

## **The Effect of Mobile User Typology on Mobile Learning Adoption in Higher Education**

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**Abstract:** Mobile user typology is absent from popular models for mobile learning adoption though understanding such typology can help with design of learning. This paper explores the salient mobile user typology by applying latent class analysis to reported use of mobile phone features collected from students at six university campuses in four countries (Barbados, Guyana, Jamaica, Trinidad and Tobago). It also relates the user types to behavioural intention to adopt mobile learning within a structural equation modelling framework. The results indicate four mobile user types which are distributed differently over the campus-territory groups and to which age, sex, programme level and programme type of the students are significantly related. Furthermore, mobile user typology is related to behavioural intention to adopt mobile learning and this avails it as a candidate for inclusion in models used for mobile learning adoption. There is some extent of cross-national specificity of mobile user typology though some user categories seem to be more generalisable

**Keywords:** mobile user, typology, mobile learning adoption, technology adoption, higher education.

### **Introduction**

Technology adoption in higher education offers many possibilities for extending the reach and impact of education (Kukulska-Hulme, 2007). The mobility and portability of mobile devices, in particular, bring with them unique opportunities and mobile devices are thought to have pedagogical affordances (Daugherty & Berge, 2017) which make them potentially good for altering the way teaching and learning is done by providing new methods of instruction (Traxler, 2007).

Mobile learning is regarded as especially useful given the flexibility that it affords learners in ways, times, and spaces that were not previously possible (Schuck, Kearney & Burden, 2017; Lau, Chiu, Ho, Lo & See-To, 2017) and it benefits from an increasingly wide range of application programs (Kim, Ilon & Altmann, 2013). Though mobile learning entails its share of challenges (see Bano, Zowghi, Kearney, Schuck, & Aubusson, 2018; Kukulska-Hulme, 2007; Hawi & Samaha, 2016; Pimmer, Mateescu, & Grohbiel, 2016; Kates, Wu, & Coryn, 2018; Felisoni & Godoi, 2018), its adoption has emerged as an important sub-domain and trend of technology adoption (Chee, Yahaya, Ibrahim & Hasan, 2017) and has gained much attention in relation to higher education (for example, Alrasheedi, Capretz & Raza, 2015; Pimmer et. al., 2016; Al-Emran, Mezhuyev, & Kamaludin, 2018; Crompton & Burke, 2018).

Studies on mobile learning adoption are often concerned with intention to adopt and they often apply established models among which the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, G. B. Davis, F. D. Davis, 2003) are quite popular. These models focus on technology acceptance and use in general and they include several factors and individual characteristics as predictors of behavioural intention and behavioural intention as a predictor of actual use. However, these models do not include user typology and this might account, to some extent, for the paucity of segmentation studies on mobile users in relation to mobile learning. Essentially, researchers, guided by the established models, might either regard mobile user typology as unimportant to mobile learning or might not consider it at all. This is

troubling since an understanding of user typology can assist with design of learning (Zawacki-Richter, Müskens, Krause, Alturki, & Aldraiweesh, 2015). The authors argue that designing mobile learning with consideration to the types of mobile users targeted is likely to affect mobile learning adoption and this is hence an area that should be researched. This paper explores mobile user types and their explanations in the context of higher education and evaluates the impact of mobile user typology on mobile learning adoption in higher education with a focus on mobile phones. This paper makes important contributions to the literature since understanding the mobile user typology can enhance the designing of mobile learning and because it, as far as we are aware, introduces mobile user typology as a potential predictor of mobile learning adoption.

## Literature

### Media User Typology

Mobile user typology is concerned with delineating homogenous groups that are heterogenous between in relation to their use of mobile features. Such studies often focus on the mobile phone which has become very popular in the populations studied. Mobile phone user segmentation studies largely track usage data through service providers or using applications installed on the devices. Such studies provide rich insights about the use of various features (for example, Do, Blom & Gatica-Perez, 2011; Yang et al., 2014; Zhao et al., 2016; ) that are quite useful for service providers, applications developers and manufacturers of the devices for example and which can also be useful in higher education. However, an important challenge in the context of education stems from such studies focusing much more often on the general population than on people enrolled in educational programmes.

Hamka, Bouwman, de Reuver and Kroesen (2014) find six latent classes of smartphone users among Finnish and Dutch customers. This includes 1) very minimal smartphone users, 2) basic users with limited smartphone app use, 3) average users with moderate amounts of app and web use, 4) information seekers with heavy amounts of web searching, but low app use, 5) users with extensive app use, and 6) users with high use of web utilities but low use of installed apps. Though these typologies capture frequency of use of features, they also differentiate among the actual features used thereby conveying preference for various applications. This was a study done on a general population and the data were obtained by tracking activity using an application installed on the devices.

In another study of mobile phone users done in the USA, Elhai and Contractor (2018) uncovered two latent types – heavy use and light use. The heavy use type emphasises social networking, audio and visual entertainment, and image and video-taking whereas the features emphasised in the light use segment include social networking, audio entertainment and image- and video-taking. This mobile user typology is based on reported usage of eleven smartphone features (Voice/Video Calls, Text/Instant Messaging, Email, Social Networking, Internet, Music/Podcasts, Gaming, Pictures/Videos, Watching TV/Movies, Reading, Maps/Navigation). They represent both usage frequency and preference for various features. The participants of this study were all students.

The foregoing results for mobile user typology bear some similarities with the media user typology literature. A meta-analysis in the field of Human Computer Interaction (HCI) done on 22 studies (published between the years 2000 and 2010) identifies an eight-category framework for classifying media users. The categories advanced are 1) non-users, 2) sporadics, 3) debaters, 4) entertainment users, 5) socializers, 6) lurkers, 7) instrumental users, 8) advanced users and these are based on frequency of use, variety of use and content preferences (Brandtzaeg, 2010). Subsequent work by the author confirmed five user types: sporadics, lurkers, socializers, debaters and advanced users with respect to social networking sites in Norway (see Brandtzaeg, 2012) and non-users, sporadics, entertainment users, instrumental users and advanced users with respect to the Internet use in Europe (five countries) (see Brandtzaeg, Heim, & Karahasanović, 2011). These subsequent studies utilised k-

means cluster analysis and the results suggest that even when the same approach is used, different user types might.

Adding to this, Zawacki-Richter et al. (2015) identify four profiles of media usage at German universities – entertainment users (recreational), peripheral users (low acceptance of all media), advanced users and instrumental users (focused educational usage) – having applied latent class analysis. Though the number of segments is not the same as that reported by Brandtzaeg and colleagues and the names assigned are somewhat different, there are similarities in results. For example, there is an advanced and an entertainment user segment. Many studies also focus on use of particular applications, services or platforms. For example, in relation to use of social media in the general population, Blunt and Doğan (2017) found eight user types: advanced users, business-oriented users, communication seekers, dawdlers whereas Constantinides, Alarcón del Amo and Lorenzo Romero (2010) found four categories: beginner, habitual user, outstanding user and expert users.

The fact that the names assigned to the segments in various studies are sometimes different does not negate the similarities between the results of studies on media user typology and those that focus specifically on mobile user typology. For example, the heavy users and those with extensive application usage seem similar to advanced users in the media typology or expert users whereas light users and basic users and those who make limited use of mobile phone applications seem similar to sporadics and nonusers in the media user typology or beginner. The difference in the number of classes and the description of the user groups that emerged in the studies might be due to contextual (inclusive of domain, country, culture and study group composition) differences in the target populations. Differences might also result from the different techniques applied to the data. The variability in the results obtained in different studies suggest a need for data driven determination especially when new territories and new domains are the foci of research.

People engage with mobile technology in different ways and though general use of mobile features does not translate into voluntary educational usage (Nwachukwu & Onyenankaya, 2017; Kaliisa, Palmer, & Miller, 2017), it seems likely that especially advanced users who both engage with a wide variety of features and use them often will be more inclined to adopting mobile learning. This argument holds if indeed mobile user typology captures the disposition of the users towards usage of the mobile features.

### **Who Use Mobile Features?**

The discussion about who use mobile features takes into consideration both the mobile and media user literature. In addition, it draws on the research on the educational purposes for which people use mobile phones in general to explore relationships that might have a bearing on mobile user typology.

Research indicates that media user typology is linked to socio-demographic variables including access to facilities and to country (Brandtzaeg et al., 2011). However, the existing (and limited) evidence for differences in the use of mobile features across individual characteristics is mixed. This paper focuses on age, sex, study level, discipline and on national differences<sup>1</sup>. The variables have all been used in the literature on mobile and media user typology and also in studies focus on how individual characteristics affect usage of mobile features. As each variable is discussed, evidence of their use and the results of their inclusion in relevant studies are provided. While there are other potential variables that might also be relevant, they are not all captured in the available data and as such the list of variables used is a result of both consideration of relevance and availability.

**Age.** The literature includes both evidence for and against a significant relationship between age and the use of smartphones as a whole for learning purposes. Whereas some find that age is positively

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<sup>1</sup> National differences is used in a not so strict manner here due to inclusion of the University of the West Indies's Open campus.

associated with device ownership, usage and the amount of time spent using the devices (Nwachukwu & Onyenakeya, 2017) others find no age effect on use of smartphones for learning purposes (Elhai & Contractor, 2018). However, older students (>33 years) are more likely than younger students to use their smartphones for transactions and payment of fees (Elhai & Contractor, 2018).

Older individuals might concentrate on features with which they are already familiar and which suffice for their instrumental purposes as in the case of media users in general (Zawacki-Richter et al., 2015). This argument is contingent upon age thresholds that represent large age gaps. In the context of higher education institutions, the presence of an effect of age may therefore depend on the mix of students and may emerge when there are enough older students represented in the sample. In the mobile phone user study by Elhai and Contractor (2018), the average age of the students is 19 years and the absence of older students might account for the lack of an effect of age that they report.

**Sex.** Sex differences in media usage perhaps track back to gender roles and might reflect societal inequalities (Brandtzaeg et al., 2011). Nevertheless, the evidence for sex differences is conflicting with some reporting an absence of such differences in usage patterns (Ashour, Alzghool, Iyadat, & Abu-Alruz, 2012; Elhai & Contractor, 2018) and others reporting the presence of sex differences (Taleb & Sohrabi, 2012; Naidu, 2018).

Subhash and Bapurao (2015) find no general difference on several usage characteristics except that females use their smartphones to access the Internet significantly more than males on a daily basis. Furthermore, there is some evidence that females use their mobile devices more than males for educational purposes including communicating academic problems (Alzougool & Almansour, 2017; Taleb & Sohrabi, 2012) and of females being more skilled in multimedia and calendar applications than males (Manteghi, 2010). However, there is also some evidence of males being more skilled in advanced communication, educational and recreational use of mobile phones (Manteghi, 2010).

Whereas greater gender equality in society is a potential explanation for an absence of gender differences in user classification (Internet user) (Brandtzaeg et al., 2011) this does not explain why the evidence does not point unequivocally in a single direction within some studies (for example, Alzougool & Almansour, 2017; Manteghi, 2010). Given that there are also sex differences in the educational purposes for which people use smartphones, sex differences might affect mobile user typology.

**Study Discipline.** The evidence for discipline effects on usage of mobile and smartphone features is also mixed. Taleb and Sohrabi (2012) and Alzougool and Almansour (2017) report an absence of academic discipline effects on mobile phone usage for educational purposes and Wai, Ng, Chiu, Ho and Lo (2018) find no such differential usage between business and engineering students. However, Delialioğlu and Alioğlu (2015) find the strongest preference for features for collaboration and learning among engineering students and that such features are least preferred by medical students. In addition, Alzougool and Almansour (2017) find that business majors tend to use their smartphones for administrative tasks (student transactions, registering for courses, and checking grades) more than non-business majors and Naidu (2018) find that students from the science disciplines preferred practical application videos and commerce students preferred online tutorial applications.

Study disciplines might concentrate on different types of activities leading to emphasis on various mobile features when they are employed to aid education. This might occur especially if the features are of special relevance to what the respective disciplines involve.

**Study Level.** There appears to be no clear basis for expecting user typology differences between graduate and undergraduate students beyond that which might be accounted for by age. Some support for this position is found in the lack of such level of study differences in adopting smartphones for mobile learning reported by Lau et al. (2017).

**Country.** Cross-national differences in usage patterns of mobile features seem likely to arise in relation to differences in access to facilities and other contextual variables including culture. For example, in relation to Internet user typology, Brandtzaeg et al. (2011) report national differences in the share of user types among European countries. Specifically related to mobile devices, some studies have highlighted cross-national variations in usage patterns. For example, Turkish and Chinese students show greater preference for using mobile technology to search for information than their American counterparts (Hao, Cui, Dennen, Turel, & Mei, 2017) and South Korean undergraduate business students use the camera and their mobile phones for gaming and watching videos more than their American counterparts (Lee & Song, 2015). No difference is noted by Alzougool and Almansour (2017) between Kuwaiti and non-Kuwaiti students in using smartphones for learning activities, but they indicate that Kuwaiti students use their smartphones for processing transactions and payment of fees more than non-Kuwaiti students.

## Methodology

### Data

The data for this study were collected through a web survey that was executed between October 2012 and February 2013<sup>2</sup> at six university campuses in the Caribbean: University of the West Indies (UWI) Cave Hill (Barbados), Mona (Jamaica), St. Augustine (Trinidad and Tobago) and Open Campus campuses, the University of Guyana (Guyana) and the University of Technology (Jamaica). The data from the campuses in Jamaica were combined to form a single territory group so that ultimately five such groups are accounted for in the data set. It is also important to clarify that the students of the UWI Open Campus are from several territories in the region. Hence, the group variable is not strictly indicative of territories.

Survey invitations were sent to the entire student populations at the universities and any registered student was able to participate voluntarily and anonymously. In total, 1726 students completed the questionnaire. For the university-territory groups, the sample sizes are 649 (Barbados), 243 (Guyana), 262 (Jamaica: 150 (UWI Mona), 112 (University of Technology), 333 (Trinidad and Tobago), and 239 (UWI Open Campus). The subsample for Barbados is disproportionately large in the data set and to control the voice of Barbadians in the combined sample to some extent, a random resampling of 350 respondents (299 respondents dropped) was done with the gender distribution preserved. Barbados therefore remains the largest subsample, but its dominance of the data is reduced by the resampling done. The effective sample size for this study is therefore 1445.

In the survey, the respondents were asked to indicate which mobile devices they owned and the mobile phone emerged as most popular by a large margin. Given that approximately 94% of the respondents owned a mobile phone compared to the 27% that owned an MP3 player which is the closest competitor. The popularity of mobile phones in the data is consistent with external evidence including that of mobile phone being used most frequently for relevant research (for example, Kaliisa & Pickard, 2017; Wu, Wu, Chen, Kao, Lin, & Haung, 2012; Chee et al., 2017; Crompton & Burke, 2018). This paper reports results for the mobile phone.

### Measures

**Mobile Usage.** In relation to mobile phones, the respondents were asked about the frequency with which they use eleven features and facilities: calling, text messaging, photographs, listening to music, emailing, reading, browsing, chatting, social networking, audio recording, video recording. Here, chatting refers to use of online/web-based applications whereas text messaging<sup>3</sup> refers to use of the paid messaging service offered by the telephone company. Notably, gaming is not among the features/facilities investigated.

<sup>2</sup> More recent data to support this study is not available.

<sup>3</sup> Text messaging was ultimately drop during the analysis.

Table 1 UTAUT Measures

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.
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 responses were obtained on an eight-point scale (*1 – several times a day, 2 – about once per day, 3 – 3-5 times per week, 4 – 1-2 times per week, 5 – once every few weeks, 6 – a few times per month, 7 – less than a few times per month, 8 – never*) and were recoded into three categories: 1 – once to several times per day, 2 – one to five times per week and 3 – a few times per month or less often. This recoding was done for two main reasons. Firstly, category 5 and 6 of the original response be overlapping. Secondly, the recoding into fewer categories limit sparseness in the classification tables given the method of analysis employed and results in a clearly categorical scale.

In another preliminary step, audio and video recording (Spearman correlation = 0.70) were combined into a single variable by averaging the scores and rounding to the nearest whole number to produce a new variable – production. A similar approach was taken to combine social networking and chatting

(Spearman correlation = 0.74) into a new variable. The name social networking was reused for this new variable.

**UTAUT Factors.** Behavioural intention to adopt mobile learning is measured as in the UTAUT model (Table 1). The other factors of the UTAUT model; performance expectancy (perceived usefulness), effort expectancy (ease of use), social factor and facilitating conditions, are employed as controls when the relationship between behavioural intention and mobile user typology is evaluated. Each of these factors is measured as per the UTAUT model with items that have been widely used and evaluated (see Table 1) and each is expected to have a positive impact on behavioural intention to adopt mobile learning as in the UTAUT (Venkatesh et al., 2003).

**Individual Variables.** The covariates included in this study are age (measured in years), sex (female = 1, male = 0), faculty (science = 1, non-science = 0)<sup>4</sup>, programme (graduate = 1, undergraduate = 0), campus-territory (Barbados = 1, Guyana = 2, Jamaica = 3, Open Campus = 4, Trinidad & Tobago = 5). Age has an average of 26.33 years whereas 74.62% of the respondents are females, 3.64% are in science faculties and 90.59% are pursuing undergraduate programmes.

## Method

With respect to determining typologies in general, researchers have employed a variety of approaches across many disciplines. Some focus on determining latent typologies by allowing the segments to emerge from the data and in so doing uncover contextually nuanced classes with the possibility that the names assigned are different depending on the perspective of the researchers. Both cluster and latent class analyses allow segments to emerge from the data and are popular for studying such typologies. However, whereas latent class analysis is a model-based approach to such classification for which there are many statistics and indices to assist with evaluating the number of classes and the quality of class assignments, traditional (k-means) cluster analysis is a much more arbitrary procedure that provides no guidance on the appropriate number of classes (Magidson & Vermunt, 2002). This paper adopts the latent class approach and specifically applies latent class cluster analysis (LCCA) (Lazarsfeld & Henry, 1968; McCutcheon, 1987; Magidson & Vermunt, 2002) to determine the latent mobile user typology.

Several measures are available for evaluating the appropriate number of classes for LCC models and though no particular measure is universally superior, the Bayesian Information Criterion (BIC) is very popular and quite good at helping to determine the number of latent classes (Hagenaars & McCutcheon, 2002). Along with the BIC, the log-likelihood value and the likelihood ratio chi-squared statistic,  $L^2$ , are reported. In this paper, the best model is regarded as the most parsimonious with non-significant  $L^2$  and with the lowest BIC value (Magidson & Vermunt, 2004). Nevertheless, the interpretability of the model and the usefulness of the classes that emerge are also important considerations (Nylund, Asparouhov, & Muthén, 2007) and are employed as necessary. To determine the number of classes, estimation begins with the 1-class model and the number of classes is increased until the best model is obtained.

Model estimation is done using Latent Gold 5.0 with the covariates included as inactive so that they do not affect the classifications of individuals into the latent segments (Vermunt & Magidson, 2013). Subsequent to segmentation of the data, a multinomial logistic regression model relating the demographic variables to the latent classes is estimated.

For relating the mobile user typology to behavioural intention to adopt mobile learning, a structural equation model with behavioural intention as endogenous and with the other UTAUT factors as exogenous factors is estimated with Mplus. This model includes the mobile user typology as predictors of behavioural intention. Model estimation is done with the robust maximum likelihood estimator and overall fit is determined by a majority of the root mean square error of approximation (RMSEA) less than

<sup>4</sup> The combination of disciplines in faculties at different universities are different. Reduction of the variable to science versus non-science avoids the complexity while providing an interpretable result.

or equal to 0.06, comparative fit index (CFI) greater than or equal to 0.95 and the standardised root mean square residual (SRMR) less than or equal to 0.05 (Byrne 1989; Hu & Bentler 1999).

For the structural equations model, the data are pooled across the universities-territory combinations. This pooling of the data is supported by a previous study which found that the measures to demonstrate metric invariance (Thomas, Singh, & Renville 2020). The structural models are estimated several times with different baselines for the categorical predictors to facilitate direct comparisons of the categories. The tabulated results are however presented for only one configuration of the model.

## Findings and Discussions

### Clusters in the Data

An initial estimation of the models with 1 class up to the model with 7 classes reveals that calling and text messaging do not discriminate much among the latent segments. In particular, the posterior probabilities for the response *once to several times per day* for these two variables are large (above 0.74 to 0.90 for calling and above 0.56 to 0.84 for text messaging) in each latent segment regardless of the number of segments allowed (between 1 and 7). These variables therefore do not assist with interpreting the latent segments and at the same time their inclusion would affect the quality of the classifications by tending to lower the entropy value. Ultimately, the two indicators – calling and text messaging – are dropped and the models are re-estimated.

Table 2 Model Fit

Model	LL	BIC <sub>LL</sub>	L <sup>2</sup>	df	p-value	Class. Err.
1-Cluster	-9331.74	18764.46	5078.88	1343	0.00	0.00
2-Cluster	-7809.91	15829.00	2035.23	1328	0.00	0.02
3-Cluster	-7574.72	15466.81	1564.84	1313	0.00	0.10
<b>4-Cluster</b>	<b>-7450.23</b>	<b>15326.03</b>	<b>1315.87</b>	<b>1298</b>	<b>0.36</b>	<b>0.12</b>
5-Cluster	-7397.84	15329.45	1211.09	1283	0.92	0.15
6-Cluster	-7350.74	15343.43	1116.88	1268	1.00	0.17
7-Cluster	-7315.58	15381.32	1046.58	1253	1.00	0.19

When the data are segmented without calling and text messaging included, both the BIC and the L<sup>2</sup> statistic indicate that the 4-class model is the best fitting since both the first non-significant L<sup>2</sup> and the minimum BIC occur for the 4-class model (see Table 2). Based on L<sup>2</sup>, the 4-class model explains approximately 74% of unexplained variance in the initial model ( $[L^2_{1\text{-class}} - L^2_{4\text{-class}}] / L^2_{1\text{-class}}$ ) whereas the 5-class model explains approximately 76% of it. Therefore, from a practical standpoint, moving to the 5-class model does not offer much improvement in the explained variance. Given the evidence already obtained from the BIC and L<sup>2</sup>, the 4-class model is accepted as best for the data.

The 4-class model has an entropy of 0.79 which is close to the 0.80 benchmark suggested by Clark and Muthén (2009). This indicates that the quality of the classifications is good though there are still some uncertainties. Nevertheless, the results can be used in further modelling as intended in this paper. The latent classes 1, 2, 3 and 4 in the data account for 36%, 32%, 21% and 11% respectively of the individuals.

The profiles of the classes (the probabilities of the responses to the items given class membership) are presented in Figure 1. These profiles are used to interpret the latent classifications.

Except for production software which is used on a monthly basis, the probabilities are largest for the first response for each variable in class 1. For production, the middle response has the highest probability in this class. The individuals in class 1 therefore use a wide variety of features and facilities often (*once to several times per day*). We label this class as *eclectic user*. These users also constitute the largest latent segment in the data.

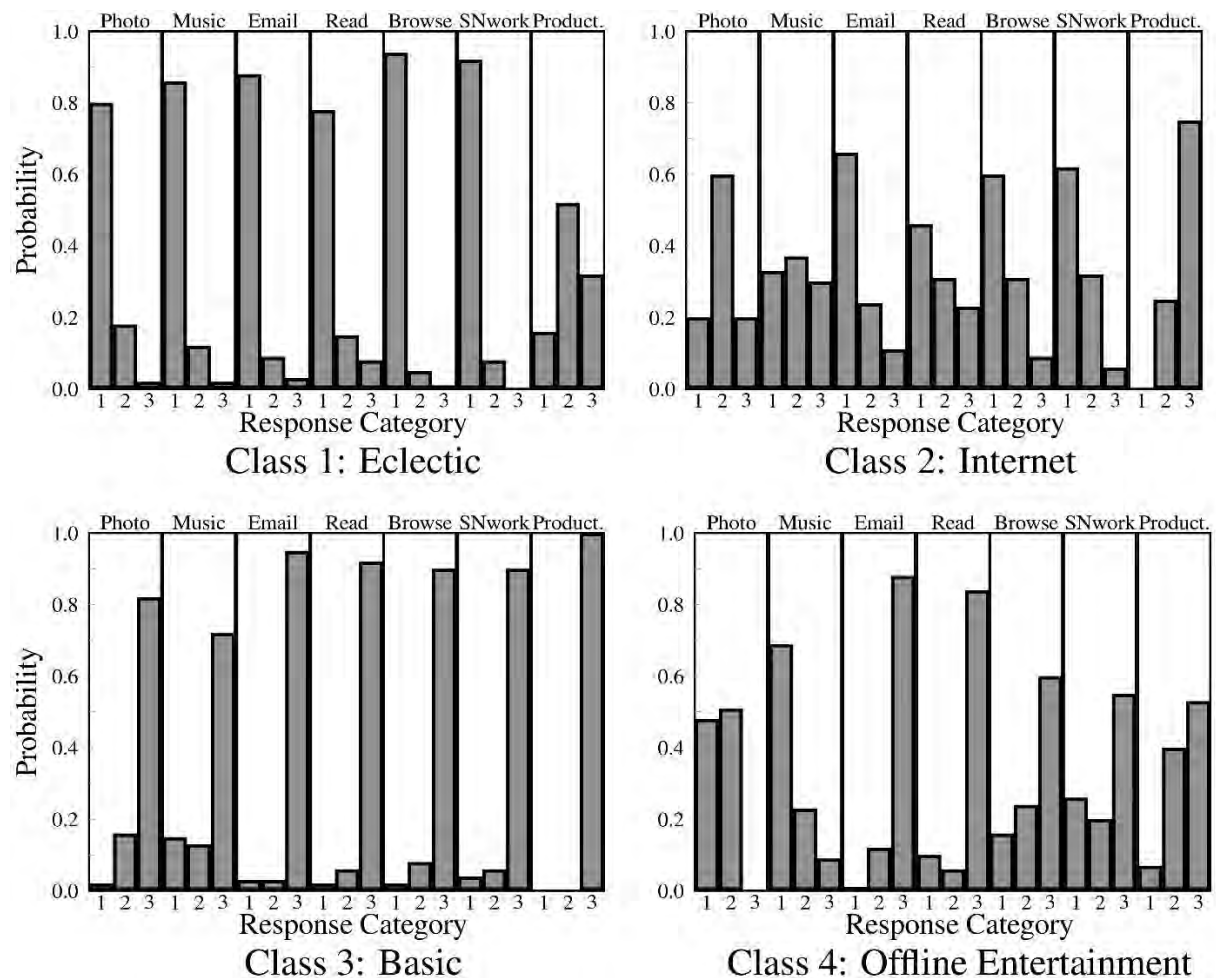


Figure 1. Class Profiles

Class 2 of the data includes individuals who use features that require Internet connection on a daily basis. These individuals use their mobile phones for social networking, browsing and emailing often. However, they use their mobile phones to take photographs on a weekly basis and make use of production software once to a few times per month. Another observation is that the frequencies of usage of the mobile phones for music and reading are mixed indicating that many of the individuals may or may not use these facilities often or usage frequency may also be middling. We refer to this segment as *Internet user*.

The profile probabilities for class 3 are all high for the least frequent use of each feature. The usage level of the phone features is therefore low overall. Taking into account that calling and text messaging, which are not included in the model, are used frequently by all classes, we label this group *basic user*. In class 4, the usage frequency is high for music, middling to high for taking photographs and low for the other features. The individuals in this group therefore use their mobile phones frequently for entertainment and we therefore label this segment *offline entertainment user*.

### Impact on Mobile Learning Adoption

The impact of mobile user typology on mobile learning is investigated given that its relationship with behavioural intention to adopt mobile learning is a key dependent variable in both the UTUAT and the TAM. Initially, a model is estimated with mobile learning typology as the only predictor of behavioural intention. Another model is then estimated with only the UTAUT factors followed by one with both sets of predictors.

The structural equation model with mobile user typology as the only predictor of behavioural intention fits the data well (RMSEA = 0.03, CFI = 1.00, SRMR = 0.01). The relationship is significant at the 5% level and mobile learning typology independently explains approximately 11% of the variance in behavioural intention to adopt mobile learning (Table 3).

On closer examination, the results for mobile user typology (Table 3) reveal the following:

1. Compared to *eclectic users*, each of the other mobile user categories is associated with lower behavioural intention to adopt mobile learning.
2. Compared to *internet users*, *basic* and *offline entertainment users* are associated with lower behavioural intention to adopt mobile learning.
3. Compared to *basic users*, *offline entertainment users* are associated with higher behavioural intention to adopt mobile learning.

Therefore, behavioural intention to adopt mobile learning is highest among *eclectic users* followed by *internet users* then *offline entertainment users* and finally by *basic users*.

The model with only the UTAUT factors as predictors of behavioural intention also fits the data well (RMSEA = 0.04, CFI = 0.97, SRMR = 0.05). Except for facilitating conditions for which the convergent validity is low (average variance extracted is 0.46), the level of convergent validity of the UTAUT factors in the model, including behavioural intention, are all high (average variance extracted range from 0.58 to 0.80). The model explains approximately 45% of the variance in behavioural intention and as expected, each of the exogeneous factors impact significantly and positively on behavioural intention. When mobile user typology is added as a predictor, the revised model fits well based on a majority of the indices (RMSEA = 0.05, CFI = 0.95, SRMR = 0.07) and it explains a slightly lower percentage (43%) of the variance of behavioural intention. Another difference in the results when the two sets of predictors are included is that the effect of effort expectancy (ease of use) is no longer significant (Table 3). It would seem therefore that not only is mobile user typology a significant predictor of behavioural intention to adopt mobile learning, but it also accounts for the explanatory ability of effort expectancy.

Table 3. Relationship with Behavioural Intention

Model	Independent	Behavioural Intention	R-squared
Mobile User Typology Only	Internet	-0.14* (0.03)	0.11
	Basic	-0.37* (0.03)	
	Offline entertainment	-0.16* (0.03)	
UTUAT Factors Only	Performance Expectancy	0.32* (0.03)	0.45
	Effort Expectancy	0.07* (0.03)	
	Social Factors	0.12* (0.03)	
	Facilitating Conditions	0.38*	

Model	Independent	Behavioural Intention	R-squared
		(0.04)	
UTAUT factors and Mobile User Typology	Internet	-0.06*	0.43
		(0.03)	
	Basic	-0.17*	
		(0.03)	
	Offline entertainment	-0.08*	
		(0.03)	
	Performance Expectancy	0.30*	
		(0.04)	
	Effort Expectancy	0.04	
		(0.03)	
	Social Factors	0.13*	
		(0.03)	
	Facilitating Conditions	0.37*	
		(0.04)	

\* significant at the 5% level. All effects are standardised.

### Relationships with Demographic Variables

The relationships between the latent segments and the demographic variables are investigated with a multinomial regression model which uses the four-category, latent classifications as the dependent variable. Overall, the model is significant with each independent variable significantly related to the mobile user typology (Table 4). However, the pseudo r-square is low (0.05) which means that important antecedents of class membership are not included in the model and furthermore that the variables included are not the most important determinants of class membership.

**Age.** The ages in the *Internet* and *basic user* classes (classes 2 and 3) are more likely to be older than the age of the *eclectic users* (class 1). However, age is similar among *eclectic users* (class 1) and *offline entertainment users* (class 4) (Table 4). Furthermore, age is more likely to be older among *basic* than *Internet users* and more likely to be older among *Internet* and *basic users* than *offline entertainment users*. Age is therefore similar and youngest among *eclectic* and *offline entertainment users* and oldest among *basic users*, with the age of *Internet users* in-between these two groupings of segments, but significantly different from both.

**Sex.** Compared to *eclectic users*, there is a tendency for greater representation of females in each of the other classes (Table 4). In addition, whereas females are relatively more likely to be *offline entertainment users* than *Internet users*, there is no difference in the gender distribution between *basic users* and *Internet* or *offline entertainment users*. Females are therefore less likely than males to be *eclectic users* compared to any other type of user, but are more likely than males to be *offline entertainment users* compared to *Internet users*. The latent segments therefore form three homogeneous groups based on sex distribution. These groupings consist of *offline entertainment users* and *basic users* with the highest relative likelihood for females compared to males, and *eclectic users* for which the likelihood for females versus males is lowest, with the likelihood for females among *basic* and *Internet users* lying in-between.

Table 4 Multinomial Regression for Latent Group Membership on Individual Variables

Variable	Eclectic Users (Baseline)	Internet Users	Basic Users	Offline Entertain. Users
Age		0.05* (0.01)	0.08* (0.01)	0.00 (0.02)

Sex (Baseline = male)	0.36*	0.51*	1.05*
	(0.16)	(0.19)	(0.27)
Faculty (baseline = non-Science)	0.58*	0.68*	0.42
	(0.17)	(0.19)	(0.23)
Programme (Baseline = Undergraduate)	0.63*	-0.24	-0.31
	(0.24)	(0.30)	(0.42)
Camus-Territory (Baseline = Barbados)			
Guyana	-0.88*	-0.61*	-0.52
	(0.23)	(0.26)	(0.34)
Jamaica	-0.10	0.15	0.06
	(0.21)	(0.24)	(0.31)
Open Campus	-0.17	0.02	0.61*
	(0.23)	(0.26)	(0.31)
Trinidad & Tobago	-0.33	0.06	0.35
	(0.20)	(0.23)	(0.28)
Constant	-1.86*	-3.07*	-2.25*
	(0.31)	(0.36)	(0.49)

\* Significant at the 5% level

LR Chi-Square = 141.36, degrees of freedom = 21, Pseudo R-squared = 0.04

**Study Discipline.** Compared to students of non-science disciplines, students of science programmes are more likely to be in the *Internet* and the *basic user* classes than the *eclectic user* class. However, the study discipline distribution is similar among *eclectic* and *offline entertainment users*. Science students also have a greater likelihood of being *Internet users* than either *basic* or *offline entertainment users* whereas the distribution of disciplines over the latter two segments is similar. The latent classes therefore form three homogeneous groups with respect to study discipline representation. *Internet users* is the group with the highest relative likelihood for students of science programmes whereas the relative likelihood for science students is lowest among *offline entertainment* and *eclectic users*, with the relative likelihood of individuals from science versus non-science disciplines being among *basic* and *offline entertainment users* lying in-between.

**Programme Level.** Undergraduates are less likely than graduates to be in the *Internet user* segment compared to each of the other latent classes. These are the only distributional differences for the students' programme of study. The latent classes therefore form two homogeneous groups with respect to programme level.

**Campus-Territory.** Campus-territory differences in the composition of latent classes emerge only when the campus-territory combinations are compared to Barbados and Guyana. Compared to Barbados, the Open Campus and Trinidad and Tobago have greater representation among *offline entertainment* than *basic users* whereas the Open Campus has greater representation among *offline entertainment* than *eclectic users* (Table 4). In addition to this, compared to Barbados, students from Guyana have relatively lower representation among *Internet* and *basic users* than among *eclectic users* (Table 4). There are no other differences involving the territory-campus combinations except when Guyana is involved in the comparisons of *eclectic users* to the other classes. In particular, students from Guyana compared to those from Jamaica, Open Campus, and Trinidad and Tobago are more likely to be among the *eclectic users* than *Internet* and *basic users* and when compared to those from the Open Campus and from Trinidad and Tobago they are more likely to be among *eclectic users* than among *offline entertainment users*.

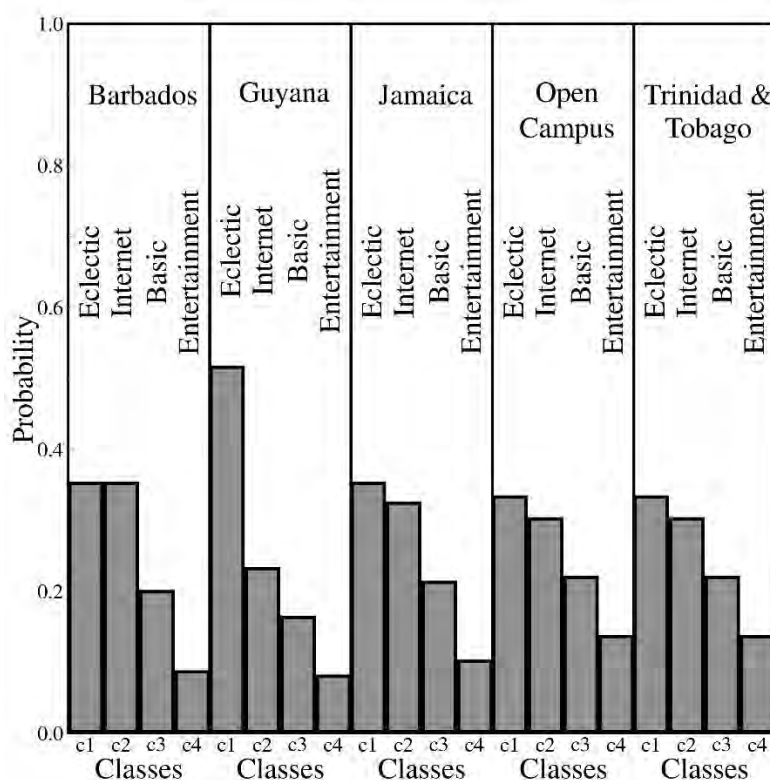


Figure 2 Campus-Territory Mobile User Profiles

Another perspective on the comparison of the user profiles between the campus-territory combinations is provided in Figure 2. Consistent with the model results, the probabilities of being classified into the various types are similar for each respective type at the Open Campus, Trinidad and Tobago and Jamaica and differences emerge in relation to Barbados and Guyana. The chart also confirms that classification into *eclectic users* is much more likely in Guyana than elsewhere. It is more difficult to discern from the chart the similarities between Jamaica and Barbados and between Jamaica and Guyana as indicated by the regression model. This might be due to variability that is unobserved in the chart, hence, we rely on the results of the multinomial regression model.

## Discussion

Four latent classes of mobile phone users – *eclectic users*, *Internet users*, *basic users* and *offline entertainment users* – emerge from the data. Though user these types indicate the general tendencies of individuals to prefer various mobile phone features and the corresponding intensity of usage, an individual is not necessarily entirely of one type (Brandtzaeg, 2011). This is further supported by the entropy of 0.79 indicates that there is some remaining uncertainty in the classifications (Clark & Muthén, 2009). Each individual has some probability of classification into each segment and is therefore not distinctly and entirely of one type though the tendency towards being a particular type is strongest.

The user types encountered show some similarities with the results of previous studies on media user typology. The *eclectic user* class is similar to the advanced users identified in these previous studies in that the individuals classified use the features with high frequency (see Brandtzaeg, 2010 & Zawacki-Richter et al., 2015). There is also overlap between the *basic users* encountered and the peripheral users (Zawacki-Richter et al., 2015) and non-users (Brandtzaeg, 2010) described in other studies and the emergence of *entertainment users* is noted elsewhere (Brandtzaeg, 2010; Brandtzaeg et al., 2012, & Zawacki-Richter et al., 2015). These observations support some tendency towards generalisability of the existence of at least *eclectic* and *basic users* and perhaps less of entertainment users. One difference that we have encountered with entertainment users is that they seem to operate offline.

In spite of the points of similarity with other studies, the number of latent segments encountered is larger than the two segments found by Elhai and Contractor (2018) who employed a similar technique (latent class analysis) with similar indicators with data from the USA, and smaller than the number of media user types found by both Brandtzaeg (2012) in Norway and Brandtzaeg et al. (2011) in European countries. Two potential explanations for these differences are culture and other country differences. Culture is known to affect usage of mobile applications (Peltonen et al. 2018) and to affect technology adoption in general (Huang, Teo, Sánchez-Prieto, García-Peñalvo, & Olmos-Migueláñez, 2019) and is hence likely to impact on mobile user typology. Against this backdrop, it is reasonable to conclude that greater cultural differences between countries would likely results in larger disparities in the salient user typologies such as the absence of some segments.

These observations about cultural and national effects challenge the assumption that there is a fixed set of relevant mobile user segments across countries and cultures and underscores the necessity of context specific investigation to determine contextually nuanced typologies. The importance of such investigation is apparent when it is considered that mobile user typology can be used to help with the design of mobile learning (Zawacki-Richter et al. 2015). This is not necessarily a warning against the usefulness of a unifying theory on user typology. Instead, it means that a unifying theory needs to be flexible enough to accommodate contextual differences and should therefore benefit from evidence of user typology from a diverse set of contexts.

Even when the same set of user types are relevant, national differences in the distribution of individuals to the types can be expected as in the case of Internet users in Europe (Brandtzaeg et al., 2011). Hence, it is not only the existence of a user type that might affect mobile learning adoption but also the relative abundance of the types. The results indicate that *eclectic users* are relatively most abundant in Guyana, though there is no significant difference between Guyana and Jamaica on the relative size of this class. If for example, mobile learning is enhanced when there is a larger group of more sophisticated users, students in Guyana would have an advantage with respect to being poised to adopt mobile learning whereas those from Barbados a disadvantage given the relatively greater representation of *basic users* (except in comparison to Jamaica). Nevertheless, previous research indicates that the level of behavioural intention to adopt mobile learning is similar in the two territories (Thomas et al., 2014). In the present study, *eclectic users* (36%) and *Internet users* (32%) account for 68% of the students and since *eclectic users* also use features requiring Internet access with high frequency, requiring the use of Internet on mobile phones in support of learning is likely to result in ease of adoption for a majority of the students. However, 32% of the students will likely find the requirement of internet usage on their mobile phones to support learning discomforting. This conclusion is tempered by the reality that the students may not necessarily engage in educational activities as often as they do other activities using their mobile phones (Nwachukwu & Onyenankeya, 2017; Kaliisa et al., 2017). As an example, Alzougool and Almansour (2017) indicate that university students in Kuwait use their smartphones for more administrative activities than learning-related activities. Though targeting the features that the students already use frequently may enhance mobile learning adoption, it is not a panacea from the perspective of the purpose for which students might use their phones.

Mobile user typology is related to mobile learning adoption given the significant relationship with behavioural intention to adopt mobile learning. Given that high frequency of use of all the mobile phone features is evident among *eclectic* (advanced) *users*, this class likely contains the more sophisticated users (Zawacki-Richter et al. 2015) who will find greater ease of use whereas the *basic user* category likely contains the more unsophisticated mobile phone users who will find usage of mobile devices more difficult. This is consistent with the result that ease of use loses significance upon introduction of mobile user typology into the model as a predictor of behavioural intention to adopt mobile learning. The mobile user typology therefore accounts for ease of use (effort expectancy).

The user typology in this paper does not address the nature of usage of the features or content preferences as done in some media user typology studies (for example, Brandtzaeg, 2012) and it independently explains only approximately 11% of the variance in behavioural intention to adopt mobile learning. The variable can therefore potentially include more information which will likely produce improve its independent explanatory capability. There is a marginal drop in explained variance in the full model (from 45% to 43%) when user typology is included and this might indicate shared variance with other included factors especially effort expectancy which lost significance. Nevertheless, given the potential for enhanced meaning of the variable, a mobile user typology variable seems to be a better inclusion in the technology adoption model than effort expectancy as defined in the UTAUT and the TAM. This, however, needs to be evaluated further.

Differences in the composition of the user types can be expected with respect to individual variables and some of these differences are consistent with that reported by other studies. In particular, that males are more likely than females to be in the class of *eclectic users* whereas females are more likely to be in other classes and furthermore that older individuals are more likely to be among the *basic users* whereas age is youngest among the *eclectic* and *entertainment users* seem consistent with the results reported by Zawacki-Richter et al. (2015) for advance and peripheral users respectively. Sex differences in the composition of the groups can be due to the state of society with respect to gender issues such as equity and gender roles (Brandtzaeg et al., 2011). As it relates to the effect of age, Zawacki-Richter et al. indicate that non-traditional students who are older, may have jobs and may have no access to the Internet among other possibilities, tend to have greater relative representation among the peripheral users who do not use the Internet and lower relative representation among entertainment users.

### Conclusion, Limitations and Recommendations

This study has a few limitations. Firstly, the population of the study is students of higher educational institutions in the Caribbean region. This introduces a limitation on the generalisability of the results to other regions of the world. Secondly, the data are now a bit old and the extent to which the results for the mobile types are representative of the current circumstances might be affected by the age of the data. Nevertheless, even if this possibility is reality, it does not affect the investigation of the relationship between mobile typology and mobile learning adoption. The results about the mobile types are regarded an exploratory starting point to the discussion of the topic in the Caribbean region even as they contribute to the global discussion in the higher educational contexts.

Against the backdrop of the limitations identified, there is a need for further research on the usefulness and explanatory capability of mobile user typology in mobile learning adoption models. This should be done both in the Caribbean and other regions of the world to (1) confirm the results described in this study and (2) help to establish the extent to which the results can be generalised beyond the Caribbean region. Essentially, this line of research would help to determine whether modifications of the existing models to include mobile user types are useful in general.

Further research on mobile user typology should be done in the Caribbean region with new data. This could be done as several national studies or cross-national studies. The results of such studies would eliminate speculation regarding whether the mobile types and perhaps more so the proportions of persons within the segments have changed over time. In addition, the mobile features included can be updated to capture whatever is relevant at the time as technology develops.

Future research should expand the mobile user typology used in this paper to encompass the nature of usage and content preferences in addition to frequency of use and preference for various features. This would enhance the information contained and perhaps lead to a richer mobile use typology. It would be important to re-evaluate the effect of this richer mobile user typology and behavioural intention to adopt mobile learning and to determine if it enhances the explanator ability of the variable.

Though it is suggested that understanding the mobile user typology can assist with design of learning, this particular matter was not the focus of the present study. There is scope for research focusing on optimising the design of mobile learning based on the mix of mobile user types targeted. Such studies would be of benefit to educators in general and would avail tools for optimising delivery of education to students via their mobile devices.

Four mobile user types appear to be relevant in the higher education context in the Caribbean region. The types and their relationships with explanatory variables show some similarities but also some differences with respect to the literature thereby reinforcing the need for context specific determination of mobile user types and their relationships with explanatory variables. Mobile user typology independently predicts behavioural intention to adopt mobile learning and when it is included in the UTAUT model, it results in redundancy of effort expectancy. Mobile user typology might therefore provide an avenue for modifying and enhancing the study of mobile learning adoption.

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