Impact of Technology-Enabled Personalization on the Adoption of Mobile Banking

An Experimental Study

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Abstract: New technologies such as artificial intelligence and Big Data offer an opportunity in terms of personalization of products and services, particularly in mobile banking services. Previous researches have provided mixed results regarding the causal or moderator role of personalization in the adoption of mobile services. This research aims to provide a response to this discordance by using an experimental method in the context of mobile banking services. Results regarding the impact of technology-enabled personalization along with age on the adoption of mobile banking services confirm the causal impact of technology-enabled personalization on facilitating conditions (FC), hedonic motivation (HM), perceived confidentiality (PC), and the intention to use mobile banking. Findings and discussions across age and gender groups could guide future empirical research in this area.

Keywords: M-Banking, Experiment, UTAUT, Technology-enabled Personalization, perceived privacy

Introduction

With a large customer base, banks can benefit from new marketing and communication tools, which offer the possibility of mass customization while offering innovative products. This is a major challenge because many organizations today are saturated with mass automation and homogenized products and services (Martins *et al.*, 2014).

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The growth of the smartphone market has encouraged the banking sector to create innovative digital applications that provide customers with the convenience of carrying out transactions. These are mobile banking services (Saparudin *et al.*, 2020).

Motiwalla et al. (2019) admit that emerging technologies allow personalization of system functionality based on contextual variables derived from the experiences and demographics of each user group, such as gender, age, education and income information.

According to Dauda & Lee (2015), technology acceptances are theories that focus on factors that influence the decision of accepting and using a specific technology. In this context, the most studied models in the literature on technology acceptance are the technology acceptance model (TAM) (Davis, 1989); the theory of planned behaviour (TPB) (Ajzen, 1991), which is developed from the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975); and a hybrid model combining the constructs of TAM and TPB (Taylor & Todd, 1995). Additionally, the following theories were largely adopted in the field of technology acceptance: the theory of diffusion of innovation (Rogers, 1983); the social cognitive theory (Bandura, 1986); the PC use model (Thompson *et al.*, 1991); the motivational model (Davis *et al.*, 1992); and the Unified Theory of Acceptance and Use of Technology (UTAUT) that was published under two versions UTAUT1 and UTAUT2 (Venkatesh *et al.*, 2003; Venkatesh *et al.*, 2012).

In terms of the mobile application literature, little attention has been paid to the role that personalization plays in technology acceptance (Cheng *et al.*, 2020). In the banking sector, we have noticed that studies generally focus on online banking services (Salem *et al.*, 2019; Wang *et al.*, 2017). Regarding M-banking, previous research has focused on studying customer satisfaction (Albashrawi & Motiwalla, 2015; Altobishi *et al.*, 2018). The relationship between personalization and the UTAUT 1 and 2 theories (Venkatesh *et al.*, 2003; 2012) has been discussed in different contexts, such as mobile news applications (Cheng *et al.*, 2020), e-government services (Krishnaraju *et al.*, 2016), and online banking (Wang *et al.*, 2017). Thus, this study is motivated by the lack of literature on the role of personalization in M-banking services.

After an in-depth review of the literature on the role of personalization in the adoption of mobile services in several contexts, and the examination of the factors which influence the adoption of these services in the banking sector, it appears that results of previous research are not unanimous regarding the moderating impact (Albashrawi & Motiwalla, 2015; Cheng *et al.*, 2020) or causal impact on the adoption of mobile banking services (Saeed, 2011; Asif & Krogstie, 2013; Altobishi *et al.*, 2018; Zalloum *et al.*, 2019). Hence, the relevance of using

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experiment, which proves to be an adequate method for analysing the role of personalization (Lee *et al.*, 2012; Krishnaraju *et al.*, 2013; Wessel & Thies, 2015).

This study conducted firstly an experiment to confirm the role of personalization in the adoption of mobile banking services at the level of the UTAUT relationship, perceived confidentiality and the intention of adopting mobile banking services. Secondly, based on the experiment results, relationships of the research model are assessed using a Structural Equation Modelling (SEM) analysis.

Literature Review

Technology-enabled personalization (TEP) is defined as the integration of physical and digital personalization dimensions at the point of sale to provide individual customers with relevant, context-specific information, based on combined historical and real-time data (Riegger *et al.*, 2021).

According to Albashrawi & Motiwalla (2015), personalization involves personalizing the user interface and graphics according to the needs of each user. Personalized mobile banking applications require the use of customer profiles, customer preferences, prior mobile banking usage data and social media data.

Technology-enabled personalization (TEP) has become possible in the context of M-Banking thanks to the following technologies: artificial intelligence, machine learning, recommendation systems, the Internet of Things, and Blockchain. TEP encompasses two dimensions: the physical dimensions of M-Banking personalization services, such as locations, facial expressions and real-time interactions (video banking); and the digital dimensions of personalization, which concern banking data, social networks, e-commerce, and websites (Khemiri & Jallouli, 2022).

Previous researches argue that the UTAUT was widely used to study individual usage behaviour of various information systems. The UTAUT demonstrates good generalization and high explanatory power in computer system research, and it has rarely been combined with a data mining tool that can improve its validity in the context of mobile banking (Albashrawi *et al.*, 2017). According to Venkatesh et al. (2012), UTAUT2, which is an evolved form of the UTAUT (Venkatesh *et al.*, 2003), is composed of performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), social influence (SI), hedonic motivation (HM), price value (PV), and habit (HT).

In addition, Venkatesh *et al.* (2012) show that different cohorts of consumers attach different weights to various factors that influence their technology use, which can potentially be attributed to differential learning abilities and social roles by age, experience, and gender.

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Results of previous studies are not unanimous regarding the role of age and gender in accepting Internet and mobile services. Indeed, according to Laukkanen (2016), age and gender appeared to be significant variables in the acceptance of mobile banking services. On the other side, for non-adopters of mobile banking, the rejection decision is explained by gender, while age explains the rejection of Internet banking. Additionally, results show that women appear more likely to reject mobile banking than men. Furthermore, the study by Faqih et al. (2015) shows that the gender dimensions has no influence on the adoption of m-commerce technology.

After careful consideration of previous publications regarding the nature of the impact of personalisation, gender and age on mobile banking adoption factors and intention to use M-banking, this research provides the theoretical foundation of the set of hypotheses related to the UTAUT2 theory and perceived confidentiality in the M-banking context, subject to the experimental protocol that will be adopted in a second step.

According to Islam (2017), personalization has a positive impact on behavioural intention in the case of mobile Internet. Indeed, personalization was found to be an important factor alongside the existing factors of the UTAUT model. Moreover, Salem et al. (2019) admitted that customer value for online personalization has a causal impact on the use of online banking services. Thus, the preceding developments support the following hypothesis:

H1: Personalization based on new technologies has a positive impact on the intention to use M-Banking services.

Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh *et al.*, 2003, p. 447). According to Wang et al. (2017), personalization has a significant impact on the performance expectations and responses of customers who are either inexperienced with e-banking in general or familiar with a completely different system. This shows that personalization leads them to find more utility in their experience. Additionally, personalization helps reduce the time required to complete tasks, improve efficiency, and deliver the desired information in the right form to targeted users (Cheng *et al.*, 2020). Moreover, Fernandez-Lanvin et al. (2018) found that there is consistency in the execution times of individuals across different tasks on e-commerce websites, and that age and gender are sufficiently determining factors to allow for personalized automatic profiling. According to Yapp et al. (2018), personalization is important for female users, because it could contribute to enhance their performance expectations. Results show that women express their need to have services capable of solving their problem related to machine interaction and doing more work in a short time.

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Thus, in this research the following hypotheses are stated:

H2-1: Personalization based on new technologies has a positive impact on performance expectancy.

H2-2: The impact of personalization based on new technologies on performance expectancy is moderated by age.

H2-3: The impact of personalization based on new technologies on performance expectancy is moderated by gender.

Regarding the third variable, Effort expectancy is defined as "the degree of ease associated with the use of the system" (Venkatesh *et al.*, 2003). The results of Cheng et al. (2020) show that personalization does not have a moderating impact on the relationship between effort expectancy and continued use intention of mobile news applications. Moreover, according to Wang et al. (2017), personalization will have an impact on the expected effort for online banking services. Indeed, customers indicate that personalization leads them to find more utility in their experience and improve their perceived ease of use of e-banking. Kumar et al. (2004) suggest that, at the level of users' perception of a personalized interface, personal characteristics such as age and gender have an effect on the perception of the ease of use of web pages. The following hypotheses are stated:

H3-1: Personalization based on new technologies has a positive impact on effort expectancy.

H3-2: The impact of personalization based on new technologies on effort expectancy is moderated by age.

H3-3: The impact of personalization based on new technologies on effort expectancy is moderated by gender.

The variable "facilitating conditions" is defined as "the degree to which an individual believes that an organisation's and technical infrastructure exists to support the use of the system" (Venkatesh *et al.*, 2003). Furthermore, Cheng et al. (2020) admit that through personalized news applications users must feel like they are getting a special service. In this sense, facilitating conditions refer to quality services, such as the timely delivery of updates, push notifications, or breaking news to users on their favourite topics, instantly and without any technical malfunction.

According to Krishnaraju et al. (2016), the moderation effect of Web Personalization on facilitating conditions was not significant. On the other hand, Siyal et al. (2024) admit that personalization has a significant and positive effect on facilitating conditions for mobile commerce applications. Additionally, Wijaya & Sari (2021) prove that the relationship between Customer Relationship Management (CRM) chatbots and user preferences is

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influenced by demographic variables including age and gender. This study discussed the attributes involved in human chatbot interaction considered as facilitating conditions of using CRM systems.

Based on these developments, the following hypotheses are stated:

H4-1: Personalization based on new technologies has a positive impact on facilitating conditions.

H4-2: The impact of personalization based on new technologies on facilitating conditions is moderated by age.

H4-3: The impact of personalization based on new technologies on facilitating conditions is moderated by gender.

As for "social influence", this variable is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh *et al.*, 2003). As for the role of personalization, according to Cheng et al. (2020), personalization does not have a moderating impact on the relationship between social influence and continued use intention of mobile news applications. On the other hand, the study by Blom & Monk (2003) showed that personalization was incorporated by many of the participants' friends and it was a major cause of adoption. Oyibo et al. (2017) found that, in general, men and women, as well as younger and older people, differ in their susceptibility to social influence strategies in persuasive technology. In fact, men and younger people are more susceptible to the respective persuasive strategies than women and older people.

H5-1: Personalization based on new technologies has a positive impact on social influence.

H5-2: The impact of personalization based on new technologies on social influence is moderated by age.

H5-3: The impact of personalization based on new technologies on social influence is moderated by gender.

Regarding hedonic motivation, this variable is defined as "the fun or pleasure derived from using technology, and it has been shown to play an important role in determining technology acceptance and use" (Venkatesh *et al.*, 2012). As for personalization, according to Haq & Ghouri (2018) personalization does not influence consumer behaviour towards adoption through emotional value. On the other hand, Krishnaraju et al. (2016) admit that, with a higher level of web personalization based on a recommendation system, hedonic motivation will have a stronger impact on the intention to use E-government. Additionally, Sung et al. (2009) suggested that personalization helps technology users feel increased attachment to a product, which can help accelerate emotional engagement. Furthermore, the research by

Abdullahi et al. (2019) on the personalization of persuasive health interventions found that women and older adults (over 65 years old) are more strongly associated with emotional well-being to promote subjective well-being. Based on these results, the following hypotheses regarding hedonic motivation are stated:

H6-1: Personalization based on new technologies has a positive effect on hedonic motivation.

H6-2: The impact of personalization based on new technologies on hedonic motivation is moderated by age.

H6-3: The impact of personalization based on new technologies on hedonic motivation is moderated by gender.

Price value is defined as "consumers' trade-off between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh *et al.*, 2012). According to Tyrväinen et al. (2020), personalization has reduced customer search and cost evaluation, which has increased their loyalty. Rust (2020) acknowledged that the low cost of personalization in the information services environment makes personalization more feasible. Moreover, Bloom (2003) admits that it is easy to understand that the cost of personalizing can affect a user's disposition to personalize, especially for users in younger age groups. In addition, Lastner et al. (2019) admit that personalized dynamic pricing is influenced by gender. Indeed, their study reveals a significant interaction between gender and reference price.

Based on these developments, the following hypotheses are stated:

H7-1: Personalization based on new technologies has a positive impact on price value.

H7-2: The impact of personalization based on new technologies on price value is moderated by age.

H7-3: The impact of personalization based on new technologies on price value is moderated by gender.

Habit is defined as "the extent to which people tend to perform behaviours automatically" (Venkatesh *et al.*, 2012). Krishnaraju et al. (2016) confirm that website personalization has no moderating effect on the relationship between habit and behavioural intention. However, Cheng et al. (2020) admit that the benefits of both utility and personalization features contribute to strengthening the effect of habit on the use of new apps, especially when users are satisfied with their experiences of obtaining preferred content. Hutto et al. (2015) argue that the multitude of details provided by users about their personal usage habits of social media technologies, their sharing behaviours, their communication practices, their

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preferences, their problems, and their concerns constitute a rich source of relevant information for personalization. Indeed, older women, who have greater technological confidence and more positive attitudes towards ICT, tend to access social media from their home personal computer and generally want to stay connected with their family. Therefore, we state the following hypotheses:

H8-1: Personalization based on new technologies has a positive impact on habit.

H8-2: The impact of personalization based on new technologies on habit is moderated by age.

H8-3: The impact of personalization based on new technologies on habit is moderated by gender.

According to Westin (1967), information privacy is defined as "the individual's ability to control when, how, and to what extent his or her personal information is acquired and used". Oliveira et al. (2014) admit that mobile banking is a highly personalized and highly sensitive service, and users are mainly concerned about privacy and security. Therefore, policymakers and financial institutions should focus on establishing a trusting relationship with the customer from the beginning.

Saeed & Bekhet (2018) show that personalization is an insignificant predictor of the intention to use mobile marketing. On the other hand, Hmoud & Varallyai (2020) acknowledge that, despite the fact that AI-based business information systems are in their early stages of diffusion, respondents have shown marginal trust despite not having used them yet. Furthermore, Guo et al. (2016) indicate that the effects of personalization on trust to use are stronger among young people. In addition, Sheehan (1999) proves that women are more concerned about their privacy than men in several types of online information gathering situations. In this research, we state the following hypotheses:

H9-1: Personalization based on new technologies has a positive impact on perceived confidentiality.

H9-2: The impact of personalization based on new technologies on perceived confidentiality is moderated by age.

H9-3: The impact of personalization based on new technologies on perceived confidentiality is moderated by gender.

Figure 1 provides an overview of the theoretical framework that summarizes the hypotheses proposed in this section.

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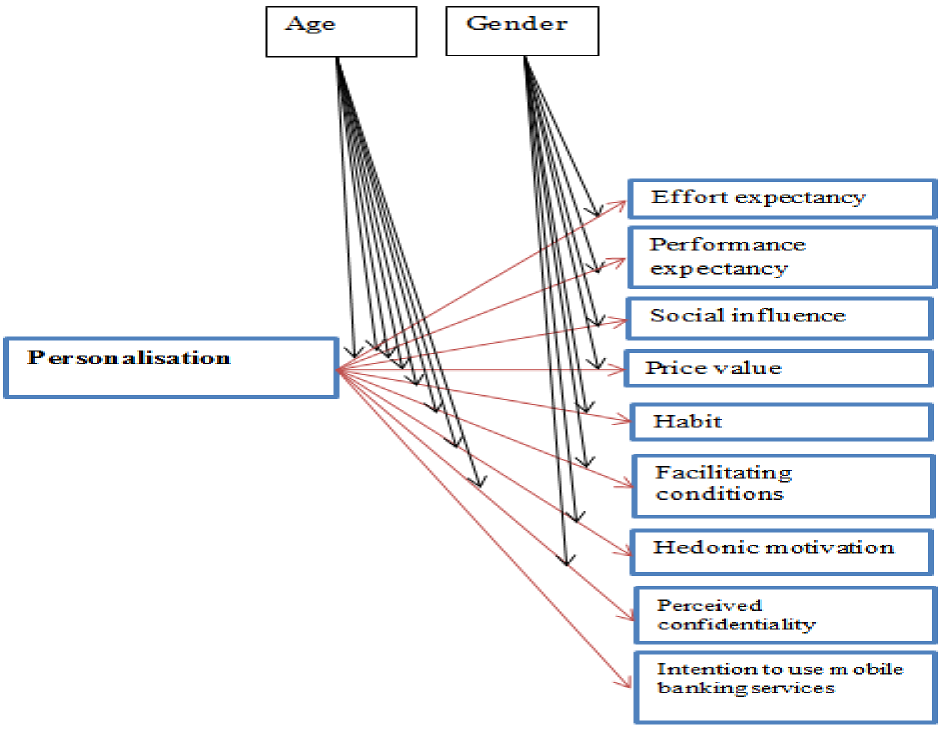

Figure 1. Conceptual framework of the impact of personalization on adoption factors and intention to use mobile banking services

Experimental Study

An experiment was conducted to study the effect of technology-based personalization on the adoption factors and adoption intention of mobile banking services. The explanatory variable is personalization. Thus, the dependent variables are performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, social influence, perceived confidentiality, price value, habit, and intention to use mobile banking services.

Design of the research experiment

A statistical experimental plan is designed following a factorial design of 12 cells (2x2x3), namely:

- 2 types of questionnaires — "A" (personalized application) and "B" (non-personalized application);
- 2 types of gender — "man and woman";
- 3 age groups — "under 30 years", "between 30 and 50 years", and "over 50 years".

A total of 986 participants were randomly assigned to one of the groups, in which questionnaire "A" was manipulated via an experimental design and questionnaire "B" was presented to a control group.

After explaining the design of the study and before carrying out the experiment, we have first checked the internal and external validity.

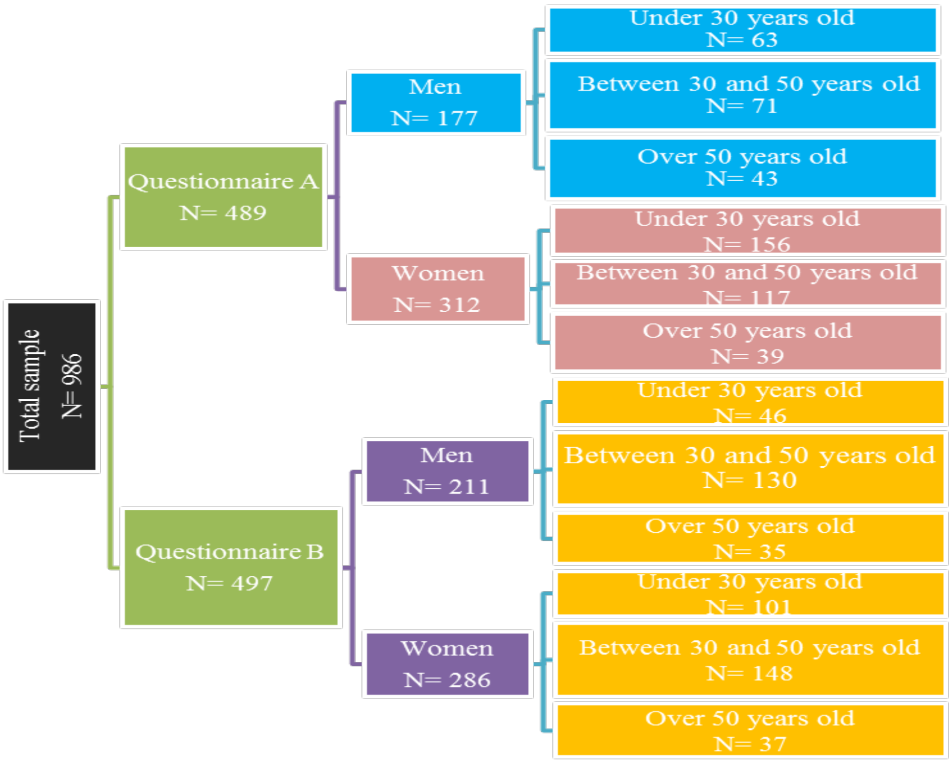

Figure 2. Sample structure

Concerning the history effect, we ensured that no events external to the experiment occurred at the same time and which could affect the dependent variable. In addition, to avoid the testing effect, two samples from the same population and with the same characteristics were used; one for testing and the other for experiment. Also, to minimize the selection effect, we proceeded to a random assignment of subjects to groups (A and B).

To reduce the effect of the instrument, we systematically tested the questionnaires with subjects representing the target population in order to obtain their qualitative feedback in terms of understanding, difficulty of response and duration of administration.

The experiment was carried out according to the following steps:

Step 0: *Introduction of the questionnaire*

The participant was informed that the questionnaire was part of scientific research in marketing.

First step: *Participant/client identification*

To simulate the customer's banking identity, the participant was asked to fill out an identification sheet concerning nationality, profession, gender and age.

Second step: *Classification of participants*

The respondent (test unit) is automatically assigned without their knowledge to the cells which correspond to their age and gender class (Figure 1). This action is done by the "Google form" algorithm while trying to follow the same processing that is done by artificial intelligence tools on mobile banking applications. Indeed, this processing has become possible thanks to access to vast volumes of customer and transaction data, across digital data, text, voice, image and facial expression (Davenport *et al.*, 2020).

Third step: *Description and knowledge test*

A description was introduced to explain the concept of mobile banking services to respondents: "*Banks provide their customers with applications that can be downloaded to mobile phones. It allows, among other things, to consult the balance, download account movements, order the bank card and check [cheque] books, etc. These applications are also called 'mobile banking applications'.*"

We first asked a question to test the frequency of use of the mobile application by the respondent to manage the bank account(s). We then asked the respondents to answer questions regarding the personalization variable before the experiment to avoid any kind of influence on his/her answers.

Fourth step: *Simulation of the bank card offer*

A Mobile Banking Application was chosen as the context for the experiment. We designed an image to simulate a real application (Appendix 1).

The simulation consists of displaying a poster containing a screenshot of a banking application installed on a smartphone, containing a set of services and a personalized bank card offer. Indeed, algorithm-based personalization allows applications to suggest the most appropriate content to users (Cheng *et al.*, 2020).

- The choice of services presented in the application was based on a search for mobile banking services on Google Store.
- The personalization of the card offer was manipulated by inserting two information attributes on wallpaper (the colour and the text message).

For men, we assigned the colour "blue". Cerrato (2012) suggests that blue is a masculine colour; it is very well accepted among men. For women, we used the "pink" colour. Psychologically, it is used to symbolize many characteristics, including femininity (Singh & Srivastava, 2011; Cerrato, 2012; Mohebbi, 2014). Concerning the control group, we chose the "gold" colour. Around the world, the "gold" colour is widely used by banks for cards that are offered to men and women without distinction. This colour, therefore, does not refer to any information or gender preference, based on the psychological and also contextual perspective (current practices).

For age, we inserted personalized text messages for each age group. For example, for Men under 30, the message was: “Discover our new offer for men under 30”.

Concerning the control group, a standard message was set for all cells: “Discover our new offer”.

Fifth step: *Measuring Perceived Personalization*

The objective of this step was to measure or evaluate the effect of perceived personalization after the experience. A question was assigned to the respondent: To what extent does this message above seem personalized to you (adapted to your profile: age and gender)?

Sixth step: *Measure Questions*

The participant answered the remainder of the questions regarding the dependent and independent variables based on the same measures. The questionnaire was pre-tested by face-to-face interviews and on a sample of 16 online respondents in order to ensure proper understanding of the questions. At this stage of the research, it is indeed essential to ensure that the manipulation of the different stimuli is correctly perceived by the respondents.

Therefore, it was appropriate to verify that respondents perceived a high degree of personalization (vs low) when they were faced with a personalized application (vs non-personalized)

The statistical test used to verify the hypotheses is the analysis of variance (ANOVA), which allows one to verify if there are statistically significant differences between the groups. Indeed, the statistical method conditions that have been adopted to verify the result of this research are as follows:

- Normality of data:

To assess the normality of the data, we tested the coefficients of skewness and kurtosis (Appendix 2). The results show that the data have satisfactory univariate normality.

- Homoscedasticity

The results of the Levene test (Appendix 2), which are based on the differences between the medians of the variables (Personalization/Performance Expectancy/Effort Expectancy/-Hedonic Motivation/Social Influence/Value Price/Habit/Usage Intention), are not significant ($p > 0.05$). This means that the variances of these variables are approximately equal, and that the homoscedasticity hypothesis is accepted.

For the variable “perceived confidentiality”, the results of the variance homogeneity test based on means and medians are significant ($p=0.041$; $p=0.046 \leq 0.05$). In this case, we can use Hartley’s Fmax to assess homoscedasticity. The variance ratio is therefore 1.065 /0.930=

1.14. This difference is practically equal to 1, which means that the variances of the two samples are approximately equal. Therefore, the homoscedasticity hypothesis is also accepted for the variable “perceived confidentiality”.

The apps are manipulated so that respondents are exposed to one (personalized) app or one (non-personalized) app. Respondents were then asked to indicate the degree of personalization of the application displayed, using a five-point Likert scale. A test of significance and comparison of the averages makes it possible to verify that these objectives were achieved (Table 1).

Table1. T-test for comparison of means of the degree of perceived personalization

Variable	Two-sided significance	Means B (without Personalization)	Means A (with Personalization)
Personalization measure	0.001	2.29	2.52

This result shows a significant difference (sig=0.001<0.05) between the means of the personalization measurement, which goes from a value of 2.29 for questionnaire “B” (non-personalized application) to a value of 2.52 for questionnaire “A” (personalized application). We can therefore deduce that the manipulation is correctly perceived by the respondents.

Experimental results

Table 2. Comparison of means

Variable		N	Mean	F	Sig.
Perceived personalization	A	489	2.52	12.027	0.001
	B	497	2.29		
PE (Performance Expectancy)	A	489	1.01	1.118	0.291
	B	497	1.06		
EE (Effort Expectancy)	A	489	0.93	3.364	0.067
	B	497	1.02		
FC (Facilitating Conditions)	A	489	1.14	12.712	0.000
	B	497	1.32		
HM (Hedonic Motivation)	A	489	0.40	8.409	0.004
	B	497	0.25		
SI (Social Influence)	A	489	0.65	0.341	0.559
	B	497	0.62		
PC (Perceived confidentiality)	A	489	0.57	4.256	0.039
	B	497	0.45		
PV (Price Value)	A	489	0.26	0.005	0.943
	B	497	0.26		
HABIT (Habit)	A	489	0.74	1.853	0.174
	B	497	0.81		
INTENTION (Intention to use)	A	489	0.87	6.857	0.009
	B	497	1.00		

For the variable “intention to use”, the result shows that there is a significant difference between the means (F=6.857, sig.=0.009<0.05). Thus, personalization based on new technologies has an impact on the intention to use.

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Table 2 also shows that there is a significant difference between the means of the variables “hedonic motivation” ($F=8.409$, $sig.=0.004<0.05$). This finding confirms that personalization based on new technologies has an impact on hedonic motivation.

Concerning the perceived confidentiality variable, the results show that there is a significant difference between the means of the variables ($F=4.256$; $sig.=0.039$). Personalization based on new technologies has therefore an impact on perceived confidentiality.

For the variable “facilitating conditions”, the results of Table 2 show that there is a significant difference between the means of the variables ($F=12.712$; $sig.=0.000$). This shows that personalization based on new technologies has an impact on facilitating conditions.

In addition, the results of Table 2 show that there is no significant difference between the means of the variables “performance expectancy”, “effort expectancy”, “social influence”, “price value”, and “habit”. As a result, hypotheses H2-1, H3-1, H5-1, H7-1, and H8-1 are rejected. Consequently, the hypotheses concerning gender (H2-2, H3-2, H5-2, H7-2, H8-2), and age (H2-3, H3-3, H5-3, H7-3, H8-3) are rejected.

Structural Equation Modelling Analysis and Validation of the Theoretical Framework

In the next step, we tested the size and the sign of the impact of personalization on the variables that were retained from the experience. The retained variables are: intention to use, hedonic motivation, facilitating conditions, and perceived confidentiality. In this case, we refer to sample “A” (personalized application).

Method

Based on the experimental results, the SEM analysis was pursued to assess, firstly, the direct relationships presented in the theoretical framework and confirmed with the experiment; and, secondly, the moderating variables that were argued in the theoretical part. First, we describe sample “A” for which the questionnaire that included personalized application was administered. Then, we present the measurement scales of the retained concept. Next, we perform confirmatory factor analysis to evaluate the validity of the variables. Finally, we analyze the results of the direct and indirect relationships in the research model. These analyses are performed with SPSS 23 and AMOS22.

Descriptive statistics

Sample “A” is composed of 489 participants, mostly women (63.8%), while men represent (36.2%). In terms of age, the respondents are divided into three age groups. Respondents under 30 years old represent 44.8%, those between 30 and 50 years old represent 38.4% of the total sample, and those over 50 years old represent 16.8%. Finally, the socioeconomic categories are well represented in the sample. It is noted that a good part of the respondents is made up of Managers, Engineers, Technicians, Teachers, and Administrators (47.6%), followed by Students (27%), and Self-employed professionals (5.7%). Business owners and managers represent 3.3%. Workers represent 4.3%, the unemployed represent 7.8%, and, finally, retirees represent 4.3%. These statistics are shown in Table 3.

Table 3. Demographic profile of the participants

Demographic variable	Sub-category	Frequency	Proportion (%)
Gender	Male	177	36,2
	Female	312	63,8
Age	Under 30 years old	219	44,8
	Between 30 and 50 years old	188	38,4
	Over 50 years old	82	16,8
Profession	Student	132	27,0
	Unskilled worker	21	4,3
	Engineer, technician, teacher, administrator	233	47,6
	Business owner, manager	16	3,3
	Self-employed professional (lawyer, doctor, etc.)	28	5,7
	Retired	21	4,3
	Unemployed	38	7,8

Measurement scales and reliability

According to Malhotra *et al.* (2017), measurement model validity depends on reliability, the quality of fit indices, and evidence of construct validity, particularly convergent and discriminant validity.

Table 4 summarizes the main results of reliability, in addition to the main references used to retain these measurement scales and the related reliability indicators. The exploratory analysis in Table 4 shows good results for all measurement scales adopted in this research. We used SPSS 23 and AMOS 22 to conduct our statistical analyses.

Table 4. Measurement scales, references and main reliability indicators

Measurement scales		Reliability analysis (of this study)		Previous studies	
Variable	Number of items	Cronbach's alpha	Jöreskog's rho	Authors and context	Reliability index
Personalization	3	0.858	0.861	Xu *et al.* (2011) (location-aware marketing)	0.80
				Albashrawi & Motiwalla (2015) (M-banking)	0.920
Effort Expectancy	4	0.911	0.913	Venkatesh *et al.* (2012) (Information technology)	0.910
				Baabdullah *et al.* (2019) (M-banking)	0.867

Measurement scales		**Reliability analysis (of this study)**		**Previous studies**	
Variable	Number of items	Cronbach's alpha	Jöreskog's rho	Authors and context	Reliability index
Performance Expectancy	4	0.811	0.811	Venkatesh *et al.* (2012) (Information technology)	0.880
				Baabdullah *et al.* (2019) (M-banking)	0.897
Facilitating Conditions	3	0.750	0.758	Venkatesh *et al.* (2012) (Information technology)	0.750
				Baabdullah *et al.* (2019) (M-banking)	0.802
Hedonic Motivation	3	0.799	0.798	Venkatesh *et al.* (2012) (Information technology)	0.860
				Baabdullah *et al.* (2019) (M-banking)	0.750
Social Influence	3	0.853	0.857	Venkatesh *et al.* (2012) (Information technology)	0.820
				Baabdullah *et al.* (2019) (M-banking)	0.869
Price Value	6	0.850	0.883	Venkatesh *et al.* (2012) (Information technology)	0.85
				Baabdullah *et al.* (2019) (M-banking)	0.766
				Hariyanti *et al.* (2020) (M-banking)	>0.6
Habit	4	0.840	0.846	Venkatesh *et al.* (2012) (Information technology)	0.820
				Baabdullah *et al.* (2019) (M-banking)	0.759
Perceived Confidentiality	6	0.883	0.876	Casaló *et al.* (2007) (E-banking)	0.88
				Baabdullah *et al.* (2019) (M-banking)	0.857

Results of the Structural Equation Modelling (SEM)

The Chi-square (χ^2) test gives a ratio of less than 5 (Schumacker & Lomax, 2004). The GFI, AGFI, CFI, and TLI indices are close to 1. The RMR value does not exceed 0.1, and the RMSEA is significant, since it remains less than 0.08. The parsimony indices are between 0 and 1 (Malhotra *et al.*, 2017). Overall, the quality of fit can be considered acceptable. The results are presented in Table 5.

Table 5. Global model fit indices

Index	**Absolute Indices**				**Incremental indices**			**Parsimony Indices**		
	GFI	**AGFI**	**RMR**	**RMSEA**	**TLI**	**NFI**	**CFI**	**PGFI**	**PNFI**	**Chi-squared (χ^2)**
Model Value	0.909	0.880	0.066	0.077	0.915	0.905	0.927	0.688	0.776	3.858

http://doi.org/10.18080/jtde.v12n1.891

The convergent validity of the variables in the model is satisfactory, because the average variance extracted (AVE) for each dimension is greater than 0.5, which is the generally accepted threshold for convergent validity. Regarding discriminant validity, we verified that the square root of the AVE of each construct exceeded its maximum correlation with any other construct. This implies that there is no correlation between the different variables (Malhotra *et al.*, 2017).

Table 6. Convergent and discriminant validity

	AVE	Personalization	FC	HM	PC	INTENTION
Personalization	0.691	**0.831**				
FC	0.572	0.463***	**0.756**			
HM	0.594	0.435***	0.540***	**0.771**		
PC	0.626	0.389***	0.439***	0.539***	**0.791**	
INTENTION	0.635	0.502***	0.711***	0.582***	0.554***	**0.797**

*** Significant at the 5% level

Results for direct relationships

The results of hypothesis testing for direct relationships between variables are presented in Table 7. Personalization based on new technologies has a positive impact on the intention to use M-Banking services (β = 0.805, t = 14.449, p = 0.000) and, therefore, H1 was accepted. Similarly, the results show that personalization based on new technologies has a positive impact on the variables facilitating conditions (β = 0.750, t = 13.077, p = 0.000), hedonic motivation (β = 0.694, t = 12.527, p = 0.000), and perceived confidentiality (β = 0.631, t = 10.730, p = 0.000). Thus, H1, H4-1, H6-1, and H9-1 are accepted, respectively.

Table 7. Structural equation model path analysis results

	Estimate (β)	S.E.	C.R. (T)	P
INTENTION <--- Personalization	0.805	0.063	14.449	***
FC <--- Personalization	0.750	0.061	13.077	***
HM <--- Personalization	0.694	0.063	12.527	***
PC <--- Personalization	0.631	0.069	10.730	***

*** Significant at the 5% level

Results for indirect relationships

In order to test the moderating role, we used complete invariance multi-group analysis (in Amos 22). The calculation of the Chi-squared difference test allows the determination of a probability level that will be compared to the recommended minimum threshold of 5%.

For the gender variable, Table 8 shows that the Chi-squared value is not significant (p=0, 0.11>0.05). Thus, gender has no moderation impact between personalization and the variables facilitating conditions, hedonic motivation, and perceived confidentiality. Therefore, hypotheses H4-2, H6-2, H9-2, are rejected.

Table 8. Chi-squared difference test for gender

Chi-squared difference test			
	Chi-Squared	**Df**	**P**
Model 0 (constant model)	468.37	117	0.00%
Model 1 (free model)	456.83	110	0.00%
Chi-Squared	11.54	7	11.67%

Concerning the age variable, Table 9 shows that the Chi-squared test is significant between age groups. (p=0.0002<0.05). Thus, age has a moderation impact between personalization and the variables facilitating conditions, hedonic motivation, and perceived confidentiality. Therefore, hypotheses H4-3, H6-3, H9-3, are accepted.

Table 9. Chi-squared difference test for age

Chi-square difference test			
	Chi-Squared	**Df**	**P**
Model 0 (constant model)	547.65	187	0.00%
Model 1 (free model)	575.67	194	0.00%
Chi-Squared	28.02	7	0.02%

Table 10 represents the statistical results of the differences between age groups (below 30; 30-50; above 50). Indeed, we can deduce from Table 10 that personalization showed a stronger effect on the variables FC, MH and CP among the youngest respondents, as the "C.R." values for this age group are consistently larger than for the older age groups.

Table 10. Statistical results of the differences between age groups

	Below 30			**30–50**			**Above 50**		
	Estimate	S.E.	C.R.	Estimate	S.E.	C.R.	Estimate	S.E.	C.R.
FC <--- Personalization	0.372	0.056	6.615	0.354	0.079	4.494	0.431	0.096	4.507
PC <--- Personalization	0.420	0.061	6.857	0.307	0.081	3.799	0.339	0.116	2.919
HM <--- Personalization	0.429	0.054	7.959	0.262	0.074	3.537	0.383	0.123	3.125

Discussion

This study investigated how personalization based on new technologies influences individuals' intention to use mobile banking services, referring to the UTAUT2 model, which was extended with perceived confidentiality and moderated by age and gender. Overall, our findings show that personalization has an impact on the intention to use. This research converges with the study by Salem et al. (2019), which states that the use of Internet banking is positively related to customers' value for online personalization. The results show that users appreciate personalized mobile banking applications, they think that these services are practical and adapted to their needs and preferences.

Furthermore, in line with the findings of the study by Siyal et al. (2024) in the context of mobile commerce applications, this research admits that personalization based on new technologies has a positive impact on facilitating conditions. This shows that the personalized offer (credit card) that was displayed on the mobile application provided more information about facilitating conditions of using this service. Thus, new technologies such as intelligence and recommendation systems can constitute additional resources for the use of mobile banking applications. Personalization was found to have a stronger effect on the youngest respondents' facilitating conditions when compared to the older studied group.

In contrast to the study by Wang et al. (2017), which was conducted in the context of e-banking, our study found that personalization does not affect performance expectancy or effort expectancy. Indeed, participants do not perceive personalized mobile applications as a technology that provides them with benefits in terms of usefulness and ease of use.

In addition, our study proves that personalization based on new technologies has an impact on hedonic motivation. This result indicates that participants place more importance on emotional benefits. Indeed, their reaction to the design of the personalized application made them feel feelings of amusement or pleasure. This result confirms the finding of Riegger et al. (2021), who discovered that consumers perceive intrinsic satisfaction from technology-based personalization (TEP) in stores, particularly due to the positive emotions associated with personal recognition and affirmation. Indeed, we admit that personalization showed a stronger effect on the variables HM among the youngest respondents.

Concerning the perceived confidentiality variable, the results show that personalization based on new technologies has an impact on perceived confidentiality. This result indicates that the participants, more precisely the young respondents, believe that the bank can guarantee the confidentiality of their personal data, in order to offer relevant information adapted to their preferences. When compared with the study of Ho & Kwok (2002), which admits that privacy concerns related to personalization discourage customers from turning to a mobile commerce service provider offering personalized services, it is understandable that the context of banking services could provide more perceived confidence and data privacy precautions than other mobile commerce applications.

Conclusion and Recommendations

This study consists of an experiment that aimed to study the impact of technology-enabled personalization, along with gender and age, on the adoption factors and the intention to use mobile banking services. Results prove that personalization has a positive impact on hedonic motivation and a negative impact on performance expectancy and effort expectancy in the context of mobile banking applications. Findings show that respondents perceive personalized mobile applications as a technology that brings them hedonic benefits rather than usability and functionality benefits. Based on this research, mobile banking applications based on new technologies are expected to provide personalized services tailored to the aesthetic and emotional needs of users. This can help accelerate emotional engagement and attachment to the services offered.

The efforts of this research highlight the considerable role of technologies that enable personalization, to implement segmentation, targeting and positioning strategies in terms of age and gender. Indeed, personalization has been shown to have a stronger effect on the enabling conditions of younger respondents than older respondents. Then, the use of personalized mobile banking services based on new technologies could intensify their feeling of joy and entertainment. Moreover, results show that younger people do not have a problem to share their confidential information to obtain personalized banking services. This study could orient banks to compare the adoption factors of mobile applications for different user groups in order to tailor effective marketing decisions for each segment.

Concerning future research, we suggest the use of advanced data analytic methods like clustering and text-mining techniques to analyze large databases of customers' comments or e-mails regarding the use of mobile applications (Benslama & Jallouli, 2020; Chebil *et al.*, 2021). Another recommendation for future work suggests adopting this research experimental method for more mobile banking services, such as personalized real-time location services.

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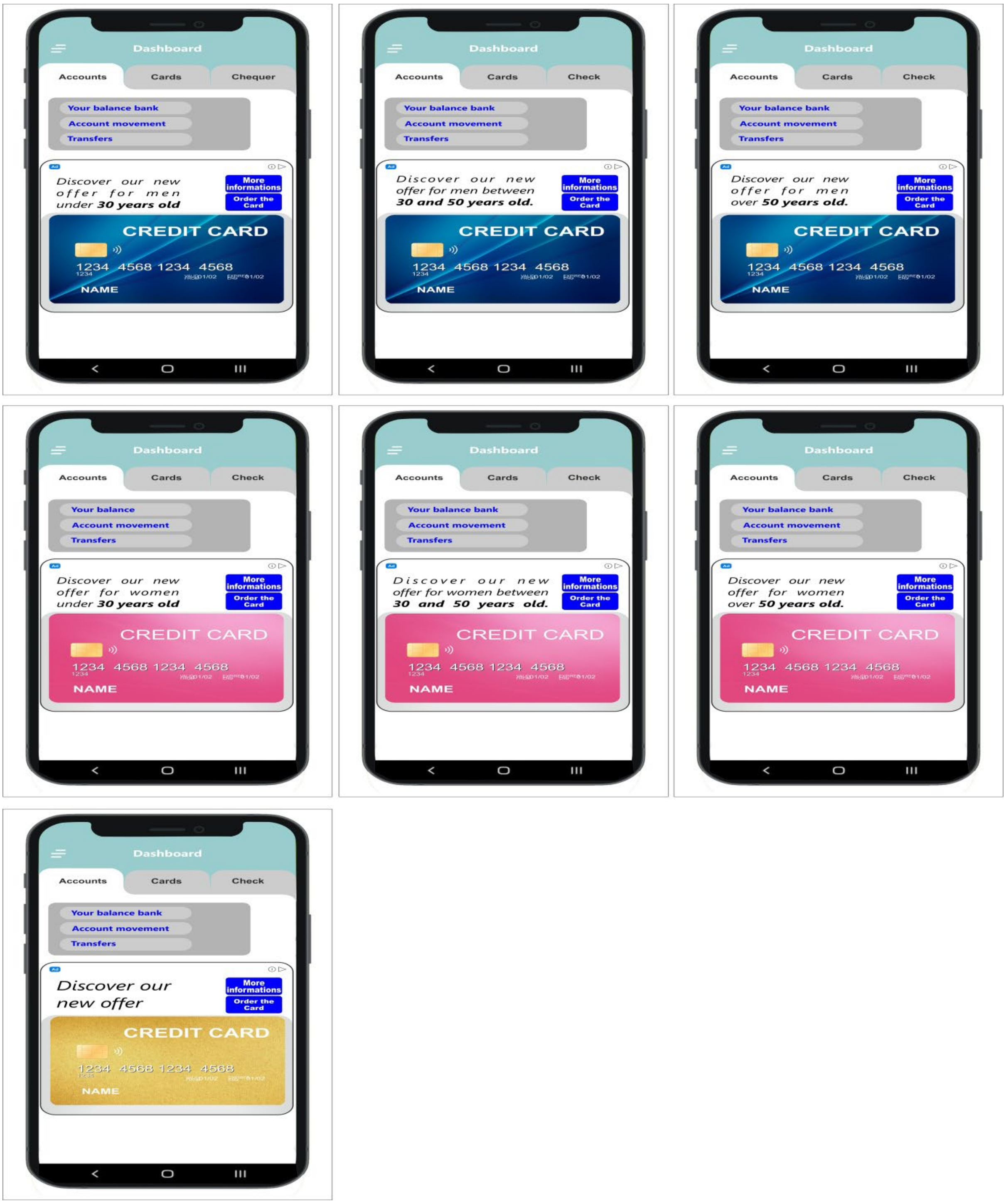
Appendix 1. Simulation of the mobile banking application



Appendix 2. Normality of data and Homoscedasticity

Normality of data

Features			
		Statistics	Standard error
Mobile banking apps provide personalized services tailored to the user's needs.	skewness	-.767	.074
	Kurtosis	-.082	.148
Mobile banking apps provide relevant information tailored to the user's preferences.	skewness	-.747	.074
	Kurtosis	-.019	.148
Mobile banking apps provide convenient services that the user enjoys.	skewness	-.829	.074
	Kurtosis	.099	.148
I find that this app is useful in everyday life (you can use it anywhere and anytime).	skewness	-1.413	.074
	Kurtosis	2.432	.148
This app increases the chances of accomplishing tasks that are important (for example. making transactions and transfers between banks).	skewness	-1.266	.074
	Kurtosis	2.153	.148
This app helps to accomplish tasks quickly and easily.	skewness	-1.355	.074
	Kurtosis	2.381	.148
Using this app increases efficiency.	skewness	-.736	.074
	Kurtosis	.194	.148
Learning how to use this app is easy.	skewness	-1.233	.074
	Kurtosis	1.856	.148
The interaction with this app is clear and understandable.	skewness	-1.217	.074
	Kurtosis	1.896	.148
This app is easy to use	skewness	-1.222	.074
	Kurtosis	2.082	.148
It is easy to master this app.	skewness	-1.215	.074
	Kurtosis	2.102	.148
I have the necessary resources (mobile phone and Internet) to use this app.	skewness	-1.633	.074
	Kurtosis	3.787	.148
I have the necessary knowledge to use this app.	skewness	-1.400	.074
	Kurtosis	1.846	.148
I can get help when I have difficulty using this app.	skewness	-.809	.074
	Kurtosis	.094	.148
Using this app is fun.	skewness	-.510	.074
	Kurtosis	-.234	.148
Using this app is enjoyable.	skewness	-.753	.074
	Kurtosis	.556	.148
Using this app is entertaining.	skewness	-.382	.074
	Kurtosis	-.078	.148
People who are important to me think it is necessary to use mobile banking apps.	skewness	-.783	.074
	Kurtosis	.190	.148
People who influence me think it is necessary to use mobile banking apps.	skewness	-.634	.074
	Kurtosis	-.041	.148
People whose opinions I value prefer that I use a mobile banking app.	Asymmetry	-.760	.074
	Kurtosis	.475	.148
I think banks care about the privacy of their mobile app users.	skewness	-.758	.074
	Kurtosis	.050	.148
I feel safe when I send personal information using this app.	skewness	-.475	.074
	Kurtosis	-.724	.148
I think mobile banking apps comply with data privacy laws.	skewness	-.682	.074
	Kurtosis	-.177	.148
I think mobile banking apps only collect the user's personal data that is necessary for its operation.	skewness	-.683	.074
	Kurtosis	-.168	.148
I think mobile banking apps respect the user's rights when obtaining personal information.	skewness	-.712	.074
	Kurtosis	-.020	.148
I think the bank will not provide my personal information (entered when using mobile banking services) to other companies without my consent.	skewness	-.630	.074
	Kurtosis	-.137	.148
By using mobile banking apps, I can save money (because I don't need to go to the bank).	skewness	-.974	.074
	Kurtosis	.330	.148

Features			
		Statistics	Standard error
Mobile banking apps are reasonably priced.	skewness	-.330	.074
	Kurtosis	-.769	.148
Mobile banking apps offer good value for money.	skewness	-.289	.074
	Kurtosis	-.708	.148
At the current price, mobile banking apps offer good value.	skewness	-.517	.074
	Kurtosis	-.319	.148
I have no concerns about the cost of Internet when using mobile banking apps.	skewness	-.754	.074
	Kurtosis	-.240	.148
The cost of using mobile banking apps is not burdensome for me.	skewness	-.562	.074
	skewness	-.467	.148
Using mobile banking apps has become/can become a habit for me.	skewness	-1.080	.074
	Kurtosis	.733	.148
Using mobile banking apps has become/can become an addiction for me.	skewness	.004	.074
	Kurtosis	-1.102	.148
I must use mobile banking apps.	skewness	-.790	.074
	Kurtosis	-.125	.148
Using mobile banking apps has become/can become natural for me.	skewness	-1.168	.074
	Kurtosis	1.592	.148
I intend to use mobile banking apps in the future.	skewness	-1.307	.074
	Kurtosis	2.281	.148
I will try to use mobile banking apps frequently in my everyday life.	skewness	-1.099	.074
	Kurtosis	1.196	.148
I plan to use mobile banking apps frequently.	skewness	-.954	.074
	Kurtosis	.757	.148
I will recommend mobile banking apps to other people.	skewness	-1.061	.074
	Kurtosis	1.106	.148

Homoscedasticity: Levene test

Variance homogeneity test					
		Levene's test	ddl1	ddl2	Sig.
Personalization	Based on mean	.507	1	1056	.477
	Based on median	.916	1	1056	.339
Performance expectancy	Based on mean	.615	1	1056	.433
	Based on median	.151	1	1056	.698
Effort expectancy	Based on mean	2.502	1	1056	.114
	Based on median	1.057	1	1056	.304
Facilitating conditions	Based on mean	.374	1	1056	.541
	Based on median	.160	1	1056	.689
Hedonic motivation	Based on mean	1.778	1	1056	.183
	Based on median	1.823	1	1056	.177
Social influence	Based on mean	1.461	1	1056	.227
	Based on median	1.344	1	1056	.247
Perceived confidentiality	Based on mean	4.762	1	1056	.029
	Based on median	4.777	1	1056	.029
Price value	Based on mean	.915	1	1056	.339
	Based on median	1.100	1	1056	.294
Habit	Based on mean	1.047	1	1056	.306
	Based on median	.499	1	1056	.480
Intention to use	Based on mean	.003	1	1056	.958
	Based on median	.876	1	1056	.350

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