Performance impact of mobile banking: using the task-technology fit (TTF) approach

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Abstract

Purpose – This paper investigates the determinants of m-banking for individual performance and to discover if there are any age or gender differences.

Design/methodology/approach – The research model is based on the TTF theory, which integrates elements of task and technology characteristics, technology use, and individual performance, while combining the age and gender subsamples. The empirical approach was based on an online survey questionnaire of 256 individuals. Partial least squares based on the multi-group analysis were used to analyze the proposed framework construct relations,

Findings – The results reveal that TTF and use are important precedents of individual performance. We find statistically significant differences in path use to performance impact for the age subsample, and not statistically significant differences for the gender subsample.

Originality/value – The paper highlights the TTF model to understand the determinants that influence the individual performance of m-banking, and to discover if there are any age or gender differences. While most of earlier research focuses on m-banking adoption, our approach diverges from the majority by examining the individual performance, which was not considered before in previous studies.

Keywords: Mobile banking (m-banking), Task-technology fit (TTF), Individual performance, Gender, Age.
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1. Introduction

Mobile banking (m-banking) is an expanding application of mobile commerce, which has claimed the attention and interest of e-commerce researchers (Kourouthanassis and Giaglis, 2012). These applications offered by the financial industry are applicable to mobile devices such as personal digital assistants (PDA), mobile telephones, smartphones, and tablet computers (Yun et al., 2012). Mobility offers banks the opportunity to tailor products and services to their customer exact needs - or exact location, in order to retain them (Floh and Treiblmaier, 2006). M-banking enables users to access account balances, pay bills, transfer funds, and perform other financial services. Many banks have chosen to focus their investment on the development of platforms for channels that eliminate the need to visit a branch and offer convenient access to bank services and products. This also allows banks additional benefits such as cost savings (Hoehle and Huff, 2012).

In the last decade there has been an increase in the number of mobile devices. Over 6.8 billion user subscriptions are recorded for the second quarter of 2013, and there are almost as many mobile-cellular subscriptions as people in the world (International Telecommunication Union, 2013). Despite the exponential growth of the number of mobile devices, the use of m-banking has remained limited. For Zwass (2003), there are challenges associated with m-banking services in terms of the customer’s experience with the user interface of the corresponding device, such as small screen, uncooperative keypad, communication bandwidth and other constraints. Some studies have established the importance of the appearance of display, graphics and colours and how these factors affect customer satisfaction (e.g. Jarvenpaa and Todd, 1996). However, not only technical challenges but also social influence, age (Morris and Venkatesh, 2000), and gender (Riquelme and Rios, 2010) differences may affect (initial) trust in m-banking and its adoption (Kim et al., 2009). M-banking enables users to conduct financial services in a more efficient and effective way and thus offers many advantages for individuals such as time savings and ease of perform banking transactions.
While most of earlier research focuses on m-banking adoption’s factors (e.g. Luo et al., 2010, Lin, 2011, Kim et al., 2009), our approach diverges from the majority by examining the individual performance. We apply the task-technology fit (TTF) theory, defined as “the degree to which a technology assists an individual in performing his or her portfolio of tasks” (Goodhue and Thompson, 1995). This theory suggest that individual performance is a consequence of the use and the better fit between the technology and the task it supports (Goodhue and Thompson, 1995), which is a fundamental issue in the m-banking context.

We bring two contributions to the literature related to individual performance in the m-banking phenomena. Firstly, to the best of our knowledge, there is no earlier research on m-banking individual performance. By providing anytime and anywhere interaction with the user’s accounts (Liang and Wei, 2004), m-banking differs in many ways from traditional storefront banking or even internet banking. At the same time, TTF theory posits that individual performance is a function of superior fit of both task and technology characteristics and use, which is commonsense but too imprecise to provide generalization to m-banking. Our work combines these elements in a novel way. Secondly, earlier research demonstrates that age and gender play an important role in the patterns of information technology (IT) adoption and use, but rarely considers these separately in the individual performance context. Consequently, this study investigates individual performance on the young and old subsamples and also male and female subsamples. We bring new insights regarding the determinant factors that influence individual performance of m-banking. Moreover, we help researchers and practitioners of the financial industry to define comprehensive strategic demographic groups.

The structure of the paper is as follows. We next examine earlier approaches in the literature for m-banking and explain TTF theory and its model. We then present the research design, methodology and results. Finally, the results are discussed, including the implications for m-banking adoption theory and practice, and further possible research directions are suggested.

2. Literature Review

2.1 Mobile Banking

Mobile devices combine the traditional functionality of a telephone and the data-processing features of an information system (IS) (Zwass, 2003). The proliferation of
new IT within the financial industry has influenced the way banks service consumers. In
particular, self-service technologies have enabled banks to follow an electronically
multi-channel strategy. Today automated teller machine (ATM), telephone banking,
Internet banking, and m-banking are all efficient ways of selling products and services
to banking customers (Hoehle and Huff, 2012). These electronic banking channels
largely reduce the consumer’s need to visit a branch and offer convenient access to bank
accounts. Banks also benefit from self-service technologies as they can cut costs
incurred in the traditional branch network (Peevers et al., 2008), and establish a stronger
relationship with their customers.

M-banking is defined as the subset of applications of mobile e-commerce
offered by the financial industry (Kim et al., 2009). In fact, mobile commerce is also
known as a subset of e-commerce that uses radio-based wireless devices to conduct
business transactions over the web (Keng and Zixing, 2003). In recent decades the
banking industry has been facing several challenges and transformations. The evolution
from a focus on local-centric (branches and ATM) to place-centric (internet banking)
and then to equipment-centric (accessible anywhere, 24 hours per day and 7 days a
week) has brought time savings and avoided customer queues. Equipment-centric vision
brings the customer closer to the bank since (s)he only needs only a mobile device to
carry out a financial service. In local-centric banking customers need to go to a physical
place (a branch or an ATM), which may not be close to them. In place-centric banking,
customers can conveniently carry out the vast majority of banking transactions remotely
provided that they have a computer with internet access. Consumers favour specific
banking channels for specific product categories. Hoehle and Huff (2012) noted that
branches are used for complex products categories (for example, mortgages and loans)
while more simple operations such as bill payments or other domestic transactions
could be done through self-service technology. Many banks charge a fee for domestic
transactions made at branches to encourage customers to adopt self-service technology.

The composite services and products offered on the mobile platform range from
simple accounting balance inquiries to payment of services, funds transfers, and more
complex products, such as stock exchange transactions (Suoranta and Mattila, 2004).
Complex transactions are quite difficult to perform on mobile devices due to their
hardware limitations, such as small screens and clumsy input mechanisms.
Consequently, consumers tend to use mobile devices for simple banking transactions, in
situations where they need instant access to their accounts and other banking channels
are not in reach (for example, checking their account balance before purchasing goods at a point of sale) (Hoehle and Huff, 2012). Based on the Forrester survey Q4 2011 made in Europe, 90% of transactions made by m-banking users are checking balance and 62% of transactions are checking recent transactions, and only 36% of transactions use this channel to transfer money between accounts (Forrester, 2011). These figures suggest that consumers tend to use mobile devices for simple transactions in situations where they need instant access to their accounts.

2.2 Task-technology fit (TTF) model

Researchers have advanced several models for technology acceptance, including the technology acceptance model (TAM) (Davis, 1989, Venkatesh and Davis, 2000), the innovation diffusion theory (IDT) (Rogers, 1995), and more recently the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003, Venkatesh et al., 2012). These theories have examined the factors impacting user acceptance of new technology from different angles and bolstered technology acceptance research considerably. Goodhue and Thompson (1995) proposed the TTF model, which extends the TAM by considering how task affects the use of technology.

In TTF theory a suitable task-technology characteristic will encourage use of m-banking, while lower TTF will reduce use intention (Lee et al., 2007a). The perception of fit amongst the task, the technology, and the users of a particular IT will positively impact the technology’s use (Goodhue, 1998, Goodhue and Thompson, 1995). When the mobile users feel that the technology is capable of supporting the task at hand, they show good performance. When discussing or defining the ability of the mobile device to support the task, we mean the functionalities of the technology that enable a smooth execution of the task, reduce the time of performing the task, and/or make the task easily accomplished.

Today we can speak of the “third era” of mobile commerce (m-commerce), which began in 2007 and continues. It is also referred to as the mobile applications (m-apps) period, the period when applications and software were designed to run on smartphones, tablet computers, and other mobile devices (Kourouthanassis and Giaglis, 2012). The financial industry is using m-apps platforms to offer more and more functionalities, which include account balances and recent transactions overview, funds transfer between a customer’s own accounts, and paying bills. Many digital banking teams are developing a range of additional functionalities based on the advancement of
phone hardware features such as position system (GPS) locators to help customers easily find the location of branches and ATMs, or make bill payments more easily by using the camera on a smartphone to scan details from a bill, through quick response (QR) codes. The channel strategy needs to continuously develop new solutions and tools to attract mobile users and stay as close as possible to their needs. For Hoehle and Huff (2012) the suitability of a particular banking channel depends on the particular banking task and instant handiness.

Consistent with this study’s goal of understanding the fit between task characteristics and technology characteristics is the belief that fit is a core construct. According to the TTF model, systems will help to improve individual performance when technology is a “good fit with the tasks it supports” (Goodhue and Thompson, 1995). In this study the concept developed is the effectiveness with which an m-banking solution can be associated with the users’ tasks. Furthermore, it seems reasonable to assume that the better the match between m-banking and banking portfolio of tasks, the greater will be the use of the service. The quality of fit depends on the attributes of the objects. The following list includes some task attributes that affect the various fit dimensions:

- Task complexity – a banking transaction task may vary from simple (for example, balance enquiry) to complex (like a loan) (Tan and Teo, 2000);
- Task frequency - the impact of regular or habitual system use has been noted in IS research (Guinea and Markus, 2009). At the end of the month users often check the account balance to verify their salary deposit;
- Task time criticality – Financial transactions, like stock market operations, are highly sensitive due to the market volatility and to the just-in-time nature.

A strategy based on any of these tasks can improve individual performance and use of technology (Topi et al., 2005), since a greater level of fit will explain the match between the technology and the task characteristics.

2.3 Individual Performance

The individual performance impact in this study is very consistent with the IS success model proposed by DeLone and McLean (1992), which states that both use and user attitudes influence the IS impact on individual performance. IS performance as “perceived outcome from IS use” reveals a very strong relationship between user satisfaction and intention to use (Au et al., 2008). Individual performance impact in an
IS context refers to the actual performance of an individual using an IS. The Goodhue and Thompson (1995) TTF model for studying individual performance effects, indicates a positive relationship between IS use and individual performance, which is also in line with the DeLone and McLean (1992) model. DeLone and McLean (1992) accounted for benefits occurring at both levels of analysis (i.e. individual and organizational), finding that the choice of what kind of impact (individual or organizational impact) to be measured depends on the systems being evaluated and its purposes. Here we are interested in examining the benefits that an individual can realize from using m-banking, mainly the benefit of time savings. Much research has addressed individual performance as shown in Table 1, but to the best of our knowledge, none has studied the individual performance using a particular technology to fill a portfolio of task, such as m-banking.

---Insert Table 1 here---

3. Research Model

The theoretical foundation for the fit dimension in the TTF perspective argues that a better fit between task requirements, technological characteristics, and individual attitudes will lead to better performance (Goodhue and Thompson, 1995). Reported studies recognize that fit affects both user’s attitude and performance (Goodhue and Thompson, 1995, Kositanurit et al., 2011). The research model (Figure 1) outlines our proposal to explain through TTF the matching between the task characteristics and technology characteristics, which explains the m-banking use and performance impact. The TTF model posits that beliefs are based on the extent of the fit between the individual, the task, and the technology (Goodhue and Thompson, 1995). The path from use to performance impact reflects the user perceptions of performance improvement from using m-banking. The essence of this construct means that the degree of using the particular system will help to gain time in performing banking tasks (Venkatesh et al., 2003). In addition, the findings of several earlier studies on age and gender also mention their role in the impact on behavioural intention to adopt an IT (e.g. Venkatesh et al., 2012, Venkatesh et al., 2003, Morris and Venkatesh, 2000). In terms of gender, male and female users have different views of IT-based services as stated in earlier studies finding that men tend to be more task-oriented than women (Venkatesh et al., 2012). In terms of age, younger consumers tend to seek novelty and innovativeness more than do
older consumers (Venkatesh et al., 2012, Morris et al., 2005). Drawing upon these findings and applying the TTF model we purpose to study the age and gender differences.

---Insert Figure 1 here---

The better the fit, the more likely it is that the user will have a positive perception of the service quality. In the context of m-banking user, TTF is the degree to which a technology can assist a user in performing his/her portfolio of services or tasks. A good match of m-banking task and technology characteristics will positively affect the degree of the TTF (Zhou et al., 2010). Specifically, TTF corresponds to the relationship of matching among task characteristics, user abilities and functionalities of technology. Thus, two hypotheses are tested in this study:

**H1:** Task characteristics of mobile banking positively affect the TTF.

**H2:** Technology characteristics of mobile banking positively affect the TTF.

The TTF model posits that m-banking will be used if, and only if, the functions offered to the end-user support (Fit) the tasks of the end-user (Zhou et al., 2010, Goodhue and Thompson, 1995). A high degree of TTF will promote use of m-banking, and the opposite, a lower degree of fit will decrease user intention to adopt m-banking (Lee et al., 2007a). Dishaw and Strong (1999) found that TTF affects users’ behaviour of IT use and also establishes that TTF will affect users’ individual performance. The TTF posits that IT will be used when it affects individual performance by how well technology options "fit" his or her task requirements. IT also impacts on task process, which can let end-users choose technologies based on that (Goodhue, 1995). TTF is directly and positively affected by the user attitude toward the technology and individual performance. When the TTF is perceived as being useful and improves individual performance (Compeau and Higgins, 1995, Davis et al., 1989), it highlights the importance of fostering reliance on the technology. Therefore, perceived TTF is predicted to be a significant precursor of m-banking use and performance impact:

**H3:** TTF positively affects use of mobile banking.

**H4:** TTF positively improves performance impacts.
Based on m-banking use, there are applications, solutions, and products available for mobile devices that make this a valuable platform for users who expect benefits anywhere at anytime connectivity (Zwass, 2003). Igbaria and Tan (1997) proposed that system use has a direct positive effect on individual perceived performance impacts (i.e., perceived impact of computer systems on decision-making quality, performance, productivity, and effectiveness of the job). Based on that, using this self-service banking channel, at anytime and anywhere, could positively affect the individual performance.

**H5:** Use of mobile banking positively affects performance impacts.

Age is one of the most important personal characteristics the category of demographic variables. From a marketing perspective the classification of age groups within a population allows segmentation for marketing purposes (Tesfom and Birch, 2011). Age differences in individual use of new technology play an important role (Morris and Venkatesh, 2000, Morris et al., 2005). In the early stages of using a new technology, younger people show a greater tendency to seek novelty and innovativeness (Liu and Li, 2010). Older end-users face more difficulties in handling new or complex information, based on the decreasing cognitive and memory capabilities, which affect their learning of new technologies (Morris et al., 2005, Kurniawan, 2008), and place more significance on the accessibility of adequate support (Hall and Mansfield, 1975). Based on that, we investigated the role of age in TTF, m-banking use, and individual performance. We posit:

**H6:** The antecedents of TTF, use, and performance on mobile banking will differ between young and old.

The effect of the IT use and the idea that males and females differ when considering their interest in and reaction to technology, has received increasing attention among researchers (Venkatesh and Morris, 2000). This gender difference in attitude about IT has been explained by some as an outcome of the socialization process. There is evidence that males and females with multiple roles experience role overload and role conflict (e.g. Barnett and Marshall, 1991, Wang, 2010). Trauth (2002) claims that there is insufficient theoretical research about gender and IT and also argues the current theories do not fully account for the variation in men’s and women’s relationships to IT. Grounded in the gender theory, Trauth (2013) has identified several IS investigations that suggest different implications for women’s and men’s attitudes and behaviour.
Venkatesh and Morris (2000) found gender differences in individual adoption and continuous use of technology in the workplace. Koenig-Lewis et al. (2010) found empirical evidence that men were significantly more likely to use m-banking than women. Riquelme and Rios (2010) found influence of social norm on intention to adopt m-banking and perceived ease-of-use on the perception of perceived usefulness were stronger amongst women than men. Püschel et al. (2010) showed that m-banking users are predominantly male. For Venkatesh et al. (2012), given the predilection of men to play with technologies, the price value assigned by men to technologies will likely be higher than the value assigned by women to the same technologies. Driven by social role stereotypes, females will use IT-based services more frequently for personal and emotional matters, while males tend to use them for accomplishing tasks (Venkatesh et al., 2003). Because the findings cited above are different, it is necessary to examine the subsample of gender. We posit:

**H7:** The antecedents of TTF, use, and performance on mobile banking will differ with gender.

### 4. Methods

#### 4.1 Measurement

The study was conducted in Portugal and targeted users with a wide range of m-banking experience. All measurement items were adapted for TTF and the constructs were chosen from Zhou et al. (2010) and Goodhue and Thompson (1995), as shown in Table 2. We developed multi-item measures for each construct in the following way. Firstly, a draft of the questionnaire, created in English and reviewed for content validity, was prepared by reviewing the literature. As the questionnaire was administered in Portugal, we translated the English questionnaire into Portuguese and then back into English by a different translator to ensure translation equivalence (Brislin, 1970). The scale of items was measured on a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7). The variable age was measured in years, and gender was coded using a 0 or 1 dummy variable, where 1 represented men. Secondly, we conducted field interviews with six managers of a banking company and modifications were made accordingly. They were asked to assess the terminology, clarity of instructions and response format.
4.2 Data collection

Data were collected using an online survey questionnaire to test the model. A pilot survey was conducted with 30 m-banking users, in order to refine the questions and gain additional comments on the content and structure. The data from the pilot survey were not included in the main survey. Given the constraint of data protection and the right to privacy, a sampling frame could not be obtained from any financial institution. A total of 856 students and ex-students from a university were contacted by e-mail, provided with the hyperlink of the survey, and asked to confirm that they were an m-banking user. A follow-up email was sent in the second stage to those who did not answer in the first stage. In total, 317 accepted the invitation to respond (37% response rate) but only 256 responses were usable for further analysis (173 early respondents and 83 late respondents). To test for nonresponse bias, the sample distribution of the early and late respondent groups was compared using the Kolmogorov-Smirnov (K-S) test (Ryans, 1974). The sample distributions of the two groups did not differ significantly, indicating an absence of nonresponse bias (Ryans, 1974). The common method bias was examined using Harman’s one-factor test (Podsakoff et al., 2003). No significant common method bias was found in the dataset. Detailed descriptive statistics relating to the respondent’s characteristics are shown in Table 3.

5. Results

Validation of the research model was performed by applying a two-step method, starting with the measurement model in order to test the reliability and validity of the instrument and then analysing the structural model (Anderson and Gerbing, 1988). Since the research is an early stage assessment of m-banking and all items in the data were not normally distributed with the Kolmogorov–Smirnov’s test (p<0.01), the partial least squares (PLS) is the most suitable method for this study (Hair et al., 2012, Hair et al., 2011). As a popular rule of thumb for robust PLS estimations one uses a minimum of ten times the largest number of structural paths directed at a particular construct in
the model (Chin, 1998, Gefen and Straub, 2005). The sample in our research met the necessary conditions for applying PLS. The estimation and data manipulation were performed using SmartPLS (Ringle et al., 2005).

5.1 Measurement model

The results of the measurement model are reported in Tables 4 and 5. We assessed construct reliability, indicator reliability, convergent validity, and discriminant validity. Construct reliability is commonly tested with the composite reliability (CR) coefficient. PLS prioritizes indicators according to their individual reliability. CR is employed as an alternative to Cronbach’s alpha (CA) to analyze the reliability of the constructs, since the former takes into consideration indicators that have different loading (Hair et al., 2011, Hair et al., 2012, Henseler et al., 2009, Werts et al., 1974) while CA assumes that all indicators are equally reliable (Raykov, 2007). As shown in Table 4, all the constructs have an adequate CR of 0.7 or greater, which suggests that the constructs are reliable as recommend by Straub (1989).

---Insert Table 4 here---

The indicator reliability was evaluated based on the criteria that the loadings should be 0.70 or greater and that every loading less than 0.4 should be unacceptable and eliminated (Henseler et al., 2009, Churchill Jr, 1979). As shown in Table 4, the loadings are greater than 0.7, with the exception of three items (TASK4, TECH3 and USE4) that are lower than 0.7 but greater than 0.4, which were excluded from the table. All the items are statistically significant at 0.1%. Overall, the instrument presents good indicator reliability.

Average variance extracted (AVE) was used as the criterion to test convergent validity. The AVE should be 0.5 or higher so that latent variable explains more than half of the variance of it indicators (Fornell and Larcker, 1981, Hair et al., 2012, Henseler et al., 2009). All five constructs have an AVE that exceeds the recommended threshold of 0.5 (see Table 4).

Discriminant validity is assessed by using the Fornell-Larcker criterion (Fornell and Larcker, 1981) and the cross-loadings between indicators and constructs. The Fornell-Larcker criterion requires the square root of AVE to be greater than the correlations between the construct. The cross-loadings criterion requires that the loading
of each indicator should be greater than all cross-loadings (Chin, 1998, Götz et al., 2010, Grégoire and Fisher, 2006). Table 5 reveals that the square roots of AVEs (diagonal elements) are higher than the correlation between each pair of constructs (off-diagonal elements) and Table 4 demonstrates that the loadings (in bold) are greater than cross-loadings. Therefore, both measures are fulfilled.

---Insert Table 5 here---

The assessment of construct reliability, indicator reliability, convergent validity, and discriminant validity of the constructs are satisfactory, indicating that the constructs can be used to test the conceptual model. These results were for the full sample, and as we will also use subsamples, we performed the same analysis for younger, older, male, and female subsamples (these tables are available from the authors on request). The results obtained in subsamples also indicate that the constructs can be used to test the conceptual model.

5.2 Structural model

Figure 2 shows the path coefficient for the full-sample model with t-statistics derived from bootstrapping (500 resamples) in parentheses. In the full sample 62.7% of the variation in TTF is explained by task characteristics (β=0.238, p<0.05) and technology characteristics (β=0.638, p<0.01), and consequently H1 and H2 are supported. 39.7% of the variation in mobile banking use is explained by TTF (β=0.630, p<0.01), providing support for H3. Finally, 60.4% of the variation in performance impact is explained by TTF (β=0.508, p<0.01) and mobile banking use (β=0.349, p<0.01), providing support for H4 and H5, respectively.

In order to test the subsamples effects of age (H6) within the model, the sample was divided into “younger” and “older” groups. The “older” group comprised those over 25 years old (67%) and the “younger” group those no more than 25 years old (33%), which is the same age division used by Moores and Chang (2006). For the older subsample, the research model accounting for 66% of the variation in performance impact, and the hypotheses H1, H2, H3, H4, H5 were all statistically significant and consistent with the full model (see Figure 2). For the younger subsample, the path use to performance impact is not significant (H5), which suggests that use of m-banking plays
no role in individual performance. The research model accounted for 54.5% of the variation in performance impact, and the H1, H2, H3, and H4 are statistically significant.

In order to test the subsample effects of gender (H7) in the model the sample was divided into male and female groups. For the female subsample, the research model accounting for 60.3% of the variation in performance impact, and the H1 to H5 were confirmed (see Figure 2), which are very similar to the full sample model. For the male subsample, the model explains 56.7% of the variation in performance impact, and H1 to H5 were again supported. The male subsample is therefore also consistent with the full sample.

---Insert Figure 2 here---

For testing the last two hypotheses (H6 and H7) we calculated a pooled error term t-test to determine statistical significance of the different path coefficients by age and gender. PLS based on the multigroup analysis (MGA) approach is suitable to perform a comparison across a group such as age and gender (Keil et al., 2000). The t-test is then manually calculated to determine the differences in paths between groups. This statistical comparison was carried out as follows:

\[
t = \frac{\beta_{(1)} - \beta_{(2)}}{\sqrt{\frac{(n_{(1)} - 1)^2}{n_{(1)} + n_{(2)} - 2} \cdot se_{\beta_{(1)}}^2 + \frac{(n_{(2)} - 1)^2}{n_{(1)} + n_{(2)} - 2} \cdot se_{\beta_{(2)}}^2} \cdot \sqrt{\frac{1}{n_{(1)}} + \frac{1}{n_{(2)}}}}
\]

Where
\[
t = t\text{-statistics with } (n_{(1)} + n_{(2)} - 2) \text{ degrees of freedom}
\]
\[
n_{(i)} = \text{sample size of the dataset for gender } i \text{ or age } i
\]
\[
se_{\beta_{(i)}} = \text{standard error of path in the structural model of gender } i \text{ or age } i
\]
\[
\beta_{(i)} = \text{path coefficient in the structural model of gender } i \text{ or age } i
\]

Table 6 shows the results for age and gender differences. Based on age, our results suggest there is a difference in the path coefficients between use to performance impact. Because use is a more important factor for the older subsample, H6 is partially supported. For gender, the discrepancy is not statistically significant, which means that
use and performance impact are equally important for both genders (H7 is not supported).

---Insert Table 6 here---

6. Discussion

Over the past decades TTF has been applied to explain an individual performance of technology use, but to the best of our knowledge, it has never been used to explain individual performance in the mobile banking context. We asked users if they felt a benefit of time savings and if they performed financial services faster by using m-banking. The findings of this study indicate differences in the age subsamples and not statistically significant differences for the gender subsamples. The results indicate that m-banking has a significant effect on an individual's performance. The analysis provides support for the model. In particular, the results demonstrate the importance of examining the use of a particular technology in explaining individual performance. They also provide evidence that individual performance is a function of both system use and TTF, which in turn provides evidence on how m-banking adds value to individual performance.

6.1 Theoretical Implications

These findings provide some interesting theoretical insights into the use and individual performance of m-banking, which have not been the focus in earlier research. Our theoretical model contributes to research by highlighting the importance of studying demographic groups, by exploring the effects of age and gender differences, revealing that use and individual performance have different results for each subsample. Considering the use of new technology, women and men have different points of views. Venkatesh et al. (2012) argues that women will use technology more frequently for personal and emotional matters, while men tend to use it more for task accomplish. Our results reveal that task characteristics has no statistically significant difference between the male and the female subsample, which contradicts the literature. Technology characteristics and use are equally important for male and for female groups and therefore impact on individual performance. Goodhue and Thompson (1995) demonstrate empirically that performance impact is a function of both use and TTF, not
use or TTF alone. However, for the age subsample, m-banking use is more likely to lead to performance impact for the older than for the younger group. This means that for m-banking the use to performance impact is not statistically significant for the younger subsample, which differs from Goodhue and Thompson (1995) findings. For the younger subsample the tendency is for an increasing importance of the novelty of new technology (Venkatesh et al., 2012), giving more importance to TTF, assuming the use has no impact on performance. Consistently, the findings also reveal that the direct effect of TTF on the older user to performance impact is weaker than on the younger.

6.2 Managerial Implications

This study provides management implications for financial enterprises to attract customers to adopt and use m-banking. M-banking users are amongst those most likely to exhibit a motivation to keep up with trends and new ways of interacting with banking channels to gain time and perform financial transactions more quickly. Therefore, it is effective to undertake strategies to attract m-banking users who would like to find new means of interaction instead of using other traditional banking channels (Hoehle and Huff, 2012). Although Zwass (2003) identified several constraints of mobile device, such as a small screen, uncooperative keypad, and communication bandwidth, there are strengths that could attract potential users and fit their needs in this channel. In line with findings of the age subsample, the challenge here is meeting customers’ needs and making it easy to use, even encouraging the use the service by promoting the benefits instead of the service. Also to be considered is the fact that management information reports might help the managers to understand what the customers are doing, but not what they might want to do. A survey or other customer feedback might help them to realize what they want to do or even capture new ideas and suggestions.

We find that the matching between those TTF and use explains individual performance. TTF plays an important function in the capability to use and to lead individual performance while striving to discover new ways or channels of performing financial transactions. Potential users can also win over addressing their concerns about performance impact. Although organizations in general continually seek new solutions to assess, understand, and strategize the running of a successful business, this study suggests some strategy insight through system development and marketing services to promote adequate services to meet end-users’ needs. For the younger group, the use plays no role on performance impact while the TTF plays a significant part, which is
important to promote the technology and task through this group. Despite this, our findings reveal no significant differences based on the gender subsamples. The analyses based on both age and gender show significant importance in the development and marketing strategy to attract customers to this channel. A possible reason is that the young group tends to have a greater degree of mobile self-efficacy coupled with less effort of use. What really matters in explaining performance impact in this group is TTF. For the older group the use is more important than in the younger group to explain performance impact, because the older tend to face more difficulty in processing new and complex information and learn more through repeated use of the new technology (Venkatesh et al., 2012).

6.3 Limitations and future research

This study has several limitations that should be taken into consideration when generalizing the results of it. Firstly, the data were gathered in the European Union (EU). To enhance generalization future research should collect cross-country data that expose national cultural values as moderators to more thoroughly explain both use and performance impacts (Lee et al., 2007b). Secondly, despite earlier research suggesting that students represent typical consumers (Remus, 1986), they may not fully represent the population of all potential m-banking users, which might be a threat. To enhance generalization and external validity, the sample for future research could include non-students. Thirdly, the model is time-sectional, it measures perceptions at a single point in time, but perceptions change over time as individuals gain experience (Mathieson et al., 2001, Venkatesh and Davis, 1996). This change has implications for researchers and practitioners interested in predicting use and performance over time, which need to be considered. Future research may include longitudinal data, and examine the research model in different time periods, thereby providing greater insight into the use and individual performance of m-banking.

7. Conclusion

The huge explosion of mobile device use and the initiatives in the electronic banking sector have drawn the attention of researchers toward m-banking adoption. However, the influence of m-banking use and individual performance considering the TTF impact has received limited attention. Our research sought to understand the determinants of TTF, m-banking use, and individual performance, while combining the age and gender
subsamples. In the full sample, TTF explains m-banking use, and TTF and use explain performance impact. In the subsample we find statistically significant differences in younger and older subsamples on path use and TTF to performance impact. Therefore, use is a more important factor for the older subsample and TTF is more important for the younger subsample. Overall, our study confirms the importance of TTF’s impact on use and individual performance of m-banking.

References


<table>
<thead>
<tr>
<th>Authors and year</th>
<th>Research Context</th>
<th>IS applications</th>
<th>Data</th>
<th>Methods</th>
<th>Results / Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Thompson et al., 1991)</td>
<td>Canada</td>
<td>Fit between job and PC capabilities</td>
<td>212 workers</td>
<td>PLS</td>
<td>Model explains 24% of the variation in fit between job and PC Capabilities</td>
</tr>
<tr>
<td>(Igbaria and Tan, 1997)</td>
<td>Singapore</td>
<td>Information technology</td>
<td>371 employees</td>
<td>PLS</td>
<td>Model explains 28% of the variation in individual impact. User satisfaction is an important factor affecting system use and has the strongest direct effect on individual impact.</td>
</tr>
<tr>
<td>(Kositanurit et al., 2011)</td>
<td>US, Thailand</td>
<td>Business processes and new information technologies</td>
<td>349 US employees, 304 Thailand employees</td>
<td>Decision Tree</td>
<td>System quality and Information quality have positive impact on utilization and performance.</td>
</tr>
<tr>
<td>(Hou, 2012)</td>
<td>Taiwan</td>
<td>Business intelligence systems</td>
<td>380 end users</td>
<td>CFA</td>
<td>High level of end users’ satisfaction increases system use and improves individual performance. Model explains 37% of the variation in individual performance.</td>
</tr>
<tr>
<td>(Lin, 2012)</td>
<td>Taiwan</td>
<td>Virtual learning system</td>
<td>165 students</td>
<td>PLS</td>
<td>Model explains 57% of the variations in perceived impact on learning.</td>
</tr>
<tr>
<td>(Huang et al., 2012)</td>
<td>Taiwan</td>
<td>Data mining</td>
<td>206 users</td>
<td>CFA</td>
<td>System enhances job performance and is easy to use. Model explains 58% of the variations in behavioural intentions to use data mining tools.</td>
</tr>
</tbody>
</table>

Note: PLS, partial least squares; CFA, confirmatory factor analysis
<table>
<thead>
<tr>
<th>Constructs</th>
<th>Items</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task</td>
<td>TASK1 - I need to manage my accounts anytime anywhere</td>
<td>(Zhou et al., 2010)</td>
</tr>
<tr>
<td>characteristics</td>
<td>TASK2 - I need to do transfer anytime anywhere</td>
<td></td>
</tr>
<tr>
<td>(TASK)</td>
<td>TASK3 - I need to have a real time control in my accounts</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TASK4 - The financial instructions I give can’t wait</td>
<td></td>
</tr>
<tr>
<td>Technology</td>
<td>TECH1 - Mobile banking provides ubiquitous services</td>
<td>(Zhou et al., 2010)</td>
</tr>
<tr>
<td>characteristics</td>
<td>TECH2 - Mobile banking provides real time services</td>
<td></td>
</tr>
<tr>
<td>(TECH)</td>
<td>TECH3 - Mobile banking provides a quick service</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TECH4 - Mobile banking provides secure services</td>
<td></td>
</tr>
<tr>
<td>Task</td>
<td>TTF1 - Mobile banking payment services are appropriate</td>
<td>(Zhou et al., 2010)</td>
</tr>
<tr>
<td>technology fit</td>
<td>TTF2 - Mobile banking account management services are appropriate</td>
<td></td>
</tr>
<tr>
<td>(TTF)</td>
<td>TTF3 - Real time mobile banking services are appropriate</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TTF4 - In general, mobile banking services are enough</td>
<td></td>
</tr>
<tr>
<td>USE</td>
<td>USE1 - I use mobile banking</td>
<td>(Zhou et al., 2010)</td>
</tr>
<tr>
<td></td>
<td>USE2 - I use mobile banking to manage my accounts</td>
<td>2010, Goodhue and</td>
</tr>
<tr>
<td></td>
<td>USE3 - I use mobile banking to make transfers</td>
<td>Thompson, 1995</td>
</tr>
<tr>
<td></td>
<td>USE4 - I subscribe to financial products that are exclusive to mobile</td>
<td></td>
</tr>
<tr>
<td></td>
<td>banking</td>
<td></td>
</tr>
<tr>
<td>Performance</td>
<td>PI1 - I gain time using mobile banking</td>
<td>(Goodhue and Thompson, 1995, Zhou et al., 2010)</td>
</tr>
<tr>
<td>impacts (PI)</td>
<td>PI2 - Mobile banking allows me to make my payments quicker</td>
<td></td>
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<tr>
<td>Distribution (n=256)</td>
<td>Obs.</td>
<td>(%)</td>
</tr>
<tr>
<td>----------------------</td>
<td>------</td>
<td>-----</td>
</tr>
<tr>
<td>Gender</td>
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<tr>
<td>Male</td>
<td>121</td>
<td>47%</td>
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<tr>
<td>Female</td>
<td>135</td>
<td>53%</td>
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<tr>
<td>Age</td>
<td></td>
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<tr>
<td>18-20</td>
<td>40</td>
<td>16%</td>
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<tr>
<td>21-25</td>
<td>45</td>
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<td>26-30</td>
<td>43</td>
<td>17%</td>
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<tr>
<td>31-35</td>
<td>41</td>
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<tr>
<td>36-40</td>
<td>29</td>
<td>11%</td>
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<tr>
<td>&gt; 40</td>
<td>58</td>
<td>23%</td>
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Table 4 - PLS Loadings and Cross-Loadings

<table>
<thead>
<tr>
<th>Construct</th>
<th>TASK</th>
<th>TECH</th>
<th>TTF</th>
<th>USE</th>
<th>PI</th>
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<tbody>
<tr>
<td>Task characteristics (TASK)</td>
<td>TASK1</td>
<td>0.93</td>
<td>0.49</td>
<td>0.52</td>
<td>0.55</td>
</tr>
<tr>
<td>(CR=0.95; CA=0.91; AVE=0.85)</td>
<td>TASK2</td>
<td>0.94</td>
<td>0.47</td>
<td>0.54</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>TASK3</td>
<td>0.90</td>
<td>0.53</td>
<td>0.54</td>
<td>0.48</td>
</tr>
<tr>
<td>Technology characteristics (TECH)</td>
<td>TECH1</td>
<td>0.51</td>
<td>0.89</td>
<td>0.68</td>
<td>0.51</td>
</tr>
<tr>
<td>(CR=0.92; CA=0.87; AVE=0.80)</td>
<td>TECH2</td>
<td>0.52</td>
<td>0.92</td>
<td>0.70</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>TECH4</td>
<td>0.42</td>
<td>0.88</td>
<td>0.68</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>TTF1</td>
<td>0.58</td>
<td>0.70</td>
<td>0.93</td>
<td>0.62</td>
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<td>Task technology fit (TTF)</td>
<td>TTF2</td>
<td>0.55</td>
<td>0.71</td>
<td>0.94</td>
<td>0.63</td>
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<td>(CR=0.96; CA=0.95; AVE=0.86)</td>
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<td>0.55</td>
<td>0.75</td>
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<td>0.56</td>
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<td>TTF4</td>
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<td>0.69</td>
<td>0.91</td>
<td>0.53</td>
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<tr>
<td>USE</td>
<td>USE1</td>
<td>0.60</td>
<td>0.56</td>
<td>0.64</td>
<td>0.94</td>
</tr>
<tr>
<td>(CR=0.96; CA=0.93; AVE=0.88)</td>
<td>USE2</td>
<td>0.54</td>
<td>0.47</td>
<td>0.57</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>USE3</td>
<td>0.51</td>
<td>0.42</td>
<td>0.56</td>
<td>0.93</td>
</tr>
<tr>
<td>Performance impacts (PI)</td>
<td>PI1</td>
<td>0.57</td>
<td>0.71</td>
<td>0.69</td>
<td>0.62</td>
</tr>
<tr>
<td>(CR=0.95; CA=0.90; AVE=0.91)</td>
<td>PI2</td>
<td>0.51</td>
<td>0.64</td>
<td>0.69</td>
<td>0.65</td>
</tr>
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</table>
Table 5 - Descriptive statistics, correlations, and root square of AVEs

<table>
<thead>
<tr>
<th>Construct</th>
<th>Mean</th>
<th>SD</th>
<th>TASK</th>
<th>TECH</th>
<th>TTF</th>
<th>USE</th>
<th>PI</th>
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</thead>
<tbody>
<tr>
<td>Task characteristics (TASK)</td>
<td>5.04</td>
<td>1.66</td>
<td>0.92</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Technology characteristics (TECH)</td>
<td>5.46</td>
<td>1.32</td>
<td>0.54</td>
<td>0.89</td>
<td></td>
<td></td>
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<tr>
<td>Task technology fit (TTF)</td>
<td>5.06</td>
<td>1.34</td>
<td>0.58</td>
<td>0.77</td>
<td>0.93</td>
<td></td>
<td></td>
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<tr>
<td>USE</td>
<td>4.57</td>
<td>2.04</td>
<td>0.59</td>
<td>0.52</td>
<td>0.63</td>
<td>0.94</td>
<td></td>
</tr>
<tr>
<td>Performance impacts (PI)</td>
<td>5.47</td>
<td>1.48</td>
<td>0.56</td>
<td>0.71</td>
<td>0.73</td>
<td>0.67</td>
<td>0.95</td>
</tr>
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</table>

Note: Diagonal elements are the square root of the AVE.
Figure 1 - Research model
Note: t-test are shown in parenthesis; *p<0.10; **p<0.05; ***p<0.01;

**Figure 2 - Path Models by Group**