to establish a baseline for comparison. The fit indices for this simultaneous configural invariance model are shown in Table 4. Notably, each fit index confirms to the criterion for good fit model.

The metric invariance model is a close fit to the baseline configural invariance model (see Table 4). Only the SRMR increased, but marginally (0.01), when this constraint is applied. Furthermore, no large modification indices for the salient item loadings emerge and JRule does not detect any misspecifications of the constrained loading. Full metric invariance is therefore achieved and this means that the measurement units are the same in each group.

Table 4: *Fit of Multi-Group Models*

	χ^2	df	$\Delta\chi^2$	Δdf	$\frac{\Delta\chi^2}{\Delta df}$	RMSEA	CFI	SRMR
Configural Invariance	535.62	345	---	---	---	0.04	0.98	0.04
Metric Invariance	574.61	373	38.99	28	1.39	0.04	0.98	0.05
Full Scalar Invariance	693.15	409	157.53	64	2.46	0.05	0.97	0.06
First Partial Scalar Invariance*	668.05	408	132.44	63	2.10	0.04	0.98	0.06
Final Partial Scalar Invariance**	655.92	407	120.30	62	1.94	0.04	0.98	0.06
Structural Model	574.61	373	38.99	28	1.39	0.04	0.98	0.05
Partial Structural Invariance†	581.52	381	6.91	8	0.86	0.04	0.98	0.06

Delta means change in. †Referenced to the structural model. †EE and SF not constrained.

*Intercept of FC3 freed in Guyana. **Intercept of PE1 freed in the Open Campus group.

The full scalar invariance model is a close fit to the configural invariance model except with respect to SRMR (Table 4). Based on the majority rule, the model can be accepted. However, closer inspection of the results using JRule reveals a few non-invariance item intercepts which need to be remedied to avoid bias in the comparisons of the factor means. In total, two equality constraints on the item means were relaxed sequentially. Specifically, equality constraints were relaxed for the first indicator of facilitating conditions in the Guyana group and for the third indicator of performance expectancy in the Open Campus group. In addition to the identified intercepts, the first indicator of performance expectancy also had a large modification index (12.96) in the Barbados group. However, the power for this parameter was quite high and the expected parameter change was small (power = 0.93, EPC = 0.10) and it was therefore not relaxed. The two modifications permitted mean that only partial scalar invariance is achieved.

Comparison of Factor Means

Table 5: *Comparison of Factor Means*

	Performance Expectancy	Effort Expectancy	Social Factors	Facilitating Conditions	Behavioural Intention
Barbados (Baseline)					
Guyana	0.56* (0.11)	0.18 (0.10)	0.19 (0.10)	0.41* (0.13)	0.13 (0.10)
Jamaica	0.35* (0.11)	0.10 (0.09)	0.09 (0.09)	0.01 (0.11)	-0.16 (0.09)
Open Campus	0.23 (0.10)	-0.15 (0.09)	0.09 (0.09)	-0.02 (0.10)	-0.14 (0.09)
Trinidad & Tobago	0.04 (0.10)	-0.08 (0.09)	0.01 (0.09)	-0.14 (0.10)	-0.04 (0.09)
Jamaica (Baseline)					
Guyana	0.18 (0.10)	0.08 (0.10)	0.10 (0.10)	0.40* (0.13)	0.31* (0.10)
Open Campus	-0.09 (0.10)	-0.24* (0.09)	0.01 (0.09)	-0.03 (0.10)	-0.03 (0.09)
Trinidad & Tobago	-0.31* (0.10)	-0.19 (0.10)	-0.07 (0.10)	-0.13 (0.11)	-0.12 (0.10)
Guyana (Baseline)					
Open Campus	-0.25* (0.09)	-0.31* (0.09)	-0.08 (0.09)	0.36* (0.10)	-0.24* (0.09)
Trinidad & Tobago	-0.47* (0.09)	-0.27* (0.10)	-0.17 (0.10)	-0.22 (0.10)	-0.15 (0.09)
Open Campus (Baseline)					
Trinidad & Tobago	-0.21 (0.10)	0.10 (0.11)	-0.08 (0.10)	0.16 (0.11)	0.09 (0.10)

PE – Performance Expectancy, EE – Effort Expectancy, SF – Social Factors, FC – Facilitating Condition, BI – Behavioural Intention.
Bonferroni correction applied in the tests for each factor.

Given that only partial scalar invariance is achieved, comparisons of the factor means are done on the basis of partial measurement invariance and the non-invariant items do not contribute to the comparisons whenever their respective groups are involved. The description of the comparisons of the means proceed from one factor to the next beginning with behavioural intention to adopt mobile learning.

Behavioural Intention

With the exception of Guyana, the groups are homogeneous with respect to the mean of behavioural intention (Table 6). The mean for Guyana is significantly higher than the mean for Jamaica and the Open Campus giving rise to two homogeneous groups of means that share two entries but with Guyana having the highest mean (Table 5). The students from Guyana therefore seem more so poised to adopt mobile learning than those from Jamaica and the Open Campus but are similarly poised as those from Barbados and Trinidad and Tobago.

Table 6: *Homogeneous Groups for Behavioural Intention*

Group 1	Group 2
Guyana	
Barbados	Barbados
Trinidad & Tobago	Trinidad & Tobago
	Jamaica
	Open Campus

Facilitating Conditions

Guyana is the only group that is significantly different from any other in relation to the facilitating conditions (Table 5). The Guyanese students perceive better facilitating conditions than the students from each of the other groups except Trinidad and Tobago. The facilitating conditions therefore appear to be a greater facility in Guyana than elsewhere in the region. A caveat to this is that for the comparison, only a single indicator of facilitating conditions (FC2) is involved given that the first indicator in the Guyana group was a cause of partial scalar invariance.

Social Factors

The groups are all homogeneous with respect to the means of social factors. The level of the social factors can therefore be regarded as similar across the campus-territories combinations.

Effort Expectancy

For effort expectancy, Barbados, Jamaica and Trinidad and Tobago form a homogeneous group with respect to the mean levels (see Table 7). The perceived ease of use of the mobile devices is therefore similar across these territories. Differences in means occur when Guyana and the Open Campus are considered. Specifically, the mean effort expectancy is higher in Guyana than both in Trinidad and Tobago and at the Open Campus, but is similar to the corresponding means for Jamaica and Barbados. In addition, the mean of effort expectancy at the Open Campus is also lower than that in Jamaica (Table 5).

Table 7: *Homogeneous Groups for Effort Expectancy*

Group 1	Group 2	Group 3
Guyana		
Jamaica	Jamaica	
Barbados	Barbados	Barbados
	Trinidad & Tobago	Trinidad & Tobago
		Open Campus

The results for effort expectancy therefore point to three homogeneous groups with group 1 sharing two entries with group 2 and with group 2 sharing two entries with group 3. The group containing Guyana is ranked highest whereas the group containing the Open Campus is ranked the lowest (see Table 7).

Performance Expectancy

With respect to performance expectancy, Barbados, Trinidad and Tobago and the Open Campus form a homogenous group with similar means (Table 8). The usefulness of the mobile devices is therefore similar across these three campus-territory combinations. Concurrently, the levels are similar between Jamaica and Guyana and between Jamaica and the Open Campus. However, the mean for Guyana is larger than the means for Barbados, Trinidad and Tobago and the Open Campus, whereas the mean for Jamaica is larger than the means for Barbados and for Trinidad and Tobago (Table 5).

Table 8: *Homogeneous Groups for Performance Expectancy*

Group 1	Group 2	Group 3
Guyana		
Jamaica	Jamaica	
	Open Campus	Open Campus
		Barbados
		Trinidad and Tobago

The differences among the means give rise to the arrangement shown in Table 8. There are three homogeneous groups with group 1 and group 2 sharing one entry and with group 2 and 3 sharing one entry. Group 1 which contains Guyana is ranked highest whereas the group containing Barbados and Trinidad and Tobago is ranked the lowest.

Comparison of UTAUT Relationships

In the modified model implemented, facilitating conditions is included as a predictor of behavioural intention. The relationships are specified and applied to the model with the factor loadings equated across the groups (see Table 4). In effect, this new model replaces the correlations among the factors in the metric invariance model with the direct effects identified. The resulting model is identified as "structural" in Table 4 and the fit indices are the same as for the metric invariance model.

Table 9: *Structural Effects on Behavioural Intention*

	Barbados	Guyana	Jamaica	Trinidad & Tobago	Open Campus
Performance Expectancy	0.41* (0.07)	0.31* (0.07)	0.23* (0.09)	0.40* (0.07)	0.43* (0.04)
Effort Expectancy	0.11 (0.07)	0.10 (0.09)	0.14 (0.03)	0.18* (0.07)	0.01 (0.07)
Social Factors	0.08 (0.06)	0.08 (0.08)	0.17* (0.07)	0.09 (0.07)	0.10 (0.07)
Facilitating Conditions	0.29* (0.09)	0.39* (0.10)	0.28* (0.10)	0.30* (0.07)	0.33* (0.09)
R-squared	0.46*	0.42*	0.41*	0.48*	0.46*

* Significant at the 5% level. ¥ Became significant when the other structural parameters were set equal. † Lost significance when the structural parameters were equated.

An important observation from the results is that two factors – social factors and effort expectancy – are not consistently significantly related to behavioural intention at the 5% level. The effect of social factors lacks significance at the 5% level in all the groups except Jamaica. Social factors are therefore important to behavioural intention only in Jamaica. Effort expectancy is a significant predictor of behavioural intention only in the Trinidad and Tobago data and is therefore important only in that group. These results evidence substantial departure from expectations about the UTAUT model (discussed subsequently). Given that each of these relationships lacks significance in four of the five groups, they are not constrained to equality in the next step.

With the respective structural effects of performance expectancy and facilitating conditions on behavioural intention equated across the groups, the fit indices indicate that a close fit to the initial structural model is achieved (Table 4). Furthermore, this partial structural invariance model is a close fit to even the metric invariance model and no misspecifications of the structural parameters are detected by JRule. Therefore, the effects of performance expectancy and facilitating conditions on behavioural intention are equal across the groups and the amount by which fixed changes in these factors impact on behavioural intention is consistent across the groups. However, though the unstandardised effects are equal, the standardised coefficients may still differ since strict invariance (all variances and covariances along with metric invariance) was not applied. The standardised structural effects are shown in Table 9 and all the significant effects are positive.

A final observation about the structural model is that the relationships specified, explain between 41% (Jamaica) and 48% (Trinidad & Tobago) of the variation in behavioural intention (see Table 9). A majority of the variance in behavioural intention is therefore left unexplained by the model in each group.

DISCUSSION

The results of this study add to the counterexamples of universal applicability of the UTAUT model even as it confirms some elements of the model.

The result that the measure of social factors lacks a significant effect on behavioural intention in four of the groups, is neither unique nor relevant only to the data used in this study (see for example, Isaias et al., 2017; Mosunmola et al., 2018). Furthermore, there was a prior indication of such an absence of effect in Guyana (see Thomas et al., 2013). The consistency of this lack of significance across the territories except for Jamaica makes it difficult to ignore. In the analysis, one indicator of social factors was dropped for low convergent validity, but even when this item is retained in the model (result not shown), the effect on behavioural remains non-significant in the four groups. An effect of social factors on behavioural intention is therefore not unequivocally established for the Caribbean.

The impact of social factors in the model presumes that the social influences can lead to adoption of the technologies. However, the influencers themselves may not see adoption of mobile learning as very realistic when there are salient contextual constraints such as relative scarcity or poor quality of resources. In addition to this, there might be cultural moderation of the relationships in the UTAUT model which goes beyond issues of resources (Al-Adwan et al., 2018). That a significant relationship emerges in Jamaica might also be due to cultural moderation though we were not able to verify this. Whereas we could find measures for cultural variables for Jamaica and Trinidad and Tobago, similar values were not available for Guyana and Barbados and this did not allow for a cultural comparison of the territories as a means of explaining the difference in result for Jamaica. An explanation of this moderation of the impact of social factors should be the subject of further research.

The lack of a significant effect of effort expectancy encountered in four of the five groups was also not altogether unexpected. Two previous studies done in Guyana indicated this absence of a significant relationship in relation to mobile learning (see Singh et al., 2016; Thomas et al., 2013). The importance of effort expectancy as a means of promoting mobile learning adoption in the region is therefore limited. However, as in the case of social factors, further research should examine the circumstances under which effort expectancy can be expected to have an effect on behavioural intention to adopt mobile learning and this explanation should also evaluate the relevance of cultural moderation beyond noting the possibility.

Using data from Guyana, Thomas et al. (2013) found a significant effect of facilitating conditions on behavioural intention. Inclusion of this effect is also consistent with other work on the UTAUT model (see Venkatesh et al., 2012). This paper, confirms the existence of a significant effect of facilitating conditions on behavioural intention in the Caribbean.

The explained variance for behavioural intention does not exceed 48% in any group. It therefore seems that when applied to the territories involved, the model indeed explains a lower percentage of the variance in behavioural intention than the 70% indicated for the UTAUT model (Venkatesh et al., 2003). A caveat is that the interaction terms identified in the UTAUT model were not implemented. However, even when interaction terms are included, the explained variance can still be as low as 39.1% (Teo, 2011). Though a lack of a significant effect of social factors might lower the explained variance, even this does not explain the result given the case of Jamaica. Furthermore, the explained variance remains low even with the addition of an effect of facilitating conditions.

The measurements of social factors and facilitating conditions had to be trimmed by dropping one indicator of each. Nevertheless, there was an absence of construct bias (Vandenberg & Lance, 2000; van Vijver & Leung, 1997; Steenkamp & Baumgartner, 1998). Apart from this, the factors showed full metric invariance which indicates equality of the measurement units (Steinmetz et al., 2009) but only partial scalar invariance (Sass, 2011; Steinmetz et al., 2009). The latter indicates the presence of some extent of item bias (van Vijver & Leung, 1997) in relation to facilitating conditions in Guyana and performance expectancy in the Open Campus group. This result for metric invariance is different from that reported by Thomas, et al. (2014) for the region but that study retained the item loadings with low validity which likely resulted in different measurements.

Though it remains useful in studying mobile learning adoption, the UTAUT model appears to underperform in the Caribbean with respect to the explained variance, the measurements of social factors and facilitating conditions and with respect to the lack of significant effects of social factors and effort expectancy in most cases. Addressing these issues would require substantial modifications of the model. In this regard, there is an extended UTAUT model (Venkatesh et al., 2012) and other proposals (for example, Dwivedi et al. (2019)) that could be a starting point. However, these studies do not address the measurement (item convergent validity) issues and those related to the effects of some factors. The measurement of the factors for mobile learning in the Caribbean are in need of some development work.

We can conclude from the results that performance expectancy and facilitating conditions clearly have significant, positive and equal effects on behavioural intention to adopt mobile learning in the Caribbean. Hence, if any of these are improved, the chances of and extent to which mobile learning is adopted are also likely to improve.

Interpretation of readiness for mobile learning can also be made from comparisons of the means of these two factors among the groups. When the factor means are considered, students in Guyana emerge as being more ready to adopt mobile learning than those in Jamaica (see Thomas et al., 2014) and at the Open Campus of the University of the West Indies. This is inferred from the result that the mean for behavioural intention is higher in Guyana. The other comparisons do not provide a basis for distinguishing any other combination of groups based on behavioural intention to adopt mobile learning.

Guyana appears in the highest ranked group for performance expectancy and facilitating conditions. With facilitating conditions having a positive impact on behavioural intention, it would seem worthwhile to address such issues everywhere. However, addressing it in Barbados, Jamaica, Trinidad and Tobago and at the Open Campus would seem to be especially important in promoting mobile learning adoption. In contrast, addressing social factors and effort expectancy is likely to affect the level of behavioural intention in Jamaica and Trinidad and Tobago respectively. In relation to facilitating conditions, the results for Guyana seem to be inconsistent with the ITU's ICT development index. In particular, Guyana is ranked 124, Jamaica 98, Trinidad & Tobago 68 and Barbados 34 on the ICT Development Index 2017 (ITU, 2017). Though the actual ranking was different in 2013, the order of the territories was the same with Guyana at 105, Jamaica 93, Trinidad and Tobago 66 and Barbados 36 (ITU, 2013). The only substantial change from 2013 to 2017 is that Guyana dropped 19 places. Nevertheless, facilitating conditions capture the evaluation of the individuals which is based on their perceptions and this may not necessarily reflect the state of ICT development.

LIMITATIONS

This study has a few limitations. While it was necessary, trimming the measurement of factors to achieve item validity might change the meaning of the measurement so that analysis of the structural relationships which came afterwards might be affected. The data are a bit old but no more recent comparable data across the region exists at present. This can potentially affect the factor means which can change over time, but it is unlikely to change the relationships among the factors especially if this is based on the cultural context. Participation in the survey was based on self-selection and voluntary participation (though the participants were directly invited) which could have affected the composition of the sample. This is an issue that affects many web surveys.

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