Mobile Commerce Adoption in a Developing Country: Driving Factors in the Case of Cameroon

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Abstract. In line with steady improvements in wireless communications, the number of people using mobile devices has skyrocketed globally while bringing about a veritable breakthrough in the use of mobile commerce (m-commerce). Against a backdrop of fast-evolving mobile commerce (including in developing countries), this study seeks to investigate factors predicting the consumer's intention to adopt m-commerce in Cameroon, but also the moderating effects of the demographic variables on such prediction. Data were collected from 262 Cameroonian respondents aged less than 45, as this age category accounts for the bulk of unconditional IT users in the country. Then, a quantitative approach analysis based on the PLS-SEM algorithm was used to test the research model. Results showed no significant moderation effect of gender and age when verifying the following hypotheses: (1) A variety of services positively influence the consumer intention to adopt m-commerce; and (2) Behavioural intention positively influences the consumer intention to adopt m-commerce. Findings of this research are expected to help companies and organizations dealing with m-commerce to better develop marketing strategies, applications and services likely to attract more users.

Keywords: m-commerce, consumer intention, demographic variables, UTAUT, TAM, adoption factors, Cameroon.

1 Introduction

The development of m-commerce is globally considered the most spectacular in the era of Information and Communication Technologies (ICTs). Both in developed and developing countries, people are becoming more and more dependent on this technology, which is virtually indispensable for their daily activities. Numerous authors have proposed definitions of mobile commerce [1]: To Yang, it is a set of transactions conducted through a variety of mobile media through a wireless telecommunication network [2]. Feng & al. argue that m-commerce is more than an extension of e-commerce because of its affordance (value chain, variety of usage models and interaction styles, etc.), which enables the technology to provide a new business model with features such as mobility and accessibility [3]. Tarasewich defines it as any activity related to a (potential) commercial transaction, carried out through communication networks using wireless (or mobile) devices [4]. A more comprehensive definition comes from Tiwari & Buse for whom m-commerce implies any transaction involving transfer of ownership or rights for goods and services, through computerized networks connecting electronic devices such as a Personal Digital Assistant (PDA) or a smartphone [5]. Better still, m-commerce represents m-business and should not be limited to transactions of monetary value, thereby neglecting other m-commerce activities such as after-sales services and the sending of games or free music to users [5]. As for Tiwari & Buse, they indicate that m-commerce does not necessarily need to operate through a wireless telecommunication network [5]. For the purpose of this research work, we adopt the definition by Chong, as it encompasses previous definitions: "any transaction involving the transfer of ownership or rights to use goods and services which is initiated and / use of mobile access to computerized networks with the help of mobile support" [6].

Numerous studies are been concerned with mobile commerce adoption in developing countries like the one from Islam et al in two major cities in Bangladesh: Dhaka and Chittagong. The results suggested that pricing and cost, rich and fast information, and security and privacy are significant predictors of the adoption of m-commerce. Self-efficacy is found to be a moderating factor for the adoption of m-commerce services [7]. Sadi & Noordin tried to identify some factors that affect the adoption of m-commerce in Malaysia based on traditional technology models and theories such as Theory of Planned behavior (TPB), Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM) and Diffusion of Innovation Theory (DOI). The results show that the thirteen (13) factors (*Perceived usefulness, perceived Ease of use, perceived trust, personal innovativeness, perceived cost, subjective norms, perceived behavioral control, facilitating conditions, self-efficacy, attitude towards use etc*) used were statistically significant and can affect the m-commerce adoption [8].

However, it is important to note that many other authors have addressed the issue of the adoption of m-commerce, by studying the barriers that would oppose it in a given population. Moorthy & al explored the resistance factors to understand the reasons for this low adoption among generation X in Malaysia. They used Innovation Resistance Theory (IRT) and Valence Framework to examine the barriers, including usage, value, risk, tradition, image, and perceived cost barriers. They found that, except the cost barrier, all other barriers significantly affect the mobile commerce adoption[9]. Mahatanankoon and Vila-Ruiz studied why consumers won't adopt m-commerce in a context of developed country like United States of America, where applications are being implemented for mobile services. Through an explanatory analysis, they found five majors factors that impede the applicability of mobile commerce: device inefficiency, unawareness, interoperability, conventional transactions and personalization needs[10]. Li & McQueen examined and categorized the country-level adoption barriers of mobile commerce services, and tests those barriers in the case of New Zealand[11].

Finally, in a global world where local enterprises are directly in competition with local and foreign competitors, m-commerce appears to be an essential instrument to get a competitive advantage. Statistics on the development of ITs in Cameroon confirm that m-commerce is a great opportunity for enterprises. In fact, the Cameroon's population is estimated at some 23 924 407 inhabitants in 2016 [12] ; the number of mobile telephony users is estimate at 16 331 852 (2016), for a penetration rate of 68.267%. Moreover, a study made by InternetLives (2016) shows that the country totals about 4.3 million Internet users, for a penetration rate of about 18%. This rate seems very much higher than the statistics of 2012, where the number of internet users reached around 1.234 million with a penetration rate of 5.7%[13].

In this context, the objective of this study is to determine the factors that influence the adoption of m-commerce in Cameroon. To achieve this objective, the two following research questions will be answered: (1) What are the key determinants of m-commerce in Cameroon? and (2) What are the moderating effects of age and gender on m-commerce adoption? Our research model has been developed drawing on theories and models such as the Technology Acceptance Model (TAM) [14], the Innovation Diffusion Theory (DOI) [15], the Theory of Reasoned Action [16], the Theory of Planned Behavior [17] and the Unified Theory of adoption and Use of Technologies (UTAUT) [18], which provided two major constructs, namely Social influence and Perceived cost. Two other constructs (Social influence and Behavioural intention) have been added. Finally, age and gender are used to moderate the effects of previous constructs on the Intention to adopt m-commerce. The remainder of this paper is structured as follows: The theoretical background aiming to define the research model is presented, followed by the methodology that is being adopted. Finally, data analysis is explained and the results are discussed, together with some limitations to the research.

2 Theoretical Background

Our structural model for this research process is made of four constructs: Variety of service, Social influence, Perceived cost, and Behavioural intention. These constructs have been already used by numerous authors on theories and models such as the Technology Acceptance Model (TAM) [14], the Innovation Diffusion Theory (DOI) [15], the Theory of Reasoned Action [16], the Theory of Planned Behaviour [17], and the Unified Theory of Adoption and Use of Technologies (UTAUT) [18].

2.1 Variety of Services (VS)

Variety of Services is a concept already used to capture the users' willingness to adopt a technology; for instance, Chong & al. have resorted to it to carry out a study in the Malaysian context [19]. The role of this construct in explaining technology adoption has been evidenced in several industries including entertainment, mobile ticketing, mobile banking [20]. With regard to m-commerce specifically, the big challenge lies in the variety of services that the companies having integrated such a commercial communication channel can deliver. So it may be assumed that the attractiveness of m-commerce platforms depends on their ability to offer such a wide variety of services. Therefore, we hypothesize that:

Hypothesis 1: Variety of services positively influences the consumer intention to adopt m-commerce.

Hypothesis 2: Variety of services positively influences Behavioural intention.

2.2 Social influence (SI)

Chong et al.(2013) define social influence as the degree to which an individual user perceives the importance that others believe that he or she should use an innovation [21]. The basic assumption for this construct is that: the influence of peers, family members, and even the media such as television, radio, and the Internet, may encourage users to use m-commerce. This is well explained in the Theory of planned behavior (TPB), by Fishbein & Azjen, which establishes that Behavioural intention is a resultant of attitude and subjective norms (social influence) [16]. Hence the following hypothesis:
Hypothesis 3: Social influence positively influences Behavioural intention.

2.3 Perceived Cost (C)

Generally, the customer perception of excessive costs limits the level of adoption of ITs, the perceived cost being defined as the degree to which an individual perceives that the use of IT is costly [20]. In others words, low costs encourage greater use of the service.[22]. As far as m-commerce is concerned, a number of research works justify why the costs of acquiring and integrating such a technology do matter; they include a study by Dai & Palvi on the comparison between China and US consumers [23]. Therefore, we hypothesize that:
Hypothesis 4: Perceived cost positively influences Behavioural intention.

2.4 Behavioural intention (BI)

Behavioural intention can be defined as the strength of one's intention to perform a specific behaviour [24]. While it measures the likelihood for a person to adopt the application, the TAM rather resorts to the actual usage to represent a self-report measure of time or frequency of adopting the application[25]. Behavioural intention has a positive direct effect on the usage of mobile devices[26]. Therefore, we set forth this hypothesis:
Hypothesis 5: Behavioural intention positively influences the consumer intention to adopt m-commerce.

2.5 Control variables (Gender, Age)

The effects of both the Variety of services and Behavioural Intention on the Consumer intention to adopt m-commerce would be significantly different for each specific group of moderators.
Hypothesis 6(a-b): Age and gender are significantly different for both the relationship between Variety of services and Consumer intention to adopt m-commerce and the relationship between Behavioural intention and Consumer intention to adopt m-commerce.
Hypothesis 7(a-b): Age and gender are significantly different for both the relationship between Variety of services and Consumer intention to adopt m-commerce and the

relationship between Behavioural intention and Consumer intention to adopt m-commerce.
Then, we conceptualize the research model below (Fig. 1.).

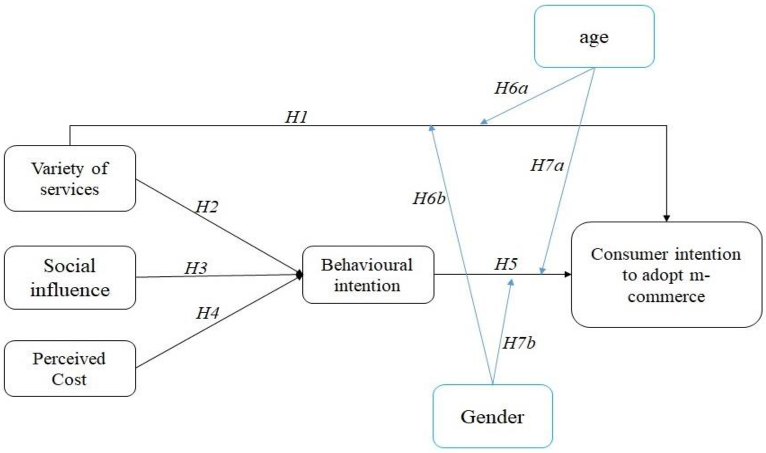

Fig. 1. Research Model

3 Methodology

The population of this study is various Yaounde-and Douala-based universities students who use smart phone with a Wi-Fi 3G or 4G connection. Data collection has been carried in two phases. First, a developed survey questionnaire was used to make a pre-test with 8 young university students (in journalism, management of information system, accounting) and 8 young professionals (education, information system). Second, once this pre-test proved the stability of the research model, the questionnaire was widely administered via an Internet link (google forms) and physically at various Yaoundé- and Douala-based universities (University of Yaoundé 1, UCAC and University of Douala) and in workplaces. We obtained 55 answers online. Concerning the physical questionnaire, we distributed 295 and received 241 of them filled-in, 34 of which were unusable (not completely answered etc.). Overall, we obtained a total of 262 usable surveys for this study, giving a return rate of 77.06%.
Consistent with previous technology adoption studies, the independent and dependent variables used in this study are derived from the existing literature [27]. A total of 14 items were used to measure the 4 independent variables, and 2 items were used to measure the dependent variable. Besides the demographic profiles (age, gender), all items were measured on a 7 point Likert Scale ranging from 1 (strong disagree) to 7 (strongly agree).
In this study, we used the smartpls-3.2.6 software for the processing and analysis of the data collected. This allowed us to assess the adequacy of the theoretical model and verify its hypotheses.

4 Data Analysis and Results

This section presents the results of our study following a proper processing of the collected data.

4.1 Demographic information

The demographic characteristics of our respondents are shown in Table 1.

Table 1. Demographic characteristics of Respondents

Profile	Description	Frequency	Percentage
Gender	M	140	53.44%
	F	122	46.56%
Age	15-17	7	2.67%
	18-25	187	71.37%
	26-35	64	24.43%
	36-45	4	1.53%
	Over 45 years	0	0

Of the 262 respondents, 140 were men (53.44%), which is a fairly average distribution. Concerning age, the majority of respondents (95.8%) were aged between 18 and 35 while those aged between 18 and 25 accounted for 71.37%. This is actually the participants' average age, which corresponds to the individuals' incline to use mobile services intensively.

4.2 Demographic of respondents

Measurement Model. To assess the measurement model, the internal reliability and a convergent and discriminant validity are used [28]. For each construct, the internal reliability is measured (Composite Reliability and the Cronbach's Alpha). The acceptable value of these measures must be greater than 0.70 [28], [29]. As for the convergent validity measured by the Average Variance Extracted (AVE), the preferred value is greater than 0.50 [28], [30]. Cross loading and correlations between constructs are also key measures for the convergent validity, because they ensure that the items being used match their correspondent constructs and that these constructs are independent. Concerning the outer loadings, Hair et al. [28] pointed that further analysis should be carried out for values between 0.40 and 0.70 and that items below 0.40 should be removed.
The results of the CR, Cronbach's Alpha and AVE are shown in Table 2.

Table 2. Constructs Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Variety of Services	0.7173	0.8269	0.8705	0.7714

	Cronbach's Alpha	rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Social Influence	0.7516	0.7610	0.8891	0.8003
Perceived Cost	0.7048	1.0989	0.7614	0.5366
Behavioural Intention	0.8741	0.8752	0.9026	0.5698
Consumer intention to adopt m-commerce	0.7471	0.7558	0.8873	0.7975

Table 2 shows that the CR value ranges from 0.7614 to 1.0989>0.7, and that the Cronbach's Alpha of the constructs range from 0.7048 to 0.8741 > 0.7, which indicates a strong internal consistency and reliability of the constructs of our research model. As for AVE, their value ranges from 0.5366 to 0.8003>0.5. Based on these previous findings, we can conclude that the convergent validity is insured.

Table 3. Heterotrait-Monotrait Ratio (HTMT)

	Variety of Services	Social Influence	Perceived Cost	Behavioural Intention	Consumer intention to adopt m-commerce
Variety of Services					
Social Influence	0.0568				
Perceived Cost	0.1302	0.1008			
Behavioural Intention	0.3453	0.3603	0.2055		
Consumer intention to adopt m-commerce	0.1962	0.2217	0.1221	0.6877	

With regard to the HTMT ratios of correlation between the constructs, the different corresponding values are set forth in Table 3. Such values are acceptable because they are below the threshold of 0.90 [28]. On the basis of the findings, both the reliability and validity of constructs are guaranteed.

Structural Model. The Bootstrapping method allows testing the significance of the relationship between the constructs featuring in the model through the interpretation of the t-statistics, as well as the correlation between these constructs by looking deeply on the values of the path coefficient.

To express some significance, the t-Statistics must be greater than 1.96. Table 4 summarizes these values.

Table 4. Structural Model Testing Hypothesis using Boostrapping

Hypothesis		Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t-statistics |O/STDEV|	p-values
H1	Variety of Services-> Consumer intention to adopt m-commerce	0.0054	0.0058	0.0573	0.0935	0.9255
H2	Variety of Services-> Behavioural Intention	0.2587	0.2641	0.0581	4.4492	0.0000
H3	Social Influence->Behavioural Intention	0.2697	0.2717	0.0582	4.6336	0.0000
H4	Perceived Cost->Behavioural Intention	-0.1550	-0.1654	0.0602	2.5749	0.0103
H5	Behavioural Intention->Consumer Intention to adopt m-commerce	0.5570	0.5641	0.0575	9.6952	0.0000

Table 5. Hypothesis testing results

Hypothesis		p-values	Test results
H1	Variety of Services-> Consumer intention to adopt m-commerce	0.9255	Rejected
H2	Variety of Services-> Behavioural Intention	0.0000	Accepted
H3	Social Influence->Behavioural Intention	0.0000	Accepted
H4	Perceived Cost->Behavioural Intention	0.0103	Accepted
H5	Behavioural Intention->Consumer Intention to adopt m-commerce	0.0000	Accepted

Table 6. R-square and R-square Adjusted

Latent constructs	R Square	R Square Adjusted
Behavioural Intention	0.1830	0.1735
Consumer intention to adopt m-commerce	0.3120	0.3067

Table 4 shows that the relationships Behavioural Intention -> Consumer Intention to adopt m-commerce (t=9.6952), Variety of Services -> Behavioural Intention (t=4.4492), Perceived Cost -> Behavioural Intention (t = 2.5749) and Social Influence -> Behavioural Intention (t = 4.6336) have significant effects on the adoption of m-commerce. Hence, these findings support hypotheses H2, H3, H4 and H5.

Table 6 shows the value R^2 and R^2 adjusted of the latent constructs "Behavioural Intention" and "Consumer Intention to adopt m-commerce". The variable "Behavioural Intention" is explained at 18% by the variables "Variety of Services", "Social Influence" and "Perceived Cost", but in turn it explains at 31% the variance of the variable "Consumer Intention to adopt m-commerce". Specifically in the case of the consumer intention to adopt m-commerce, $R^2 = 0.3120 > 0.25$. According to Hair et al., we can then conclude that our model is quite good and interesting [28].

Multigroup Analysis (MGA). The multigroup analysis assesses whether predefined data groups present significant differences for the group-specific model estimations. For this purpose, we decided to use the PLS-MGA approach (Partial Least Squares Multigroup Analysis). It focuses on the bootstrapping results for each group [31]. The PLS-MGA method [32] represents an extension of Henseler's MGA [31]. This method is an important non-parametric test for the comparison of the group-specific bootstrapping PLS-SEM results. The fact that p-value is smaller than 0.05 or is larger than 0.95 indicates a significant difference from the probability of 0.05.

Table 7. Multigroup Analysis of the Group "Gender"

	Path coefficients-diff (|GROUP_Gender(F)-GROUP_Gender(M) |)	p-value (GROUP_Gender(F) vs GROUP_Gender(M))
Behavioural Intention->Consumer Intention to adopt m-commerce	0.0573	0.3090
Variety of Services-> Consumer intention to adopt m-commerce	0.0085	0.4853

Table 8. Multigroup Analysis of the Group "Age"

	Path coefficients-diff (|GROUP_Age (18-25)-GROUP_Age (26-35) |)	p-value (GROUP_Age (18-25) vs GROUP_Age (26-35))
Behavioural Intention->Consumer Intention to adopt m-commerce	0.2233	0.0869
Variety of Services-> Consumer intention to adopt m-commerce	0.0359	0.4124

Table 6 shows no significant difference between the two groups of gender as it may appear in the relationships "Behavioural Intention->Consumer Intention to adopt m-commerce" (p-value = 0.3090 > 0.05) and "Variety of Services-> Consumer intention to adopt m-commerce" (p-value = 0.4853 > 0.05). Moreover, the path coefficients' values for each gender group are fairly equal in absolute terms (path coefficient = 0.5917 - R^2 = 0.3495 for Female and path coefficient = 0.5344 - R^2 = 0.2837 for Male for the relationship "Behavioural Intention->Consumer Intention to adopt m-commerce" and path coefficient = -0.0013- R^2 = 0.3495 for Female and path coefficient =-0.0098 - R^2 = 0.2837 for Male for the relationship "Variety of Services->Consumer Intention to adopt m-commerce"). These values reveal that the female group is sensibly stronger than the male group, which means that female respondents sensibly have more

effect on “Behavioural Intention->Consumer Intention to adopt m-commerce” than males. We also notice that for the same gender group, these values are greater for the relationship “Behavioural Intention->Consumer Intention to adopt m-commerce” although their contributions to R^2 are fairly equal.
As for Table 7, there is no significant difference between the two groups of age as regards the relationships “Behavioural Intention->Consumer Intention to adopt m-commerce” (p-value = 0.0869 > 0.05) and “Variety of Services -> Consumer intention to adopt m-commerce” (p-value = 0.4124 > 0.05). Moreover, the path coefficients' values for each age group are different in absolute terms (path coefficient = 0.5962 - R^2 = 0.3704 for age 18-25 and path coefficient = 0.3730- R^2 =0.1389 for the age range 26-35 for the relationship “Behavioural Intention->Consumer Intention to adopt m-commerce” and path coefficient = 0.0346 - R^2 =0.3704 for the age range 18-25 and path coefficient =-0.0013, R^2 =0.1389 for the age bracket 26-35 for the relationship “Variety of Services->Consumer Intention to adopt m-commerce”). These values reveal that age group 18-25 is sensibly stronger than one ranging from 26 to 35, which means that younger respondents sensibly have more effect on “Behavioural Intention->Consumer Intention to adopt m-commerce”. The same phenomenon is observed as regards the relationship “Variety of Services->Consumer Intention to adopt m-commerce”.
Based on these findings, it appears that the hypotheses H6a, H6b, H7a and H7b are not supported.

5 Discussions and limitations

Our study certainly contributes to enriching the literature on IT adoption research, especially by disseminating a relevant experience from the developing country context. The relevant literature on the development of such technology in a sub-Saharian African countries, for instance, is still a little bit poor, whereas gigantic strides are steadily made in other regions about the subject. Furthermore, by proposing a research model integrating variables from TAM and UTAUT and by adding other variables such as the Perceived cost and the Variety of services, we have been able to identify the influence of such variables on the intention to adopt m-commerce, which is a major contribution to the extant literature. Findings of our research can be summarized as follows: (i) Social influence and Variety of services positively influence Behavioural intention while the Perceived cost negatively influences Behavioural intention; and (ii) factors such as age and gender are not significantly different between the relationship “Behavioural Intention->Consumer Intention to adopt m-commerce” and “Variety of Services->Consumer Intention to adopt m-commerce”.
Out of the driving factors that can predict the adoption of m-commerce among Cameroonian consumers, our study has revealed that the variety of services, social influence and the Perceived cost significantly influence behavioural intention, and therefore the consumer intention to adopt m-commerce.
In terms of implications, this study has driven some of them: Firstly, the perceived cost has a negative influence on the behavioural intention to take adoption decision. Therefore, the increase in mobile service costs could discourage young people who are

price conscious. In reaction to this, telecoms companies and others businesses investing in m-commerce in Cameroon should develop good pricing strategies and creative promotional activities to attract young consumers. Secondly, the variety of services is found to positively influence behavioural intention, but does not influence directly and significantly the consumer intention to adopt m-commerce. In consequence, businesses investing in m-commerce in Cameroon should make more efforts to offer a greater variety of services and applications. Thirdly, the results also show that demographic variables of respondents (like age and gender), in general, are not good predictors of m-commerce adoptions. There were no significant difference between groups of respondents according to age (GROUP_Age(18-25) vs GROUP_Age(26-35)) and gender (GROUP_Gender (F) vs GROUP_Gender (M)). Finally, this research has contributed to the literature, by providing information of interest about some factors that can influence the adoption of m-commerce in a developing country like Cameroon. The present study bears a number of limitations in this study. The first one is that the cultural values of respondents were not taken into account. Future studies may consider measuring this aspect of the survey's population. The second limitation relates to the geographical restriction of the study area to only Douala and Yaoundé, whereas more Cameroonian towns (Maroua, Ngaoundere, Buea, Bamenda or Dschang) could well be involved. This is a setback to be considered in future research attempts. Lastly, additional adoption factors, such as trust, innovativeness, and compatibility, could also be integrated with the research model, and researchers should think about it.

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