UNDERSTANDING MOBILE BANKING USAGE BEHAVIOR: A MULTI-MODEL PERSPECTIVE

BY

MOUSA AHMED ALBASHRAWI
B.S. KING FAHD UNIVERSITY OF PETROLEUM AND MINERALS (2009)
M.S. UNIVERSITY OF COLORADO DENVER (2012)

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Signature of Author: **---** **Date:** **----------------------**

Signature of Dissertation Chair: **---**
Name Typed: **--------------** Prof. Luvai Motiwalla **--**

Signatures of Other Dissertation Committee Members

Committee Member Signature: **---**
Name Typed: **----------------------** Prof. Kimberly Merriman **--**

Committee Member Signature: **---**
Name Typed: ---------------------- Prof. Xiaobai Li **--**

Committee Member Signature: **---**
Name Typed: ---------------------------Prof. Asil Oztekin **--**

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MOUSA A. ALBASHRAWI

ABSTRACT OF A DISSERTATION SUBMITTED TO THE FACULTY OF THE DEPARTMENT OF OPERATIONS AND INFORMATION SYSTEMS

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Dissertation Supervisor: Luvai Motiwalla, Ph.D.
Professor & Chair, Department of Operations and Information Systems

ABSTRACT

Understanding mobile banking (MB) usage behavior is of a great value and significant to both researchers and practitioners. This dissertation reveals several theoretical and practical gaps in MB research detailed below and accordingly develop three papers to address those gaps with different IS theories and acceptance models. The first paper attempts to look at the impact of self-reported and computer-recorded experience on MB behavioral intention with a multi-analytical approach. The second paper goes beyond intention stage and examines system actual use subjectively and objectively using a novel integrative framework. The third paper goes further to investigate MB continuance intention through privacy-personalization paradox. The three papers reflect a continuum perspective starting with the first stage of usage behavior; behavioral intention, then looking at the second stage; actual use, and ending up with the third stage; continuance intention. Structural equation modeling-partial least square (SEM-PLS) has been employed to test the hypothesized relationships in the three adapted research models; TAM, UTAUT, and IS Success. Detailed results with deep analysis are presented in each paper. Theoretical and practical contributions are communicated across the three papers and synthesized in inclusive conclusion. Overall, we integrate under-investigated and relevant-context factors into well-established theories to examine their impact on user behavior in a MB context.

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Chapter 1. Introduction

This chapter gives an overview about mobile banking, highlights the study motivation, reviews succinctly acceptance models used in this area, identifies the problem (research gaps), raises the research questions, communicates, in brief, theoretical and practical contributions, and provides a road map to the rest of the dissertation.

1.1. Overview of Mobile Banking

Information technology (IT) has changed the ways in which we live, work, communicate, and transact. In general, IT innovations intersect with most industries in the market and thus brings opportunities on one side but imposes challenges on the other side. For example, the banking industry has witnessed several changes due to the advent of IT, which enforces financial institutions to cope with such changes by reshaping how their services are provided in order to survive and stay competitive in this market. It is obvious that some IT innovations, in particular, the internet and mobile devices show a higher impact on the banking industry. The internet has crossed many obstacles and enabled online banking while both have enabled mobile banking (MB). Hence, MB, as it appears, is an extension of online banking but the convenience it brings makes it much popular while security it imposes makes it more vulnerable.

MB enables access to various banking services which includes but not limited to view balance, transfer money, pay bills, and deposit checks. Compared to the traditional banking channels, MB has overcome the time and location barrier where it can be accessed from anywhere and anytime using a web-enabled mobile device. MB has become the mainstream service in the banking industry after a massive penetration rate in the recent years. According to the report issued by Federal Reserve district banks (Crowe et al., 2015), MB user adoption witnessed a significant jump from 5% to 20% in 2014. Another report highlights that MB outpaced branch banking in 2015 and forecasts that MB will be used by 81% of US adults in 2020 (Ozawa, 2015). It is important to note that such significant increase in the utilization curve of MB has been attributed to the substantial growth of smartphone industry – about 184 million people owned a smartphone in 2015 across the U.S. (Lella, 2015). Smartphones appear to be the current vehicle pushing for further MB as the Figure 1.1 shows (Meola, 2016).

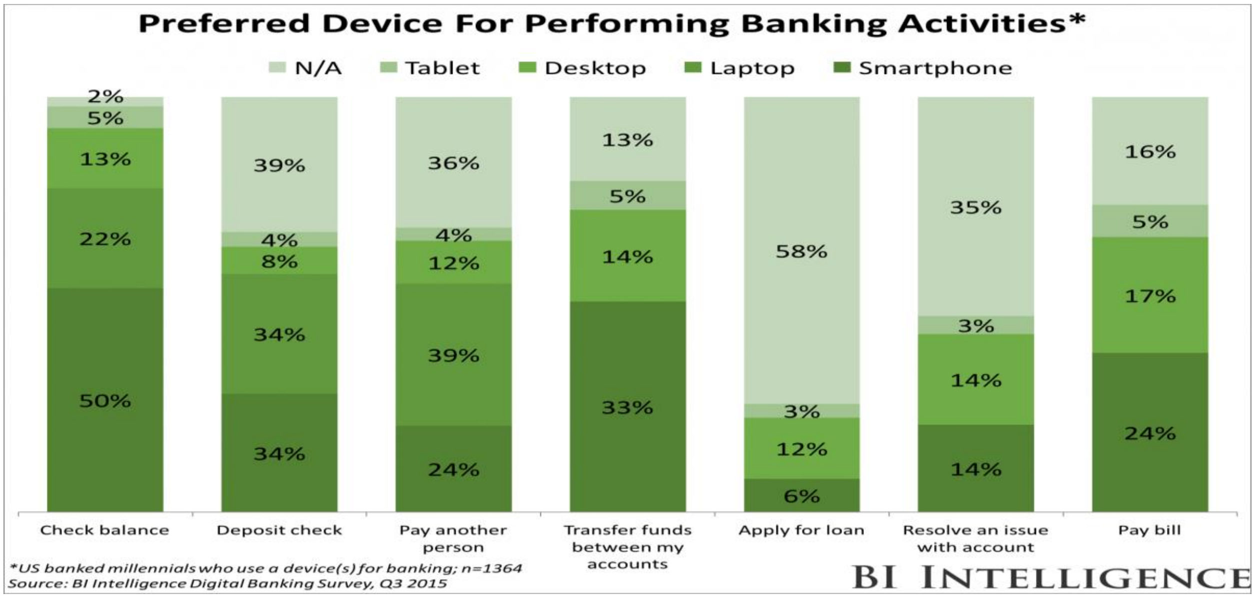

Figure 1.1. Customer Preferences to Conduct Banking Activities

However, MB has some drawbacks, like security and lack of promotion, which may undermine its adoption, actual usage, and continuance intention (Weisbaum, 2015). Thus, it is essential to allow a wider examination of relevant factors towards MB usage behavior among actual bank customers.

1.2. Motivation of the Study

Convenience is being considered the main advantage of MB that led to it's a wide adoption. But adoption or behavioral intention is just the starting stage in the adapted conceptual framework (Figure 1.2) used to explain individual usage behavior towards information technology (Venkatesh et al., 2003) as depicted in the below figure. MB adoption has been a centric topic for IS behavioral scholars but has not been given sufficient attention by IS science designers, which makes it an opportunistic area to investigate.

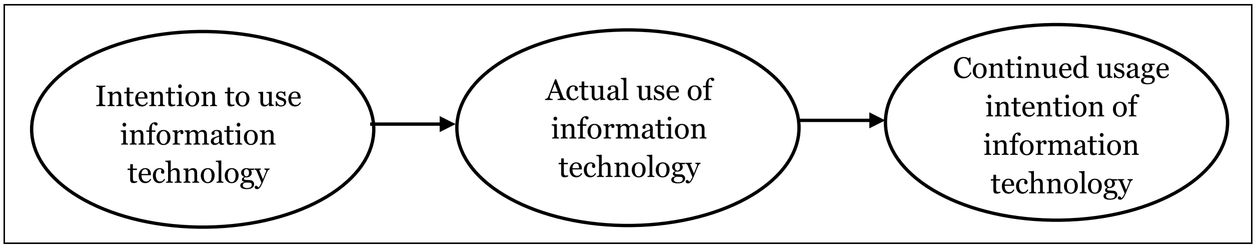

Figure 1.2. Conceptual Framework to Explain Usage Behavior of Information Technology

What follows behavioral intention, namely system actual use and continuance intention, is more important and has a greater value (Petter et al., 2013), especially in MB as an emerging information technology. System actual use is a good indicator of users' satisfaction (DeLone and McLean, 2003) while continuance intention is a good indicator of users' loyalty (Hew et al., 2016). Despite their importance, current understanding of both MB actual use and continuance intention is sparse as well as there has been a lack in investigating critical IS aspects (i.e., privacy and personalization) and their impact on the use of this technology. This has motivated us to not only examine MB behavioral intention under a design science umbrella but also direct our focus to MB system usage and continued usage intention.

1.3. Theoretical Background at a Glance

Prior research has drawn on various IS acceptance models to examine individual's MB usage behavior. For MB behavioral intention, technology acceptance model (TAM) has dominated MB adoption research (Chung and Kwon, 2009; Gu et al., 2009; Koenig-Lewis et al., 2010; Teo et al., 2012; Hanafizadeh et al., 2014). But there are other adoption models, which have been also employed in this area, for example, innovation diffusion theory (IDT) (Kim et al., 2009), task-technology fit model (TTF) (Zhou et al., 2010), and theory of planned behavior (TPB) (Aboelmaged and Gebba, 2013). For MB actual use, the unified theory of acceptance and use of technology (UTAUT) has been the most applied model to study user actual involvement to MB system (Yu, 2012; Baptista and Oliveira, 2015). For MB continuance intention, both expectation-confirmation model (ECM) and TAM have been equally used to explore the extent of users' continued usage intention (Yuan, 2014; Zhou and Liu, 2014; Mohammadi, 2015). As noticed, IS literature has paid more attention to MB behavioral intention than to actual use and continuance intention. However, in every stage of usage behavior (behavioral intention, actual use, and continuance intention), there have been some research gaps found and addressed using our multi-model perspective.

1.4. Problem Identification

Although IS scholars have devoted a plenty of research to explore MB behavioral intention - the first stage, no one has examined the role of self-reported and computer-recorded experience with a multi-analytical approach (a combination of traditional regression and neural networks) to reveal the highest-impact factors on users' behavioral intention towards MB and to disclose the hidden nonlinearity structures among the hypothesized relationships. On the other hand, the IS scholars have seldom investigated MB actual use and continued usage intention – the second and third stage. Driven by the importance, but overlooked, of those two stages on leveraging the level of satisfaction and loyalty among customers, we have diverted our attention to identify the critical factors affecting both MB actual use and continued usage intention through integrative perspectives. Furthermore, since relying only on self-reported data can lead to misleading conclusions (de Reuver and Bouwman, 2015) because of validity and bias threat (Collopy, 1996), we come to understand the significance of objective system measurement and accordingly employ it in our research by utilizing computer-recorded data. While to increase the theoretical boundaries and to augment the prediction power of the acceptance models in MB area, we have developed an enhanced, novel integrative framework for MB system usage.

1.5. Research Questions

Given the research gaps found in MB literature, we have raised three questions to address those gaps. The first research question tackles the first stage - behavioral intention - and articulated as "how different is the subjective experience from objective experience, what factors matter most to customers, and to what extent does linearity exist?". The second question tackles the second stage - system actual use – and articulated as "what is the difference between subjective and objective MB system usage through the lens of a new integrative framework?". The third question tackles the third stage - continuance intention - and articulated as "does privacy and personalization affect continued usage intention of mobile banking?".

1.6. Theoretical and Practical Contributions

This study brings a wide scope to investigate MB usage behavior and accordingly could contribute more to theory and practice. In brief, this study can extend the knowledge of this promising research area by 1) promoting a deeper understanding of MB acceptance via a triple analysis of SEM-neural network-universal structure modeling; 2) validating subjective and objective MB usage measurement through an integrative approach; 3) complementing TAM by accounting for related cognitive factors, privacy and personalization; and 4) helping industry to realize the most needed areas in MB that require further focus and improvement for retaining their current customers and attracting the interest of the potential customers.

1.7. Structure of the Study

The rest of this dissertation is composed of five chapters. The second chapter reviews the most and recent prior research conducted in MB adoption, actual use, and continuance intention. The third chapter presents the first research paper and reveals new knowledge and insights in MB adoption. The fourth chapter presents the second paper and provides a novel holistic framework for MB system usage. The fifth chapter presents the third paper and unveils the moderating effect of privacy and personalization in MB continuance intention. The sixth chapter concludes with limitations and clues for future research and synthesizes the overall theoretical and practical contributions of this research.

Chapter 2. Common Literature Review

This chapter provides a comprehensive review of literature in the three relevant areas: MB adoption (behavioral intention), actual use, and continuance intention to show the current status of research in these areas.

2.1. MB Behavioral Intention

Most research in MB area has focused on the initial adoption or behavioral intention of this technology. The below table lists the various works that have examined MB adoption so far. It is noticeable that TAM has been the most frequent used theoretical base model to investigate relevant factors affecting MB acceptance among different types of potential users, especially among university students and across countries. Also, it is noteworthy that very few studies have been conducted in a western country like USA.

Table 2.1. Prior Research on MB Adoption

Study	Theoretical Lens	Main Contribution	Sample Analyzed	Country
Chung and Kwon (2009)	TAM	Investigating the moderating effect of mobile experience and technical support on MB usage intention	156 internet and mobile banking users	Korea
Kim et al. (2009)	IDT	Revealing the impact of initial formation of trust on MB usage intention	192 working professionals	Korea
Gu et al. (2009)	TAM	Integrating external factors (e.g., trust, self-efficacy, and system quality) to TAM's key constructs	910 MB users	Korea
Zhou et al. (2010)	TTF and UTAUT	Integrating TTF and UTAUT to account for technology and task fit that can better predict MB adoption	250 university students and professionals	China
Koenig-Lewis et al. (2010)	TAM and IDT	Extending TAM with compatibility, trust, credibility, perceived risk and cost	263 young customers	Germany
Luo et al. (2010)	UTAUT	Examining multi-dimensional trust and multi-faceted risk perceptions on MB adoption	122 university students	USA
Riquelme and Rios (2010)	TAM	Finding the moderating effect of gender on MB adoption	600 internet banking users	Singapore
Shen et al. (2010)	A benefit-cost model	Employing the benefit factor (convenience) and risk factor (security) towards MB adoption	400 working class people	Taiwan
Lin (2011)	IDT	Examining the innovation attributes and knowledge-based	368 potential and repeat customers	Taiwan

		trust factors on MB adoption through attitude		
Zhou (2011)	IS Success model	Exploring initial trust on MB usage intention	210 MB users	China
Teo et al. (2012)	TAM	Extending TAM with subjective norms and demographic variables	193 university students	Malaysia
Aboelmaged and Gebba (2013)	TAM and TPB	Combining TAM and TPB to provide a holistic MB model in a developing country context	119 university students	UAE
Chen (2013)	Self-developed model	Identifying the difference between two MB sub-groups (frequent users and infrequent users) and exploring the effect of brand awareness and brand image	610 MB users	Taiwan
Oliveira et al. (2014)	TTF, UTAUT and initial trust model (ITM)	Integrating three IS theories: TTF, UTAUT and ITM to provide a holistic approach explaining MB adoption using technological, behavioral and environmental determinants	194 university students	Portugal
Goh et al. (2014)	Consumption values model	Identifying the difference between Muslims and non-Muslims in perceiving consumption values (functional, emotional, epistemic, conditional, and social) towards MB adoption	183 university students	Malaysia
Pavithran et al. (2014)	TAM	Revealing the significant factors that affect MB adoption in a developing country context	289 MB users	India
Hanafizadeh et al. (2014)	TAM	Extending TAM with unexamined factors (e.g., trust, credibility, and compatibility with life style) to explain their impact on MB's intention to use	361 university students and faculty members	Iran
This study	*UTAUT*	*Investigating the impact of subjective and objective experience using a multi-analytical approach (SEM-neural network)*	*472 customers from a local mid-sized bank*	*USA*

2.2. MB Actual Use

System actual use is the stage that comes after technology adoption. There have been a few studies about MB actual use regardless of its great importance by being a key to information system success and a better reflection of user satisfaction (DeLone and McLean, 2003). MB actual use studies are summarized in Table 2.2 below. It is obvious that UTAUT has been the mostly used in such area, indicating its adequate analytics power to explain this phenomenon. But surprisingly, not a single study with a focus of MB system usage has been conducted in the USA.

Table 2.2. Prior Research on MB Actual Use

Study	**Theoretical Lens**	**Main Contribution**	**Sample Analyzed**	**Country**
Zhou (2012)	Self-developed model	Exploring the impact of flow on MB actual use through usage intention	200 MB users	China
Yu (2012)	UTAUT	Employing UTAUT with adding some relevant factors, namely, credibility, financial cost, and self-efficacy and exploring the moderating effect of gender and age	441 participants from a shopping mall	Taiwan
Baptista and Oliveira (2015)	UTAUT2	Extending UTAUT2 with cultural moderators, i.e., power distance, individualism/collectivism, long/short term, uncertainty avoidance, and masculinity/femininity	252 mobile internet users	Mozambique
This study	*IS Success and UTAUT*	*1. Examining the subjective and objective impact of MB usage* *2. Integrating IS Success with UTAUT to establish a holistic theoretical framework for MB usage*	*472 MB users*	*USA*

2.3. MB Continuance Intention

Continued usage intention of MB is the third stage that comes after system actual use and can provide a good indication to loyalty (Hew et al., 2016). Customer loyalty is a bottom line and ultimate goal to all banks of various sizes; thus, continuance intention is even more important than system actual use. In spite of its significant implication, continuance intention lacks investigation in MB literature (Table 2.3), especially in the USA.

Table 2.3. Prior Research on MB Continuance Intention				
Study	**Theoretical Lens**	**Main Contribution**	**Sample Analyzed**	**Country**
Chen (2012)	Self-developed model	Examining relationship quality towards MB continuance intention through three factors: technology readiness, risk, and quality	390 MB experienced users	Taiwan
Rejikumar and Ravindran (2012)	TAM	Extending TAM with perceived risk, credibility, and service quality	184 MB early adopters	India
Yuan (2014)	TAM, TTF, and ECM	Incorporating three acceptance models with employing gender as a moderating factor	434 MB experienced users	China
Zhou and Liu (2014)	ECM-IT and flow theory	Investigating the impact of trust, utility, flow and user experience on users' continued usage intention	194 MB users	China
Mohammadi (2015)	TAM	Extending TAM with external factors (e.g., risk, resistance and awareness) and examining the moderating effect of subjective norms and personal innovativeness	128 LinkedIn and Facebook users	Iran
This study	*TAM*	*Extending TAM with privacy-personalization paradox with practical implications to industry*	*486 MB users*	*USA*

The above three tables show, chronologically, to what extent MB adoption, actual use, and continuance intention have been given attention in the literature. In every table, we have included our study at the end to indicate the novel contribution added to the existing literature of mobile banking.

In sum, three papers have been developed to provide a deeper analysis and understanding of MB usage behavior. The three phases of MB usage are investigated as a continuum cycle, which would help to connect the dots between each phase by carrying on the sequential understanding of this topic. Each paper has addressed a different phase of MB phenomenon. The first paper starts with the first phase of usage behavior; system behavioral intention. The second paper looks at the MB through the second phase of usage behavior; system actual use. While the third paper embraces a more research-needed area by examining continued usage intention; the third phase of usage behavior.

2.4. Three-Paper Approach

The three-paper approach has been adopted here to present the doctoral dissertation. This approach has gained popularity in academia because it enables doctoral students to break down the PhD research idea/problem into manageable pieces of work and give sufficient attention for each. Hence, I have used this approach and developed three research papers to address each aspect of usage behavior in MB. Every research paper stands alone and presented blow in a separate section since it has been developed to be submitted for a journal publication in the MIS area.

Chapter 3. First Paper: The Impact of Self-Reported and Computer-Recorded Experience on Mobile Banking Usage: A Multi-Analytical Approach

This chapter presents the first research paper that employs a multi-analytical approach to bring new insights into MB adoption research.

3.1. Introduction

Mobile banking (MB) enables bank customers to access a wide array of banking services including balance check, fund transfer, and mobile deposit. It is associated with ubiquity advantage when compared to the traditional banking and accordingly is preferred by most customers. As banking industry is moving towards internet of things, more digital offerings would be available and MB would become an inevitable resource among customers (Meola, 2016). In other words, MB is becoming a necessity to bank customers, and so if not provided, the customers may switch to another bank. However, MB imposes some constraints, such as small screens, inconvenient input, and slow responses (Zhou, 2013) that may hinder its usage.

Extant research has drawn on various IS theories and acceptance models to examine MB adoption. Few examples are unified theory of acceptance and use of technology (UTAUT) and task-technology fit (TTF) (Zhou et al., 2010), technology acceptance model (TAM) (Mohammadi, 2015), and innovation diffusion theory (Lin, 2011). While actual system use has a greater value than adoption (behavioral intention) because it is a key determinant of information system success and a better indicator of satisfaction (DeLone and McLean, 2003), it has lacked investigation in MB research (Yu, 2012; Zhou, 2012; Talukder, 2014). This motivates us to conduct further examination of the factors influencing MB actual use. Along with actual system use, experience, defined as the duration of usage for a specific system, has not been given much attention and mostly regarded as a control or demographic variable, indicating negligence for its role. But Venkatesh et al., (2012) emphasize that it is a necessary element to develop a habit that can predict IS behavioral intention and usage. More importantly, what makes experience a relevant and critical topic to investigate is its inconsistency in results across IS research (Ramayah et al., 2005; Chung, N., and Kwon, S. J. 2009a; Prasanna and Huggins 2016), which could be attributed to overestimation or underestimation of individuals' perception about their usage experience. This gives us another motivation for evaluating the impact of self-reported (subjective) experience and computer-recorded (objective) experience and to validating their correlation.

MB research (Zhou et al., 2010; Lin, 2011; Mohammadi, 2015) has focused on identifying the significant factors via traditional regression techniques (i.e. linear regression) but have not focused on identifying the most significant factors that drive system behavioral intention. As a result, practitioners cannot prioritize their managerial action for improving MB services. This calls for more complementary techniques (i.e., neural networks) that can address such practical gap. On the other hand, as the complexity of decision-making process towards adoption and usage of various types of information systems has been overlooked in IS research through investigating only the linear relationships (Tan et al., 2014), it would be necessary to employ a technique (e.g., universal structure modeling (USM)) that can account for hidden patterns of nonlinearity in a conceptual framework between independent variables and dependent variable (Oztekin et al., 2011; Turkyilmaz et al., 2013; Turkyilmaz et al., 2016). Overall, the mentioned research gaps have raised three questions:

1. Does the impact of self-reported and computer-recorded experience differ in regards to MB actual use?
2. Which factors matter most to MB users?
3. To what extent do nonlinear relationships exist when adopting MB?

These questions will be addressed via the theoretical lens of UTAUT. This model has been selected because of its parsimonious and high prediction power to explain user behavior (Venkatesh et al., 2003).

This study contributes to theory and practice by 1) highlighting the role of prior user experience on MB usage subjectively and objectively; an area that has not been addressed yet in IS research, and 2) providing banks and software vendors with the opportunity to access the key substantial elements perceived by MB users and improve them accordingly. This study also has two methodological contributions. SEM-NN technique would enable a better predicative capability by revealing not only the important determinants but also the most important ones that influence MB usage. Second, USM technique would disclose hidden nonlinearity and not theoretically suggested effects; the latter can also advance IS theory through rationalizing a new set of hypotheses. Both techniques can allow a deeper analysis and understanding of the factors impacting MB usage

The rest of this paper is organized as follows: section 2 describes UTAUT, neural networks, and USM in brief and reviews prior research that combines behavior usage and SEM-NN. Section 3 develops the research model and the hypotheses. Section 4 presents the research method. Section 5 provides the results of SEM, neural network, and USM. Section 6 discusses those results and lastly section 7 concludes with study contribution and conclusion.

3.2. Related work

In this section, we elaborate on UTAUT and its uses in IS literature, explains neural network and its applications in the two streams of IS research, show the importance of universal structure modeling, and then browse works that combine both adoption behavior and SEM-NN analysis.

3.2.1. UTAUT

UTAUT is developed by synthesizing system acceptance determinants from eight prominent theoretical perspectives, namely, theory of reasoned action (TRA), TAM, motivational model, theory of planned behavior (TPB), a model combining the technology acceptance model and theory of planned behavior, a model of PC utilization (MPCU), innovation diffusion theory (IDT), and social cognitive theory (SCT) (Venkatesh et al., 2003). UTAUT with its four pillars has shown to have a better analytics power than the mentioned standalone models and has been widely used to investigate individual's usage behavior of various information systems. For instance, in non-mobile context, Lallmahomed et al. (2013) adapted UTAUT to predict Facebook acceptance among college students. While in a mobile context, Zhou et al. (2010) used convenience sample to collect data and test it via UTAUT to explain mobile banking user adoption. Baptista and Oliveira (2015) utilized the extended UTAUT or UTAUT2 with cultural moderators to examine mobile banking adoption among smartphone users.

As evidenced by these studies, although UTAUT demonstrates good generalizability and high explanatory power in IS research, it has been rarely associated with a data analytics technique that can enhance its nomological validity in the context of mobile banking. In other words, UTAUT's nomological network has been tested frequently with traditional regression methods across various IT innovations and thus validated but it has never been tested with an analytics prediction tool, such as neural networks to extend its validity. Besides that, UTAUT proposes behavioral intention and actual use as dependent variables, which makes it appropriate to be used in the study as our theoretical base model.

3.2.2. Neural network

Neural network (NN) is one of the most popular supervised algorithms in data mining and refers to the fact that "computer models used to emulate the human pattern recognition function through a similar parallel processing structure of multiple inputs" (Chiang et al., 2006: p. 516). NN seems like a human brain but it is composed of artificial neurons (nodes) that are capable to learn from its environment and obtain new knowledge (Chong, 2013). This non-parametric technique has a big advantage compared to traditional statistical methods because it can work without assuming any data distribution for input and output variables plus it is associated with good adaptive capability across changes in a data structure (Garson, 1998).

NN has been mostly applied in decision science research to address a specific business problem, for example, re-constructing gene regulatory networks (Ma and Chan, 2007) and detecting financial fraud (Ravisankar et al., 2011). However, few studies of behavioral science have utilized NN to estimate probabilities in consumer choice (Hu et al., 1999) and to explain behavior towards web and traditional stores (Chiang et al., 2006). According to Tan et al. (2014), although NN has been utilized across different disciplines such as marketing, operations, and management, its application remains scarce in IS behavioral research and rare in mobile innovations. To the best of our knowledge, this is the first paper to employ NN with a purpose of revealing the highest-impact factors on MB behavioral intention and usage.

3.2.3. Universal structure modeling

Buckler and Hennig-Thurau (2008) introduce a new innovative research technique that can overcome limitations associated with the two traditional types of SEM: covariance-based structural equation modeling (CVSEM) and component-based partial least square (PLS). This technique has been referred to as universal structure modeling (USM) and defined as "a method that enables researchers to apply such an exploratory approach to SEM and thus helps them identify different kinds of "hidden" structures instead of testing a limited set of rival model structures. Specifically, the USM approach combines the iterative component-based approach of PLS with a Bayesian neural network involving a multilayer perceptron architecture" [p. 50]. USM has addressed the problem of "black-box" inherent to NN. While unlike CVSEM and PLS, USM can provide the following hidden aspects within a structural model:

- Hidden paths: besides identifying the proposed hypotheses in the research model, USM can detect unsuggested and not theoretically supported paths in the model. This feature has been considered a valuable mechanism for theory development.
- Hidden interactions: CVSEM and PLS help a researcher to test a hypothesized interaction effect (a moderating variable) by multiplying the constructs of interest. This process is totally controlled by scholars, meaning that an interaction effect will not be tested if not proposed in the conceptual model. On the contrary, USM assists the scholars to search for hidden interaction effects and identify those effects whether proposed or not. In other words, it can detect systemic and non-systemic moderating effects.

- Hidden nonlinearity: CVSEM and PLS can recognize only linear relationships in the structural model. While USM can account for nonlinearity structures due to the embedded Bayesian neural network estimation technique.

Most studies in IS research that have sought to examine MB adoption or behavioral intention are based on a traditional statistical analysis like linear regression (Baptista and Oliveira, 2015; Zhou et al., 2010). Such analysis over-simplifies the complexity associated with IT adoption decisions (Tan et al., 2014) and accordingly provides inadequate understanding by revealing only the linear relationships in the structural model. USM can overcome such limitation by finding the hidden nonlinearity patterns in the data. Also, it can find any hidden direct or indirect paths not theoretically supported, helping to inform further understanding about MB usage.

Overall, SEM finds which of the hypothesized relationships are significant in the structural model. Out of these significant factors, NN reveals which one has the highest-impact on MB behavioral intention and actual use with the help of sensitivity analysis. Then, USM comes to the scene and shows the hidden structures of the examined model; namely, hidden nonlinearity and hidden interaction effects. Therefore, it is plausible to say that those techniques complement each other.

3.2.4. Adoption behavior and SEM-NN

Few studies have employed a joint analysis approach, i.e. SEM-NN, to examine the effect of usage intention. Scott and Walczak (2009) investigated students' intention to use an ERP training tool by employing both SEM and NN. Leong et at. (2013) explored the acceptance of near field communication (NFC)-enabled mobile credit card system via using the same joint analysis method on a various-industry sample. Chong (2013) utilized such multi-analytical approach to measure mobile commerce adoption among college students. Yadav et al. (2016), similar to Chong (2013), measured mobile commerce adoption using the same approach among postgraduate students. Tan et al. (2014) drew on TAM and applied SEM-NN analysis to examine students' behavioral intention towards mobile learning.

As evidenced, the above studies had focused mainly on "behavioral intention" rather "actual system use" even though the latter is valued more and considered a key to determine information system success (DeLone and McLean, 2003). Second, most studies have used a student sample. Considering the generalizability issue associated with the student sample, it is important to include a more representative sample such as actual bank customers. Third, some of those studies call for further investigation of the moderating role of user experience (Leong et at., 2013) and to study its impact on system usage. Fourth, not a single study has examined the highest-impact factors in a MB context using a multi-analytical technique. Fifth, not a single study has also attempted to account for nonlinearity that may exist in customers' decisions to adopt MB or to actually use it.

3.3. Research Model and Hypotheses

In this section, we present our research model and provide a theoretical and empirical justification to develop a set of hypotheses.

3.3.1. Research model

Each context has some differences when compared to others. Such differences make it necessary to research usage behavior in every particular context (Lallmahomed et al., 2013). Accordingly, we plan to investigate usage behavior in a MB context by applying UTAUT. Our model is visualized below in Figure 3.1. As literature suggests (Baptista and Oliveira, 2015), UTAUT's four pillars are predictors of behavioral intention while both facilitating conditions and behavioral intention affect MB actual use. Experience works as an independent variable and as a moderator to MB actual use and is measured subjectively via self-reported data and objectively via computer-recorded data.

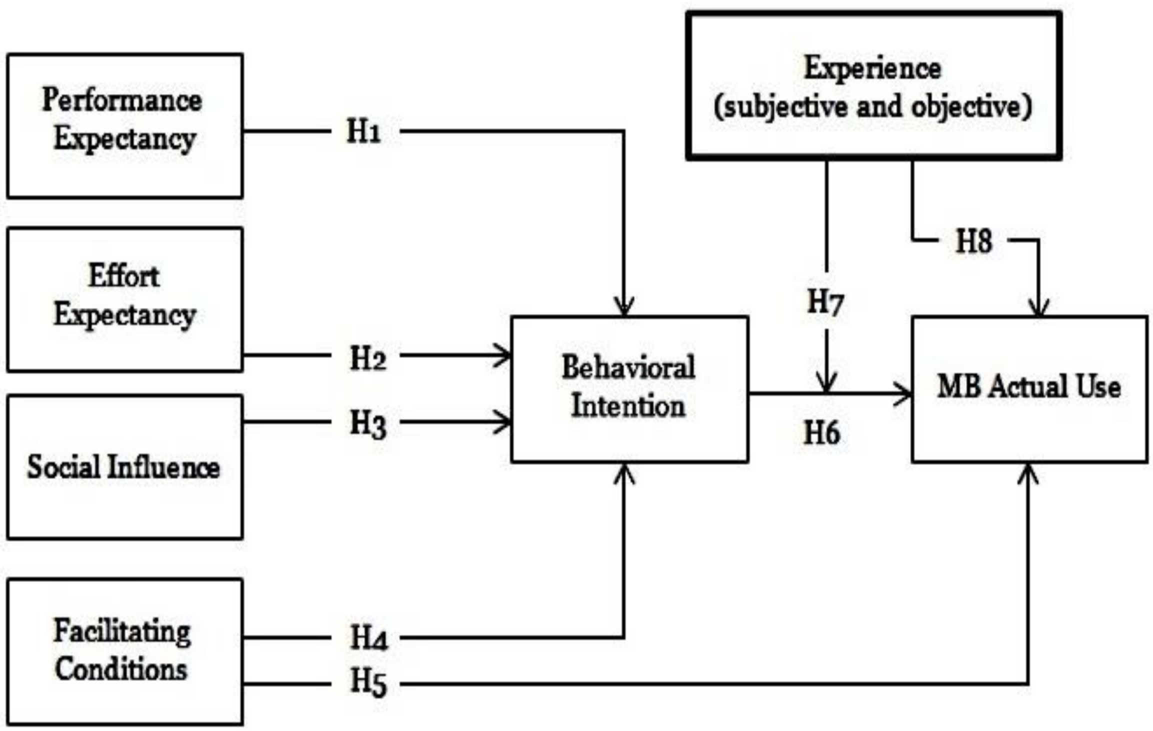

Figure 3.1. Research Model

3.3.2. Performance expectancy (PE)

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). Since this construct had been developed from TAM's perceived usefulness (Venkatesh et al., 2003), it simply indicates maximizing efficiency. Individuals normally like to adopt technologies that increase their productivity and enhance their effectiveness in accessing and conducting various system tasks on-the-go. As MB can enable such leverage, it is more likely those individuals would have a high intention towards using it. This relationship has considerable empirical support in a MB context (Baptista and Oliveira, 2015; Yu, 2012; Zhou et al., 2010), thus, we hypothesize that:

H1: *Performance expectancy is positively related to individual intention to use MB.*

3.3.3. Effort expectancy (EE)

Effort expectancy is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003: p. 450). Since this factor had been developed from TAM's perceived ease of use, MPCU's complexity, and IDT's ease of use (Venkatesh et al., 2003), it basically indicates minimizing effort. In most MB apps, the graphical user interface is simple and the embedded services are easy to navigate and learn. This makes individuals be skillful at using MB in a very short time. Such short learning curve associated with MB would make others be more interested to start using MB. The positive relationship between effort expectancy and behavioral intention has been validated within MB (Yu, 2012), hence, we hypothesize that:

H2: *Effort expectancy is positively related to individual intention to use MB.*

3.3.4. Social influence (SI)

Social influence is defined as to what degree a person feels that a MB technology should be recommended and used by his/her social network (Miltgen et al., 2013). When using technological innovations, individuals incline to share their positive or negative experience with their social circle. This circle includes but not limited to family members, friends, and co-workers. Hence, once MB users are happy with the app, they would convey such feelings to their surrounding social circle, which in turn leads to affect positively the circle's behavioral intention to use MB. Also, according to the empirical evidence found in the literature that supports this association (Lallmahomed et al., 2013; Yu, 2012; Zhou et al., 2010), we hypothesize that:

H3: *Social influence is positively related to individual intention to use MB.*

3.3.5. Facilitating conditions (FC)

Facilitating conditions refer to the degree of bank support provided to a MB system in terms of organizational and technical infrastructure (Miltgen et al., 2013). MB is facilitated by various resources. Such resources that include a how-to-use guide and help-desk support can increase individuals' intention to use MB and even leverage the current users' involvement to the system. The positive relationship between facilitating conditions and behavioral intention and between facilitating conditions and actual use has been empirically supported in a MB context (Baptista and Oliveira, 2015; Yu, 2012; Zhou et al., 2010). Thus, we hypothesize that:

H4: *Facilitating conditions is positively related to individual intention to use MB.*

H5: *Facilitating conditions is positively related to MB actual use.*

3.3.6. Behavioral intention (BI)

Behavioral intention in IS research is defined as the ‘‘degree to which a person has formulated conscious plans to perform or not perform some specified future behavior’’ (Venkatesh et al., 2008: p. 484). Psychological theorists argue that individuals’ behavioral intention is linked to the actual use (Baptista and Oliveira, 2015). Thus, individuals with a high intention to use MB most likely will break the ceiling and start using it. In addition, various studies in IS literature support this connection (Lallmahomed et al., 2013), and specifically in a MB setting (Baptista and Oliveira, 2015). Thus, we hypothesize that:

H6: *Behavioral intention is positively related to MB actual use.*

3.3.7. Experience

Experience is defined as “an opportunity to use a target technology and is typically operationalized as the passage of time from the initial use of a technology by an individual.” (Venkatesh et al., 2012: p. 161). Experience helps to build up individuals’ competence when utilizing a specific system, which in turn could sustain the usage level. For instance, individuals experienced at using a MB system would have a higher confidence to involve more and to increase their usage. Lee and Kim (2009) provide an empirical evidence confirming this relationship in a website setting. In addition, meta-analysis study based on 121 articles suggests that user experience is a significant predictor of system usage (Sabherwal et al., 2006).

Experience helps to decrease uncertainty and increase the sense of control over a MB system. Hence, gaining more MB experience can improve the behavioral intention as a predictor to actual use. This effect has been validated in a web-based system (Venkatesh et al., 2008). With increasing MB experience, individuals reinforce their habit of using the system and therefore this behavior becomes automatic (Venkatesh et al., 2012). Automatic behavior could sustain or enhance the level of system use. For example, individuals who have a long experience at using various MB services may tend to be positive about increasing their actual use. Hence, it is possible to state that when the experience increases, the impact of behavioral intention on MB actual use will increase. According to the above argument, we hypothesize that:

H7: *Experience will moderate the effect of behavioral intention on actual use, such that the effect will be stronger for MB users with more experience*

H8: *Experience is positively related to MB actual use.*

3.4. Research Method

3.4.1. Participants

Our sample is composed of local mid-sized US bank customers. The bank sent an invitation email to their customers with a survey link and donated $1000 to a charity organization as an incentive to participate in the study. Participation was voluntary and customers could opt out any time during the survey. The survey was open for about 20 days with a follow-up reminder sent every 10 days to help in collecting a sufficient sample. The full collected sample was 760 participants but got reduced to 472 participants due to the removal of missing values and the process of matching the self-reported experience with computer-recorded experience that had been collected from system log data over an 8-month period. The matching was conducted on an individual level by using email accounts. With removing these cases, our sample still represents bank population because we have fairly an equal number of male and female participants as well as most of their ages are greater than 40, reflecting a typical mid-sized bank.

Due to the different levels of education and varieties of jobs held by the bank customers, we managed to have a good-diversification sample. Such sample would enable us to have a better representation of the population and so to generalize the findings to other mid-sized banks in the United States.

3.4.2. Survey instrument

We designed the survey as closed-ended structured questions with two sections: (i) demographic questions like age, gender, education, and work status; and (ii) questions about our variables of interest (research questions).

The survey was pre-tested with a pilot of 10 bank customers via a SurveyMonkey online service. The survey items were assessed for content validity by subject matter experts and face validity by the customers. Participants were asked to comment on clarity and understandability of the questions at the end of the survey. This helped us to refine the survey and clear any confusion or miswording in the questions before sending it to the full sample.

3.4.3. Measurement

Constructs' items have been adapted from literature and modified to a MB context (Table 3.1). The items are measured using a 7-point, Likert-scale with 7 "Strongly agree" and 1 "Strongly disagree". UTAUT factors of performance expectancy, effort expectancy, social influence, and facilitating conditions are adapted from Chan et al. (2010). Both behavioral intention and actual use are adapted from Venkatesh et al. (2012). Experience is measured in months as suggested by Venkatesh et al. (2012); labeled subjective if retrieved from survey and objective if retrieved from system log data. Both subjective and objective experience as well as actual use were rescaled to fit the 7-point Likert-scale.

Table 3.1. Constructs Operationalization

Construct	Item Code	Lead Questions and Item Scales	Citation
Performance Expectancy	PE1 PE2 PE3	Q1. Using MB enables me to access bank services more quickly Q2. Using MB makes it easier to access bank services. Q3. Using MB enhances my effectiveness in accessing bank services.	Chan et al. (2010)
Effort Expectancy	EE1 EE2 EE3	Q4. I find it easy to use MB to access bank services. Q5. Learning to use MB to access bank services can be easy for me. Q6. It is easy for me to become skillful at using MB to access bank services.	Chan et al. (2010)
Social Influence	SI1 SI2 SI3	Q7. People who influence my behavior think that I should use MB to access bank services. Q8. People who are important to me think that I should use MB to access bank services. Q9. People who are in my social circle think that I should use MB to access bank services.	Chan et al. (2010)
Facilitating Conditions	FC1 FC2 FC3	Q10. I have the resources necessary to use MB to access bank services. Q11. I have the knowledge necessary to use MB to access bank services. Q12. I have a specific person (or group) available for assistance with difficulties using MB to access bank services.	Chan et al. (2010)
Behavioral Intention	BI1 BI2 BI3	Q13.I intend to continue using MB in the future. Q14. I will always try to use MB in my daily life. Q15. I plan to continue to use MB frequently	Venkatesh et al. (2012)
Actual Use	AU1 AU2 AU3	Q16. Perception of usage frequency for general activities (e.g., balance inquires). Q.17 Perception of usage frequency for bill payment, transfer, and mobile deposit. Q18. Perception of own usage on a monthly basis (light, moderate and heavy).	Venkatesh et al. (2012)

Experience	EX	Q19. How long have you been using MB on a monthly basis? (retrieved from survey and system log data)	Venkatesh et al. (2012)

3.4.4. NN and USM analysis approach

To employ NN in our study, a multilayer perceptron algorithm was used to build a network of linear classifiers. Each node computes a weighted sum of inputs and uses a threshold function on the results. We had deployed a non-linear threshold function, commonly used sigmoid function:

$$\sigma(x) = \frac{1}{(1 + e^{-x})}$$

The model was built with one input layer of attributes, one output layer of classes, and one hidden layer. One hidden layer is often good enough for the linearly separable data or a single convex region of decision space, which corresponds many of the NN problems. The weights in the network are learned from the training set by an iterative algorithm based on a back-propagation method. However, USM that functions as a universal regression method, namely a Bayesian neural network (BNN), instead of linear least squares is employed in this study. This technique is capable of quantifying and visualizing non-linear relationships as well as unhypothesized paths with interaction effects. To implement USM, the below steps indicated by Buckler and Hennig-Thurau (2008) were adapted and followed:

Step 1: Specifying the model

1.1.Determining specification matrix: mathematically speaking, USM specifies the structural model with $\hat{y}^j$ as the endogenous latent variable (here behavioral intention and actual use) defined by functions of one or more other latent variables *y* that can be exogenous or endogenous (UTAUT's fourth pillars). Formally, $\hat{y}^j$ is estimated through y^i and defined as the output of a multilayer perceptron (MLP) architecture as the below equation shows:

$$\hat{y}^j = f_{Act2}\left(\sum_{h=1}^{H} w_h \cdot f_{Act1}\left(\sum_{i=1}^{I} w_h \cdot S_i^j \cdot y^i + b_{1h}\right) + b_2\right)$$

Where:

f_{Act1}**:** the logistic sigmoid activation function of the hidden neural units.
f_{Act2}: the linear activation function of the output neural unit.
H: the number of hidden neural units.
I: the number of latent input variables y.
w: the weights.
b: the bias weights.
S^j_i: the a priori likelihood that a variable i influences another variable j.

1.2. Determining measurement model: this model is specified by estimating the latent variable as a linear combination of its manifest variables:

$$\hat{y}^j = \sum_{m=1}^{M_i} f_m \cdot x_m + f_0$$

Where:

x: the values of M_i measurement variables that determine $\hat{y}^j$.
f_m**:** the factor loadings.
f_0**:** the constant term of the function.

Step 2: Estimating the model

2.1. Estimating latent variable (LV) and then MLP for every LV: the starting values for LVs are estimated via linear principle component analysis (PCA) while paths between LVs are estimated via BNN with MLP. This helps to reveal irrelevant paths and impede overfitting. In each endogenous variable, the error function, E, is minimized when estimating neural network as shown below:

$$E_i = \beta \cdot \sum_{n=1}^{N} (\hat{y}^{i}{}_{t-1,n} - \hat{y}^{i}{}_{t,n})^2 + \sum_{h=1}^{H} \alpha_{t,h} \cdot \sum_{p=1}^{P} w^2{}_{ph}$$

Where:

n: the index for the individual cases.
N: the number of cases included in the estimation.
p: the index for the weights *w*.
$\hat{\boldsymbol{y}}^{\boldsymbol{i}}{}_{\boldsymbol{t}}$**:** the conditional estimate of LV i in the current estimation round t, derived from the structural model.
$\hat{\boldsymbol{y}}^{\boldsymbol{i}}{}_{\boldsymbol{t-1}}$**:** the estimate of the previous iteration for this LV, derived from the measurement model.
$\boldsymbol{\alpha_h}$ ***and*** $\boldsymbol{\beta}$***:*** the hyperparameters that limit the space of possible solutions, which impede the overfitting problem for the estimated model.

2.1. Estimating new scores for LV and factor loadings: the new values from neural network are inputted for computing the weights of the measurement model. The estimates of inner and outer model continue to be computed iteratively till the differences between LV scores of both models are minimal. Residual variance is diminished through the iteration process and estimable subsets are created and assigned to the minimized residual variables.

Step 3: Processing the post

3.1. Determining impact size and fit measure: the impact size is defined by overall explained absolute deviation (OEAD), which measures the strength of the relationship between the input latent variable and output latent variable. OEAD basically accounts for the amount of variance in latent variable i explained by latent variable j in the structural model and specified as:

$$OEAD_j^i = \sum_{n=1}^{N} \frac{\left| \dfrac{\hat{y}_n^i - f_n^i(y^1, \dots, \bar{y}^j, \dots, y^I)}{\hat{y}_n^i - \bar{\hat{y}}_n^i} \right|}{N}$$

Where:

$\boldsymbol{f_n^i(y^1, \dots, \bar{y}^j, \dots, y^I)}$**:** the outcome of the neural network function.
$\bar{\hat{y}}_n^i$**:** the mean of $\hat{y}_n^i$,
N**:** the number of cases used to normalize the effect.

3.2. Calculating coefficient of determination (R^2) and the goodness of fit (GoF): R^2 gives the percent of variance in an endogenous latent variable explained by the exogenous variables. While the appropriateness of the suggested model is evaluated by GoF that is specified below. These two measures help to compare between USM and SEM-PLS in terms of the overall model fit.

$$GoF = \sqrt{\left(\frac{1}{M}\sum_{i=1}^{I} M_i \cdot communality_i\right) \cdot \overline{R^2}}$$

Where:

I: the number of latent constructs in the model.
Communality: the regression coefficient between an item and its latent variable.
M: the total number of measurement variables in the model.
$\boldsymbol{M_i}$**:** the number of measurement variables for the construct i.
$\boldsymbol{\overline{R^2}}$: the mean explained variance of all endogenous latent variables of the structural model.

3.3. Test for non-linearity and interaction effect: non-linearity is identified by the additive effect through computing a-score for every case of n:

$$a_j^i = f^i(y^1, \dots y^j, \dots, y^n) - f^i(y^1, \dots \bar{y}^j, \dots, y^I)$$

Where:

$\boldsymbol{a_j^i}$: the change in y^i caused by the additive effect of y^j.
f_{NN}: the neural network function.
y^1 to y^n: the latent input variables of the structural model.

While interaction effect is identified by computing z-score for every case of n, its strength is calculated by IE:

$$z_{jk}^i = f^i(y^1, \dots y^j, \dots, y^k, \dots, y^I) - f^i(y^1, \dots \bar{y}^j, \dots, \bar{y}^k, \dots, y^I)$$

$$IE_{jk}^i = \sum_{n=1}^{N} \frac{\left| \frac{\hat{z}_{jk}^i - \hat{a}_j - \hat{a}_k}{\hat{y} - \bar{y}} \right|}{N}$$

Where:

z: the change in y^i for an individual case caused by the additive and the interactive effect of y^j and y^k.
$\boldsymbol{\bar{y}^j}$ ***and*** $\boldsymbol{\bar{y}^k}$: the mean values of y^j and y^k.
$\boldsymbol{\hat{a}}$**:** the additive scores of a polynomial regression of y on a.
$\boldsymbol{\hat{z}}$**:** the outcome of a universal regression with the two latent variables j and k as regressors on $\hat{z}_{jk}^i$.

For a better understanding and interpretation, the interaction effect is visualized by a 3-dimensional graph where y^j plot on the x-axis, y^k plot on the y-axis, and $\hat{z}_{jk}^i$ plot on the z-axis.

3.4. Estimating significance of parameters: USM, like SEM-PLS, does not assume any distribution for the examined data. Thus, bootstrapping is used for testing statistical significance of the parameters as well as of the OEADs and IEs.

Figure 3.2. Steps for USM Analysis (modified from Buckler and Hennig-Thurau 2008)

USM, enabled by Neusrel software (Buckler and Hennig-Thurau, 2008), is utilized to compare and complement PLS-NN results. USM is a good benchmark because it inevitably captures non-linear relationships and accordingly provides a higher accuracy prediction (Oztekin et al., 2011).

3.5. Data Analysis

3.5.1. Participants' demographic profile

As per table 3.2, the sample shows a little more female representation in the data; 52.54%. In terms of age, the middle-aged customers (46-55) form the majority group while the young customers (15-25) form the minority group. Regarding the education level, degree holders are considered to be more than half of the sample (about 60% had obtained a bachelor degree or higher). For work status, the regular employees dominated the survey with 64.47% and about 28 multiple of the student size.

Table 3.2. Demographic Profile for Participants

Variable	Frequency	Percentage
Gender		
Male	224	47.46
Female	248	52.54
Age		
15-25	48	10.17
26-35	60	12.71
36-45	81	17.16
46-55	115	24.36
56-60	57	12.08
> 60	111	23.52

Education		
High school	55	11.65
Some college	131	27.75
College degree	148	31.36
Graduate degree	134	28.39
Other	4	0.85
Work Status		
Full-time	309	64.47
Part-time	59	12.50
Unemployed	16	3.39
Retired	77	16.31
Student	11	2.33

3.5.2. Descriptive statistics, validity, and reliability

As per table 3.3, the mean, standard deviations, and factor loadings are presented for every item. We used SmartPLS to evaluate the model's measured variables via confirmatory factor analysis (CFA). From CFA, it seems that all loadings are good as their values are greater than 0.60 except for the third item of facilitating conditions (FC3), which had been excluded from the data.

Table 3.3. Descriptive Statistics and Factor Loading

Variable	Items	Mean	Standard Deviation	Factor Loadings
Performance Expectancy (PE)	PE1	6.02	0.99	0.928
	PE2	5.93	1.13	0.950
	PE3	5.77	1.15	0.936
Effort Expectancy (EE)	EE1	5.88	1.11	0.882
	EE2	6.00	0.96	0.928
	EE3	5.97	0.92	0.894
Social Influence (SI)	SI1	4.29	1.54	0.961
	SI2	4.36	1.54	0.966
	SI3	4.28	1.50	0.953
Facilitating Conditions (FC)	FC1	6.14	0.82	0.904
	FC2	6.24	0.70	0.881
Behavioral Intention (BI)	BI1	6.30	0.86	0.807
	BI2	5.48	1.36	0.878

	BI3	5.64	1.28	0.926
Actual Use (AU)	AU1	1.892	1.260	0.857
	AU2	1.316	0.748	0.662
	AU3	3.860	2.273	0.897
Subjective Exp.	EX1_S	4.184	1.783	1.000
Objective Exp.	EX1_O	3.314	1.911	1.000

As per table 3.4, data was analyzed for various indicators of validity and reliability. The data shows a good convergent validity because Spearman's rho and average variance extracted (AVE) for all factors are greater than 0.5. The measured factors, also, have a good reliability since their Cronbach's alpha and composite reliability (CR) values are higher than 0.70. Variance inflation factor (VIF) shows acceptable levels (< 5), which indicate no collinearity between variables. As per table 3.5, we can confirm that discriminant validity had been established in our model since Heterotrait-Monotrait Ratio (HTMT) values are below 0.9 (Henseler et al., 2015).

Table 3.4. Validity and Reliability Measures

Variables	**CR**	**rho**	**AVE**	**Cronbach's Alpha**	**VIF**
PE	0.957	0.932	0.880	0.932	2.795
EE	0.929	0.885	0.813	0.885	2.862
SI	0.972	0.962	0.921	0.957	1.136
FC	0.887	0.750	0.796	0.745	1.432
BI	0.904	0.850	0.760	0.840	1.284
AU	0.851	0.821	0.659	0.742	N/A

Note: CR: composite reliability, AVE: average variance extracted,
VIF: variance inflation factor, rho: Spearman's rho.

Table 3.5. Heterotrait-Monotrait Ratio (HTMT)

Variables	AU	BI	EE	FC	PE	SI
AU						
BI	0.460					
EE	0.214	0.814				
FC	0.107	0.558	0.660			
PE	0.271	0.848	0.865	0.586		

SI	0.230	0.394	0.309	0.151	0.360	

3.6. Results

This section shows the analysis conducted by SEM-PLS, NN, and USM. SEM-PLS analysis is conducted by including the self-reported and computer-recorded experience to help in comparison and validation.

3.6.1. PLS hypotheses testing

The hypothesized relationships are tested using SEM-PLS technique, which does not require the data to be normally distributed. The testing had been conducted in two phases. Phase one (model 1) includes only independent variables and their impact on dependent variables (i.e., behavioral intention and actual use). Phase two (model 2) includes the independent variables and interaction effect (i.e., experience). Th two-phase process is called a hierarchal regression analysis, which helps to provide incremental findings. As SmartPLS software can handle effectively this type of analysis, it was utilized to analyze the data.

Under subjective experience (Table 3.6), PLS results of model 1 indicate that all of the performance expectancy, effort expectancy, and social influence affect behavioral intention significantly and positively. Facilitating conditions affect significantly but negatively MB actual use only. Behavioral intention and subjective experience seem to influence MB actual use significantly and positively.

Table 3.6. Hypotheses Testing (Subjective Experience)

Path	Estimate	t-statistics	Remark
Model 1			

PE → BI	0.478	8.114**	Supported
EE → BI	0.262	3.805**	Supported
SI → BI	0.115	3.131**	Supported
FC → BI	0.048	0.948	Not supported
FC → Actual Use	-0.116	1.971*	Supported[a]
BI → Actual Use	0.414	7.857**	Supported
Experience → Actual Use	0.145	3.291**	Supported
Model 2 (with interaction effect)			
PE → BI	0.476	7.775**	Supported
EE → BI	0.262	3.640**	Supported
SI → BI	0.114	3.015**	Supported
FC → BI	0.052	0.920	Not supported
FC → Actual Use	-0.119	2.078*	Supported[b]
BI → Actual Use	0.444	9.951**	Supported
Experience → Actual Use	0.135	3.120**	Supported
Experience*BI → Actual Use	0.093	2.046*	Supported
** $p < 0.01$ Variance explained in BI = 60.9% * $p < 0.05$ Variance explained in Actual use = 20.1% [a, b]: this relationship is significant but with a contrary direction to the hypothesis.			

For the interaction effect, PLS results of model 2 confirm that subjective experience moderates significantly the relationship between behavioral intention and MB actual use as proposed. This means that with more experience, the impact of behavioral intention will be greater on actual use. It is noted that all significant relationships in model 1 appear to be significant in model 2. While the amount of the total explained variance accounted by the predictors on behavioral intention is about 61% and on actual use is about 20%. For a better visualization, the below model depicts all examined relationships under subjective experience

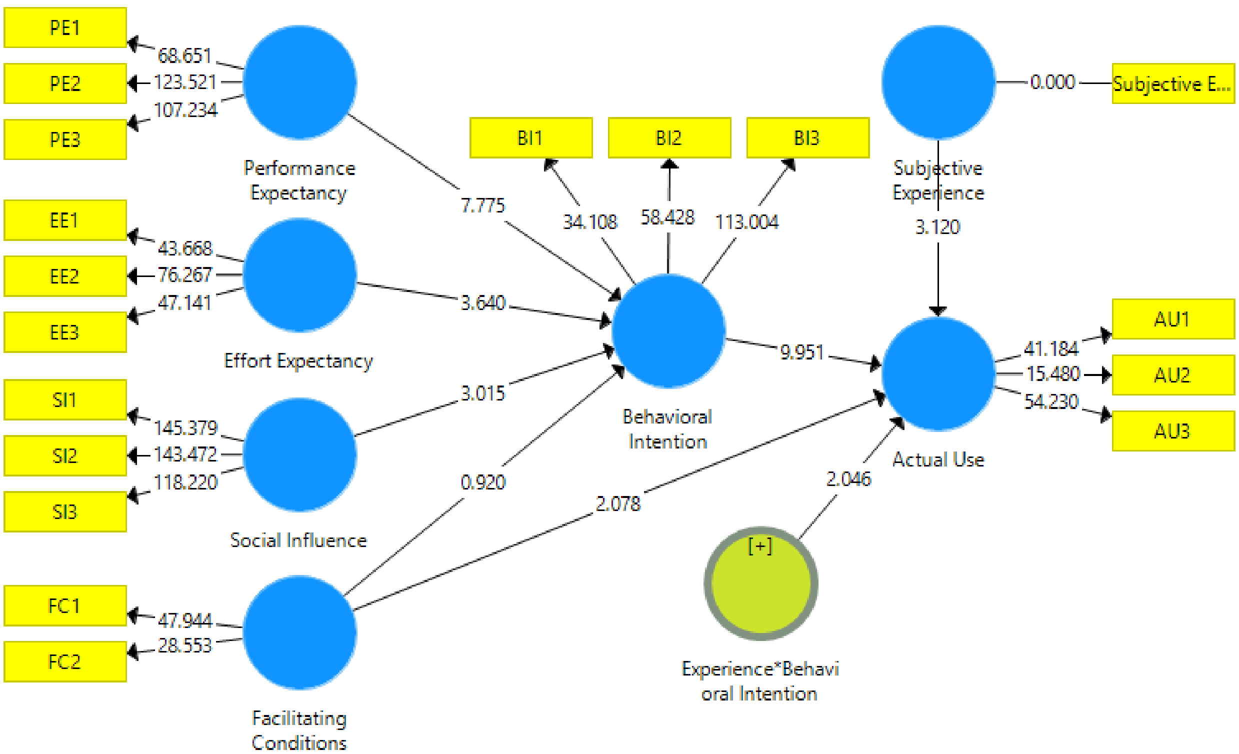

Figure 3.3. SEM Results with Subjective Experience

When considering objective experience (Table 3.7), the results of model 1 indicate that the first three pillars of UTAUT still appear to be significant while the fourth pillar (facilitating conditions) appears not. Behavioral intention keeps its positive significance. Opposed to subjective experience, objective experience shows to have no effect on actual use.

Table 3.7. Hypotheses Testing (Objective Experience)

Path	Estimate	t-statistics	Remark
		Model 1	
PE → BI	0.479	7.954**	Supported
EE → BI	0.261	3.667**	Supported
SI → BI	0.115	3.109 **	Supported
FC → BI	0.051	0.933	Not supported

FC → Actual Use	-0.111	1.812	Not supported
BI → Actual Use	0.447	8.608**	Supported
Experience → Actual Use	0.019	0.403	Not supported
Model 2 (with interaction effect)			
PE → BI	0.479	8.199**	Supported
EE → BI	0.260	3.742**	Supported
SI → BI	0.115	3.166**	Supported
FC → BI	0.051	0.909	Not supported
FC → Actual Use	-0.133	2.383*	Supported[a]
BI → Actual Use	0.507	11.937**	Supported
Experience → Actual Use	0.009	0.150	Not supported
Experience*BI → Actual Use	0.150	2.583*	Supported

** $p < 0.01$ Variance explained in BI = 61%
* $p < 0.05$ Variance explained in Actual use = 19.5%
[a]: this relationship is significant but with a contrary direction to the hypothesis.

For the interaction effect, PLS results of model 2 indicate that there is no change for the significant factors in model 1 expect for facilitating conditions. The moderator of objective experience shows a positive impact on actual use, consistent with the moderator of subjective experience. The amount of the total explained variance accounted by the predictors is quite the same for both behavioral intention and actual use as in Table 3.6. It is noted that subjective experience surprisingly shows a low correlation with objective experience; 0.465. For a better visualization, the below model depicts all examined relationships under objective experience.

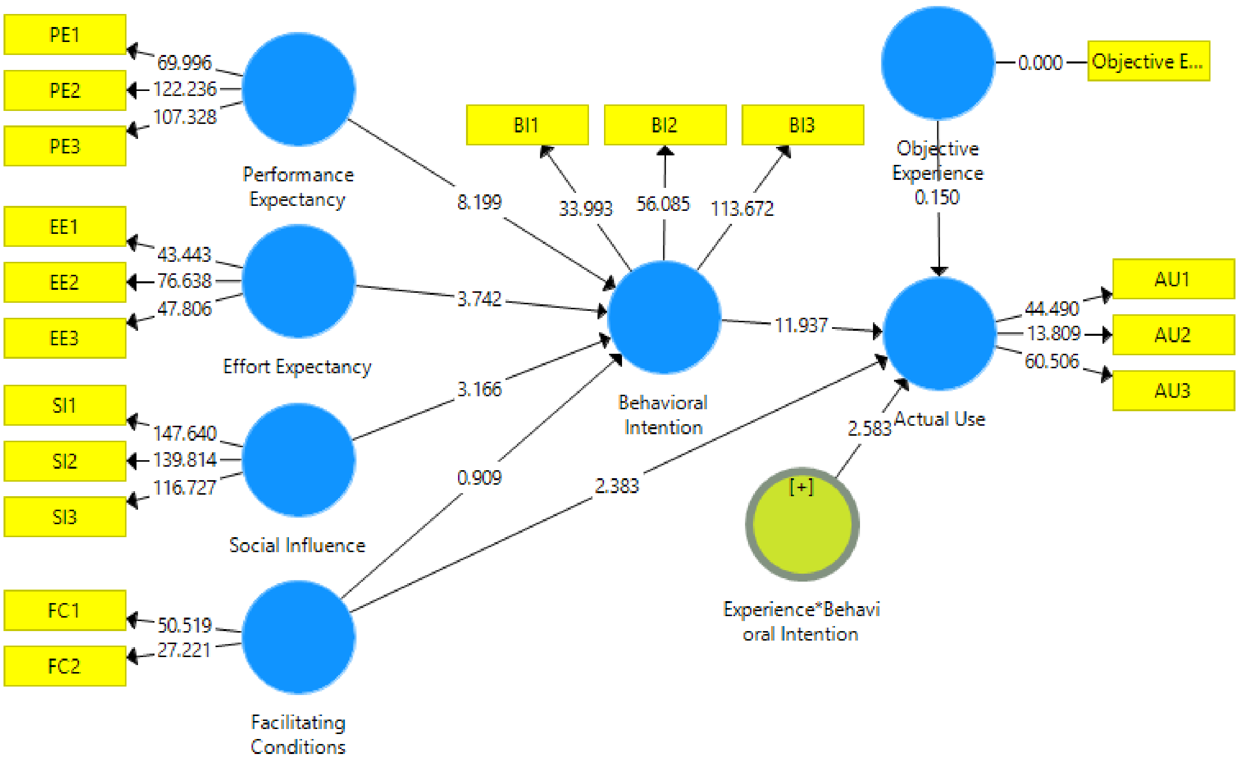

Figure 3.4. SEM Results with Objective Experience

3.6.2. NN results

Weka software had been used to build the NN model using MLP algorithm. To avoid the model overfitting, the significant determinants revealed by SEM-PLS were used as input variables in the input layer of NN, namely performance expectancy, effort expectancy, and social influence. While behavioral intention was used as an output variable in the output layer.

We split the data into two sets: 66.67% (n = 315) for training and 33.33% (n = 157) for testing. Root mean squared error (RMSE) for the training model was 0.694, while for testing model was 0.661. Since the RMSE gap between the training and testing model is small, the network model is reliable enough to capture the relationship between the input and output variables. Sensitivity analysis was conducted on the normalized variables to help revealing the relative importance for the model's factors and their respective indicators (Table 3.8 and Table 3.9). On the variable-level, performance expectancy was found to be the most important factor in predicting customer's intention to use MB, followed by effort expectancy but social influence was not that significant in this regard. While on the indicator-level, it appears that individuals are mostly concerned to what extent MB provides dynamic and responsiveness services, which make them more effective to accessing it. On the contrary, they are least concerned to what extent MB is easy to interact with and use.

Table 3.8. The Importance Ranking for Normalized Variables

Variable	**Relative Importance**
Performance Expectancy	1.00
Effort Expectancy	0.57
Social Influence	0.00

Table 3.9. The Importance Ranking for Normalized Indictors

Indicator	**Relative Importance**
PE3: Effectiveness in accessing MB services	1.00
SI2: People important to me recommend using MB	0.61
SI3: People in my social circle recommend using MB	0.49
EE3: Easy to become skillful at using MB	0.35
SI1: People influencing my behavior recommend using MB	0.33
EE2: Easy to learn using MB	0.26
PE2: Easy access to MB services	0.19
PE1: Quick access for MB	0.12
EE1: Easy to interact with MB	0.00

3.6.2. USM results

We extend our analysis by conducting USM to show the existence of hidden structures in the structural model. USM technique reveals both linear and nonlinear relationships but as the linear relationships are already presented in SEM results, we only highlight the nonlinear relationships in USM as the following figures show.

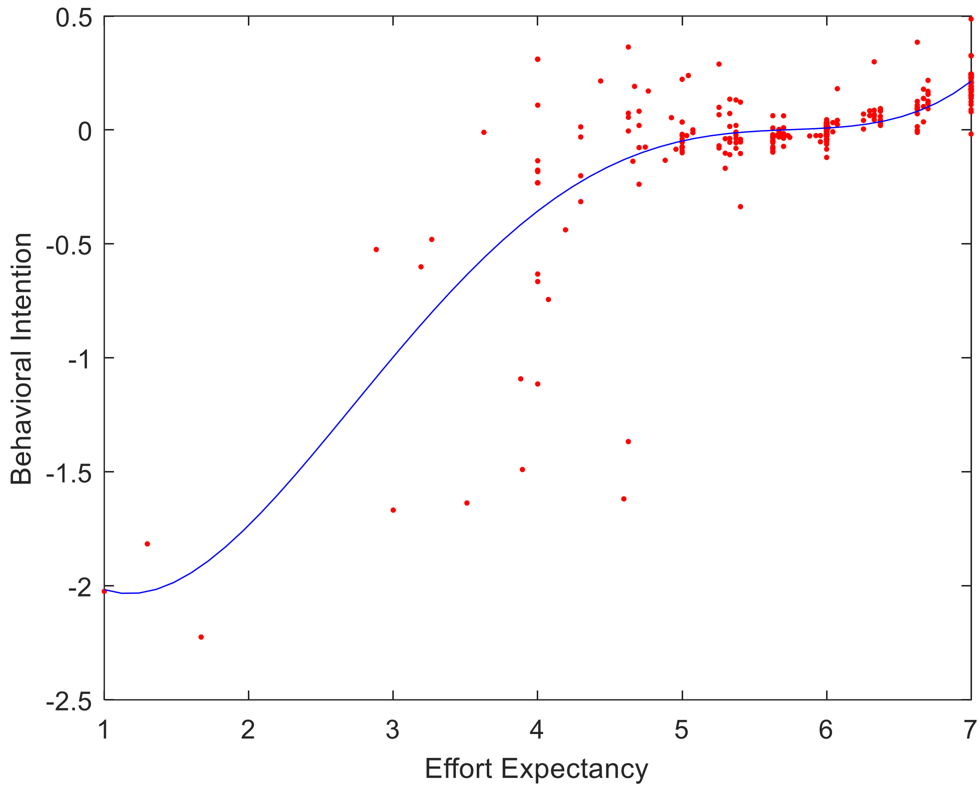

Figure 3.5. Nonlinearity between EE and BI

Figure 3.5 depicts the first nonlinear relationship that occurs between effort expectancy and behavioral intention. This figure shows that effort expectancy increases progressively with behavioral intention but after its average point, there is no much increase in behavioral intention. In other words, the increase in lower effort expectancy has more positive impact on behavioral intention.

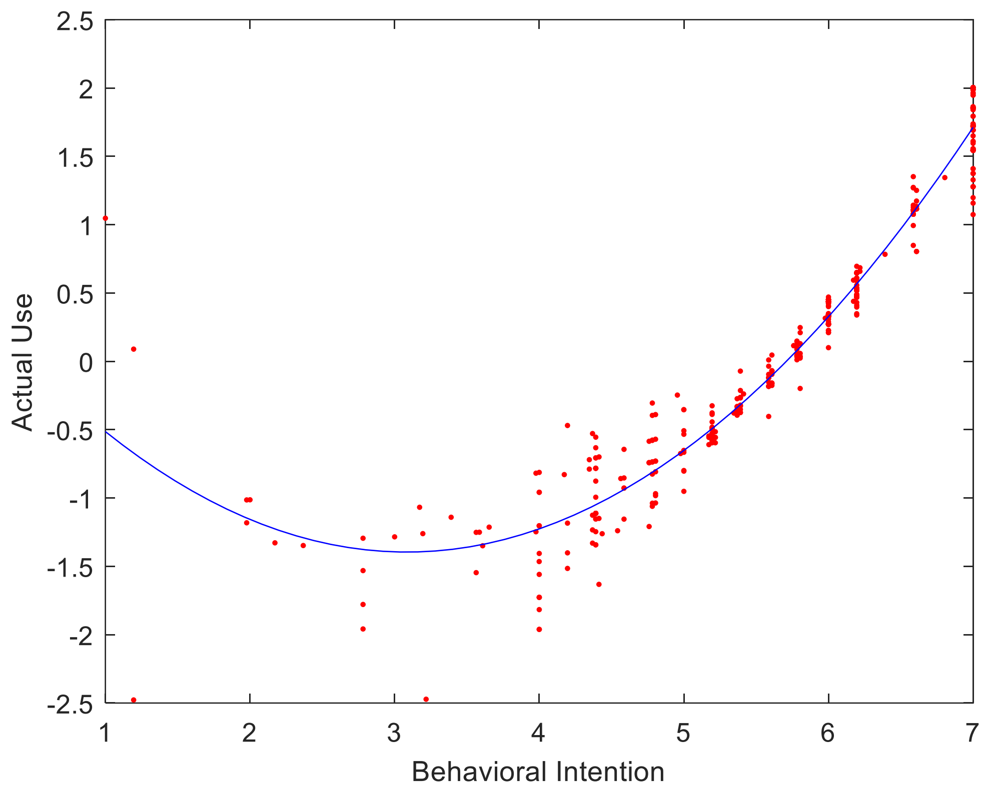

Figure 3.6. Nonlinearity between BI and Actual Use

Figure 3.6. depicts the second nonlinear relationship that occurs between behavioral intention and actual use. This figure shows that behavioral intention starts with a slight decrease then goes for a progressive increase forming a U-shape with actual use. In other words, the increase in the higher values of behavioral intention has more positive impact on actual use.

Figure 3.7 below depicts the nonlinear interaction effect of self-reported experience and behavioral intention on actual use. This moderating relationship is quite progressive even though it starts with a straight line. It indicates when lower values of experience interact with lower values of behavioral intention, it does not lead to any effect on actual use. On the contrary, when higher values of experience interact with higher values of behavioral intention, it can lead to a huge positive effect on actual use, confirming our hypothesis with increasing experience, the positive impact of behavioral intention becomes higher on actual use.

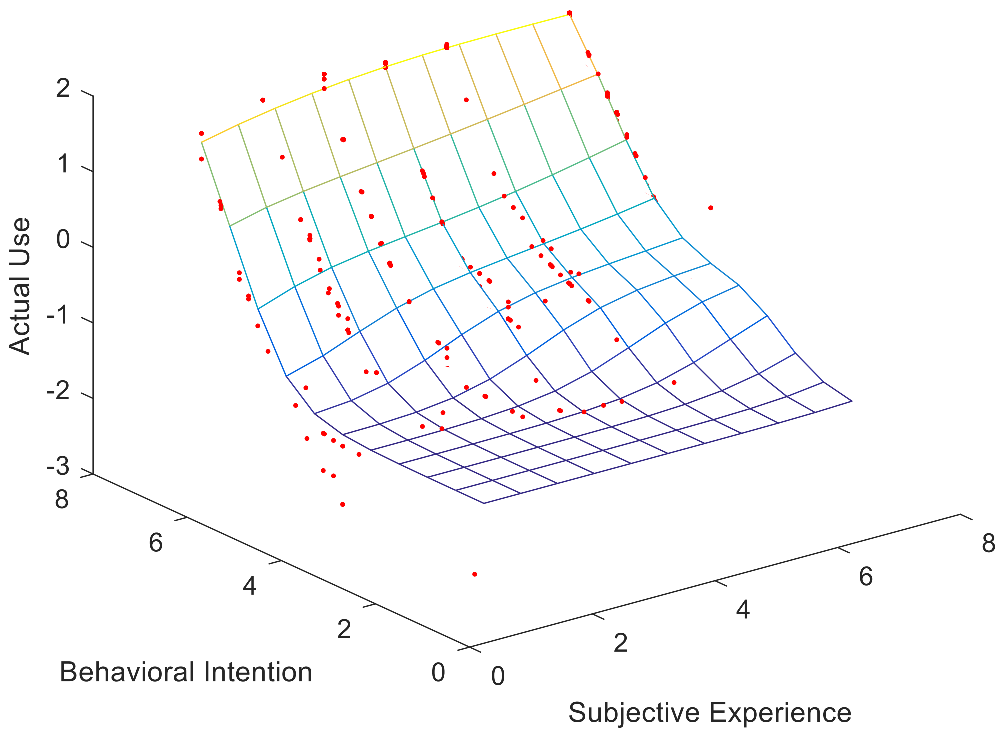

Figure 3.7. Nonlinearity in Interaction Effect of Experience and BI on Actual Use

Interestingly, USM reveals some nonlinear unhypothesized moderating effects, for example, the interaction effect of effort expectancy, social influence, and facilitating conditions with performance expectancy depicted below in figure 3.8, 3.9, and 3.10. The below figures suggest increasing effort expectancy, social influence, and facilitating conditions would lead to a greater nonlinear relationship between performance expectancy and behavioral intention.

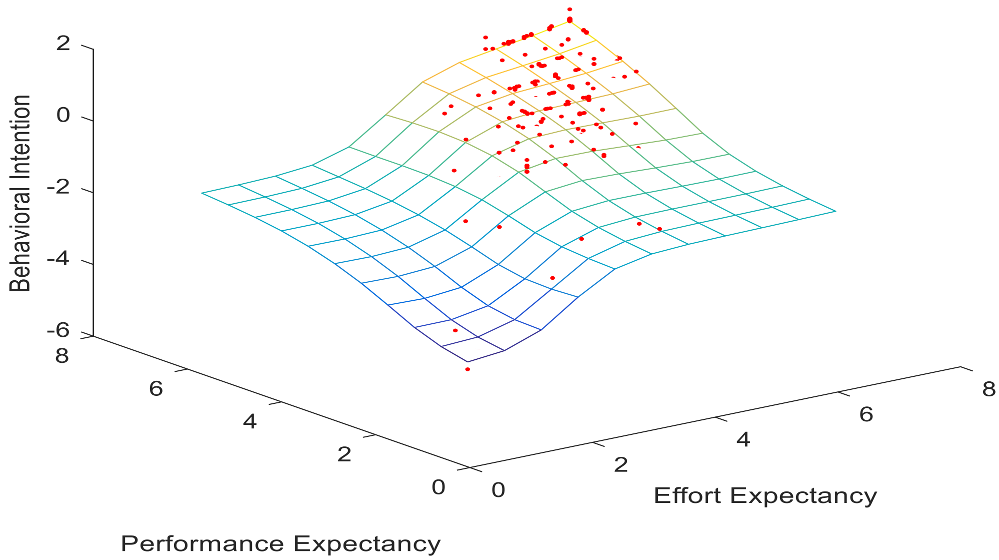

Figure 3.8. Nonlinearity in Interaction Effect of EE and PE on BI

Figure 3.9. Nonlinearity in Interaction Effect of SI and PE on BI

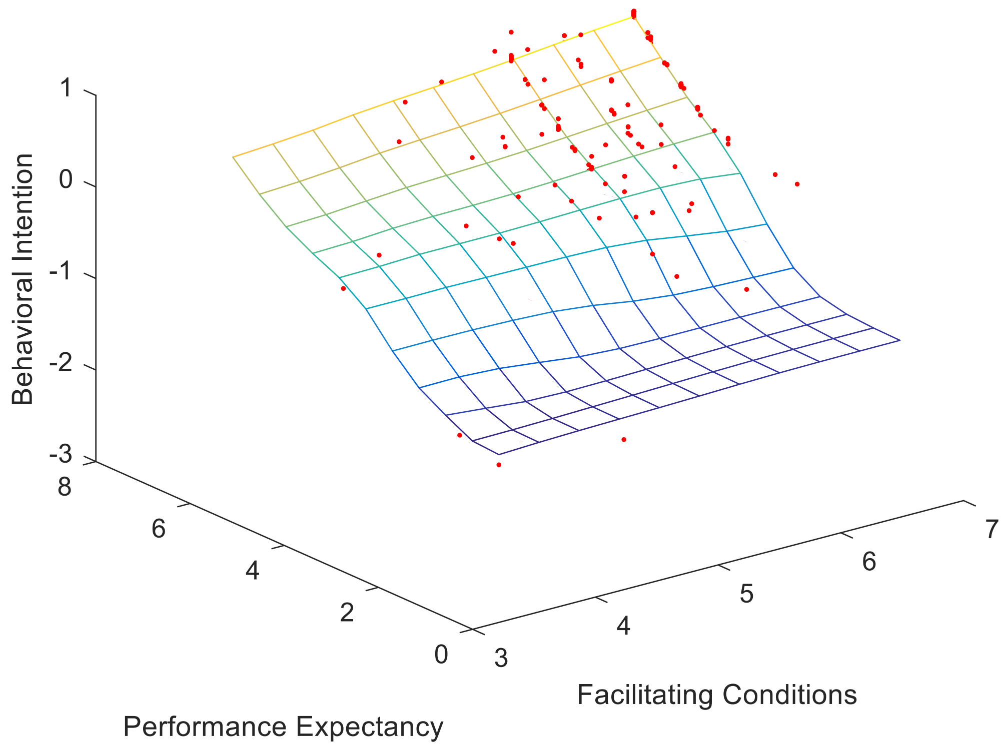

Figure 3.10. Nonlinearity in Interaction Effect of PE and FC on BI

Lastly, it is important to mention that USM shows approximately the same amount of explained variance for behavioral intention as PLS but shows higher explained variance for actual use (39%). This leads us to believe that USM has a better analytics power than PLS.

3.7. Discussion

The first three pillars of UTAUT (performance expectancy, effort expectancy, and social influence) appears to be significant and hence consistent with previous research (Yu, 2012; Zhou et al., 2010). While facilitating conditions have a significant impact on MB actual use only as supported in Baptista and Oliveira (2015). Subjective experience and behavioral intention, on the other hand, determine actual use positively. These significant relationships are consistent with prior research (Lee and Kim; Baptista and Oliveira, 2015). Taking a close look at the data may illustrate the effect of experience and MB usage. It appears that most of our survey participants are elder people who pay attention to their usage level. Hence, those people are experienced with a high intention to use and they consider themselves on an increasing curve of MB usage.

Experience as moderator, as proposed, is positively significant and confirmed in the literature (Venkatesh et al., 2008), meaning that with more experience, the impact of behavioral intention will be greater on actual use. Further interpretation of this finding may be stated as with increasing experience, the routine behavior is enhanced and becoming more automatic like a habit, which may help in sustaining or increasing the level of actual use (Venkatesh et al., 2012) due to the customers' high attention towards their MB.

However, the results unveiled by NN suggest that performance expectancy should be addressed first. While effort expectancy should be addressed second, its nonlinear relationship with behavioral intention has to be considered, meaning that enhancing effort expectancy will not always lead to a high increase of MB adoption among bank customers. Also, both behavioral intention; a direct effect, and experience; a moderating effect, are related nonlinearly to actual use. These several nonlinear relationships confirm our argument about the complexity existed in adopting IT innovations.

3.8. Implications for Theory and Practice

The results of the two models with regards to subjective and objective experience and their impact on actual system use are not all consistent. This could be attributed to that subjective experience does not highly correlate with objective experience. In other words, customers appear to overestimate their usage experience as the survey shows but system log data reflects underestimation, instead. According to this, the self-reported experience may be questioned and called for more validated measures. The existing conceptualization used for experience has been measured as the passage of time in months (Venkatesh et al., 2012; Prasanna and Huggins 2016). Such time unit may make customers overestimate their usage as what happened in our case. This can lead to less accurate inputs and accordingly not very valid results. One potential way to address that is to measure experience in less granular time unit like weeks. Such smaller time unit may help to reduce the bias in the self-reported experience. This inference is not conclusive and has to be verified by future IS research. For example, capturing experience with different time units (i.e., months and weeks) regarding the usage of a specific information technology in future studies would help to compare and inform more about the validity of each measure. This could overcome the limitation found and establish a more robust measure for experience. However, USM provides another theoretical implication through disclosing unhypothesized interaction effects. By doing so, this technique can expand the theoretical boundaries of UTAUT by detecting that effort expectancy, social influence, and facilitating conditions can moderate the relationship between performance expectancy and MB behavioral intention. Such moderating relationships can motivate scholars to investigate them further and evaluate those linkages with different IT innovations. Hence, USM does not only reveal the hidden nonlinearity structures but also can be effectively employed for theory development.

In practical side, our findings could help many banking institutions to base their forthcoming MB strategies on more improved services that can affect positively customers' usage behavior. The economic challenges nowadays make it necessary that banks use the available limited resources deliberately and wisely. Hence, banks should consider any option that may lower the improvement cost for MB services but do not affect the quality of those services. This can be accomplished through our multi-analytical approach that ranks the significant factors influencing MB behavioral intention and shows the fluctuating structures in those factors.

For the importance ranking, the variable-level analysis indicates that performance expectancy is the most significant factor and thus needs to be considered first by financial institutions. In other words, banks should start to enhance the MB aspects to make their customers feel more productive and effective, for example, offering a single authentication mechanism (a touch ID) for a quick access to balance check. The next factor for banks to improve, as suggested by NN, is effort expectancy, meaning that although MB is a friendly-to-use app, it needs to be even less complex and more intuitive. For instance, paying bill is a multi-process service and may be perceived a bit complicated by customers, hence, it should be facilitated by one-click process. The third factor for banks to improve is social influence. This means banks should work on transforming their customers into informal marketing agents to assist in increasing MB adoption rate by, for example, a word-of-mouth strategy.

However, it is important to obtain a deeper comprehension by identifying which specific items have the most weight and significance regardless of their aggregated factors. Therefore, we extend our analysis to indicator-level enabling us to access more accurate knowledge on where the bank resources should be directed first. As indicated by NN, effectiveness to access MB services appears to be the most important indicator in need for improvement, which is consistent with the variable-level analysis. But the second and third indicators for banks to improve on are the attempt to have a huge positive impact on their customers in regards to MB so that they would carry this impact to people important to them as a recommendation and affect positively their decision towards adopting MB. We are a little surprised to know that the least important indicator for banks to consider is promoting the easiness part of MB system but this could be attributed to that MB is already designed as an easy-to-use-and-navigate app.

The third practical layer of analysis provided by USM would advise when to stop improving a specific factor since it can detect the hidden nonlinear relationships in the structural model. For instance, enhancing the easy interaction of embedded MB services will lead to significantly increasing customers' behavioral intention to use MB but not always. This means there is a turning point in which the enhancement of effort expectancy should be paused and the capitals should be diverted to improving another factor, like social influence. In sum, banks and software vendors can integrate the provided insights into their MB design and refinement process. This would help them to utilize efficiently their available resources for increasing the level of satisfaction and loyalty among their MB customers and thus enhancing the retention rate.

3.9. Contribution and Conclusion

This study discloses a number of theoretical and practical contributions. First, studying the impact of experience on MB usage can enable more understanding of this technology. For example, customers with higher experience show sustained attention to their usage behavior towards MB because they may develop a cognitive lock-in. This cognitive lock-in could be transformed into a habit. As a result, with a little effort, those customers can be easily converted into loyal. Second, it is valuable to measure experience using self-reported data and computer-recorded data. This helps to validate both impact and correlation; which in turn enable us to benchmark experience with prior IS research and advise for a remedy by adjusting its conceptualization and measure. Third, as USM provides an evidence of detecting un-proposed theoretical relationships in the structural model, it gives us an insightful view in which direction UTAUT can be expanded for increasing its prediction power. From a methodological perspective, the study contributes to MB research by developing a triangular (SEM-NN-USM) approach, which enables a deeper analysis and understanding of MB usage. This approach does not only rely on providing significant relationships between factors but also finding the relationships that most matter to MB users. Additionally, it discloses the hidden structures of nonlinearity. As a result, banks and software vendors would be able to rank the influential factors on MB usage from the most important to the least important and to allocate their resources in more advantageous way for addressing the most-needed areas.

Overall, this study can extend prior research by exploring the universal impact of experience subjectively and objectively on MB usage via a multi-analytical approach. It also can lend opportunities for future research. For example, since customers can be segmented by age: young, middle-aged, and senior; or gender or another demographic variable, scholars can employ this triangular (SEM-NN-USM) method to reveal the nonlinear most influential factors on those various segmentations of customers and accordingly assist practitioners to prioritize and coordinate their managerial actions for refining MB services on each segment.

Chapter 4. Second Paper: When IS Success Model Meets UTAUT in a Mobile Banking Context: A Study of Subjective and Objective System Usage

This chapter presents the second research paper that merges between subjective and objective system usage and proposes a novel integrative framework for MB system usage.

4.1. Introduction

Mobile banking (MB) has been considered as an important source of revenue and a point of differentiation, thus, it becomes a strategic technology in the banking industry (Marous, 2013). MB provides access to various banking services including view account balance, transfer funds between accounts, pay bills, receive account alerts, locate ATMs, P2P transfer, and deposit checks via a mobile device. This emerging technology has been adopted on a large scale among different segments of customers due to the growing use of smartphones. Smartphone's penetration rate has increased from 66.8% in 2014 to 75.8% in 2015 across the United States (Crowe et al., 2015). However, retaining existing customers and attracting new ones will require banks to deliberately study their behaviors and to obtain a deeper understanding of their needs, concerns, and expectations of MB services (Wannemacher et al., 2015). This can be grasped by evaluating customers' satisfaction rather behavioral intention towards MB since the former could be more appropriate dependent variable in use environment (Brown et al., 2008). Hence, we examine the factors that may influence their satisfaction and MB usage to know the state of customers' demand. Driven by theoretical IS adoption models, factors such as performance expectancy, social influence, and facilitating conditions (three pillars of the unified theory of acceptance and use of technology (UTAUT)) and as system quality, service quality, and information quality (three pillars of IS Success model) have been highlighted as significant predictors to customer satisfaction in literature (Baptista and Oliveira, 2015; DeLone and McLean, 2003; Venkatesh et al., 2003; Chan et al., 2010), and accordingly considered in our study.

IS researchers have used various IT acceptance models, particularly technology acceptance model (TAM), to measure behavioral intention more frequently than to measure actual system use (Turner et al., 2010). Behavioral intention reveals the state that a person is willing to use, however, it is more important to look beyond the willing and intention stage to the actual use of the system (Petter et al., 2013). Actual use reflects the real act of engagement and involvement with IS/IT application, which is a key to determine the success of information system and provides a better indication of user satisfaction (DeLone and McLean, 2003). In support of this view, Wu and Du (2012) call to shift the focus of future studies to actual system use instead of behavioral intention but their call have been overlooked in IS research. Hence, the first goal of this study is to further investigate this lacking topic in IS literature.

While the existing few research examining actual system use has mostly employed self-reported data. One big concern associated with self-reported studies, besides validity threat, is the potential bias generated from overestimating or underestimating the perceived system usage (Collopy, 1996). Therefore, relying only on self-reported data can lead to misleading conclusions (de Reuver and Bouwman, 2015). One way to reduce self-reported bias when measuring system usage is to shift from subjective measurement (survey data) to objective measurement (system log data). Objective system measurement can capture the richness of the system usage, which includes intensity and appropriateness of use, besides usage frequency and duration (Delone and McLean, 2003). In spite of its significance, attention to objective measurement of system usage has faded in the IS domain, especially since 2011 and hardly ever applied in the context of mobile innovation usage (Walldén et al., 2015). This motivates us, our second goal, to examine both the subjective and objective usage measures in MB and enrich literature by making a discursive case of comparing this measure with prior research on system usage.

Both IS Success and UTAUT have been widely used and validated across different contexts including measuring the usage of mobile technologies (Chatterjee et al., 2009; Lee and Chung, 2009; Chung and Kwon, 2009; Zhou, 2013; Baptista and Oliveira, 2015). IS Success model is developed to measure satisfaction and system usage by observing the impact of system quality, service quality and information quality (DeLone and McLean, 2003) while UTAUT is developed by synthesizing previous IS adoption models providing four fundamental factors: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Yet, research remains sparse on integrating both models for more holistic view and higher explanatory power to satisfaction and actual system use. Within the MB context, we have not found any IS adoption study that has integrated both models. There have been two studies in another context that have combined these two models. The first study suggests IS Success's factors to be antecedents of UTAUT2's factors to examine the adoption of public services (Molnar et al., 2013). The second study suggests to partially combine TAM, IS Success, and UTAUT to examine IT behavioral intention (Mardiana et al., 2015). Besides the different context and different outcome variable used, both studies lack an empirical setting to validate such integration, which hampers their actual contribution and thus requires further investigation. This brings us to our third goal, that is to combine these two proven IS adoption models to provide a deeper comprehension of MB user satisfaction and use. Our integrative framework can bring new insights and understanding to MB research because each model predicts usage from a different perspective. IS Success model focuses on the impact of inner system qualities like, to name a few, reliability, attractiveness, personalization, and information relevance. On the other hand, UTAUT focuses on the impact of outer factors on the system acceptance like cost efficiency, community influence, and necessary resources. It is important to mention that IS Success's system quality overlaps with UTAUT's effort expectancy in capturing the easiness part of the system. Thus, we have excluded effort expectancy and kept system quality because the latter measures attractiveness and responsiveness of the system besides easiness. In short, the constructs of IS Success model could be considered system-oriented factors while the constructs of UTAUT could be considered non-system-oriented factors that can affect user satisfaction and system usage. Hence, we believe both models are complementary and therefore would provide a comprehensive theoretical grounding for predicting MB system usage.

Our fourth goal of this study is to look beyond MB usage into the level of sustained satisfaction, which reflects to what degree MB users are loyal. Loyalty implies long and even lasting relationships between banks and their customers, which is very essential in the today high-competing environment. And as loyalty is a significant indicator of customer retention (Lee et al., 2015), it would be necessary to study the relevant factors affecting it. Thus, loyalty is added to the model of our research study.

This study, in brief, contributes to theory and practice by introducing a holistic framework that incorporates internal and external factors affecting subjective and objective system use. Exploring such framework would help to reveal its theoretical value to study MB system usage. Second is to communicate the significant results on both dimensions of importance and performance to help professionals in coordinating their deliberate actions on improving the embedded services and promoting a higher MB usage. The rest of the paper reviews the previous works in UTAUT and IS Success models, compares objective versus subjective system usage, develops our conceptual framework and a set of hypotheses, presents our findings, discusses their implications and finally concludes with our study's contributions and conclusion.

4.2. An Integrative Framework: IS Success and UTAUT

Both IS Success and UTAUT are primarily used to measure IS acceptance at an individual level. In particular, both models have been employed to understand mobile user behaviors.

Chatterjee et al. (2009) applied the three quality pillars of IS Success to examine mobile work in healthcare. Kim et al. (2009) adapted IS Success model, too, to examine the ubiquitous computing use while Zhou et al. (2010) and Baptista and Oliveira (2015) utilized UTAUT to investigate mobile banking adoption among smartphone users. There has been an evidence in the above studies that the standalone models of IS Success and UTAUT lack to provide a pronounced explanatory power, hence, it would be necessary to consider a deliberate approach that would augment such power, for example integrating well-established acceptance models.

From another side, Venkatesh et al. (2003 and 2012) emphasized how important to integrate UTAUT with other models, particularly in consumer context in order to expand its theoretical boundaries and to gain a greater cognitive understanding of system usage behavior. Driven by this perceptive, we integrate UTAUT with IS Success model and argue about the integration authenticity in mobile research. First, IS Success model, as IS acceptance model, addresses technical, semantic and service success within the system (DeLone and McLean, 2003). These three factors are more related to what inside the system, for example, providing an attractive interface, personalized services, and relevant information. On the contrary, UTAUT, as IS acceptance model, addresses to what extent MB can reduce the time to conduct a banking transaction, to what extent MB is influenced by surrounding community, and to what extent MB is facilitated by the necessary resources of, for example, a help desk (Zhou, 2003). These three factors are more related to what outside the system. Hence, it can be stated that IS Success model focuses more on factors internal to the system while UTAUT focuses more on factors external to the system. Second, it is vital to evaluate whether this integration can provide a solid theoretical foundation for examining MB usage considering that UTAUT accounts for 70% of the variance in the outcome variable (Venkatesh et al., 2003) while IS Success accounts for about 36% of the variance (Zhou, 2014). Both models have a different underlying nature and focus, which makes their integration plausible for higher variance and explanation.

In sum, since mobile research has assessed the state of knowledge in this area by employing standalone models resulting in low prediction power, it is important to shift our theoretical base model into more comprehensive framework by combining contributions of acceptance models. Aligned with Venkatesh et al.'s (2003) goal of developing UTAUT for a greater variance, our integrative model would allow moving towards a deeper understating of this phenomenon.

4.3. Objective and Subjective System Usage

System usage, which represents the success of information systems, is defined as to what extent system capabilities are utilized by customers (Petter et al., 2013). Prior research on actual system use has been abundantly investigated by estimating the system usage via self-reported data. In the past 19 years, few studies have explored objective system usage across different IT innovations through measuring usage via computer-recorded data.

Straub et al. (1995) measured the usage of a voice mail system objectively through computer-recorded data and subjectively through self-reported data using TAM with the purpose of addressing conceptual and methodological issues associated with system usage measurement. Szajna (1996), similar to Straub et al. (1995), highlighted the issues between self-reported and computer-recorded data through measuring the usage of an electronic mail system. The period ranging from 2000 to 2003 can be considered as the golden era for objective system measurement because of the ample published studies (Walldén et al., 2015). For example, Horton et al. (2001) investigated the acceptance of intranet system by employing questionnaire and capturing system log data. Venkatesh et al. (2003) compared a number of IT acceptance models to develop UTAUT through subjective and objective measurement of system usage. Stoel and Lee (2003) utilized TAM to measure the learning system (WebCT) usage objectively via the number of pages visited in WebCT and subjectively via the duration and frequency of use.

Although the period between 2004 and 2011 has been characterized by a low publishing rate of objective system measurement studies, the focus was on web-based systems. For example, Klein (2007) adapted theory of reasoned action (TRA) to measure the objective usage of web-based patient–physician communication application via capturing the number of e-mails sent. The focus, however, has shifted to be more on e-learning systems since 2011 till present (Walldén et al., 2015). Ma and Yuen (2011) applied UTAUT to predict the usage of e-learning system in a university setting by the help of system log. Joo et al. (2014) used the access frequency to objectively measure the usage of a mobile learning system among students from South-Korean online university. In spite of the fact that objective measure for system usage is more superior than subjective measure (Straub et al., 1995), there has been a shortage to employ such measure in IS literature. Hence, this study will contribute to reducing this gap and developing a comparative case with previous studies of system usage.

4.4. Research Model and Hypotheses Development

The two acceptance models of IS Success and UTAUT have been adapted to help in measuring MB usage subjectively and objectively via survey and computer-recorded data, respectively. IS Success model has the capability to determine satisfaction and system use of IT innovations (Delone and McLean, 2003) based on its three quality factors. UTAUT, too, can predict system use (Venkatesh et al., 2003). Both models have been applied to measure adoption of various information systems, hence, they exhibit a high generalizability (Chen et al., 2010 and Zhou, 2013). According to our above argument of providing a comprehensive theoretical perspective, IS Success (factors internal to the system) and UTAUT (factors external to the system) are complementary and accordingly integrated. Figure 4.1 visualizes our integrative framework.

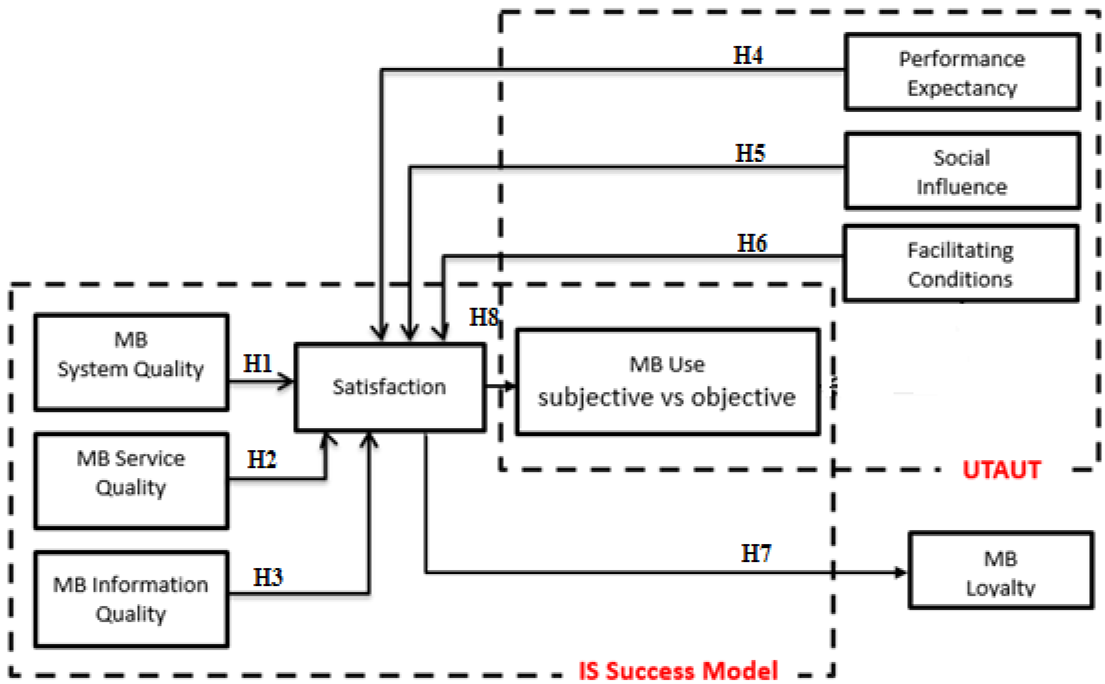

Figure 4.1. Conceptual Framework

4.4.1. MB system quality (TQ)

System quality refers to what extent MB systems are visually appealing and easy to use and navigate (Zhou, 2013). This quality is also manifested in the easy access of trustworthy services. System reliability and flexibility with attractive interface can be crucial to promote MB services and thus could affect customers' satisfaction level. It is evident that improving the overall system performance besides usability and integration, which reflects the core features of system quality, can lead to have satisfied customers (Teo et al., 2008). In other words, better system quality yields higher customer satisfaction. Literature empirically validates this relationship across different IT applications, for example, in mobile payment (Zhou, 2013), electronic service (Xu et al., 2013), and e-government system (Teo et al., 2008). Since MB shares a number of similarities with the mentioned information systems, we suggest that:

H1: *MB system quality will influence positively customer satisfaction.*

4.4.2. MB service quality (SQ)

Service quality refers to what extent MB provides reliable, timely, responsive, and personalized services (Zhou, 2013). Service quality has not only been viewed as a critical element of traditional customer service channels like face-to-face interaction, but also its role is extended to online channels like MB. Over the past 20 years, the dimensions of assurance, reliability, empathy, responsiveness, infrastructure, and/or appearance have emerged to shape service quality (Xu et al., 2013). Most MB innovations are associated with such dimensions and thus influencing customer satisfaction positively. Prior IS research confirms that high service quality can predict customer satisfaction on the empirical plane (Cenfetelli, 2008; Xu et al., 2013). This relationship is also supported in the context of mobile technology (Zhou, 2013). Therefore, we suggest that:

H2: *MB service quality will influence positively customer satisfaction.*

4.4.3. MB information quality (IQ)

Information quality refers to what extent MB provides sufficient, relevant, accurate, and timely information (Zhou, 2013). As customers may struggle to find their banking information because of the small screen size, how information is organized and presented in MB can influence their level of satisfaction. Also, when customers perceive that MB services meet their needs by providing up-to-date, precise, and above all pertinent information, they would tend to be satisfied. An empirical support has been found to relate information quality and customer satisfaction in a context of electronic service (Xu et al., 2013). As MB is an electronic service in its core, we suggest that:

H3: *MB information quality will influence positively customer satisfaction.*

4.4.4. Performance expectancy (PE)

Performance expectancy is defined by Venkatesh et al. (2003: p. 447) as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance". Simply put, performance expectancy indicates maximizing efficiency and productivity. Hence, customers who feel that MB app can offer efficient, effective, and quick-to-access services will tend to be pleased towards using it. Since performance expectancy had been developed from TAM's perceived usefulness (Venkatesh et al., 2003), it is considered as a key element to user satisfaction (Chan et al., 2010). Several studies suggested that performance expectancy is related to positive attitude and satisfaction, for example, in mobile internet services (Thong et al., 2006) and in banking information system (Brown et al., 2008). Therefore, we hypothesize that:

H4: *Performance expectancy will positively influence customer satisfaction for using MB.*

4.4.5. Social influence (SI)

Social influence refers to what extent a person feels that a MB technology should be used by his/her social network (Miltgen et al., 2013). People normally share their positive and negative experience of using technological innovations with others. This is more manifested in the younger generation (Miltgen et al., 2013). Individuals may show levels of commitment and satisfaction towards MB when it is being accepted and recommended by their social network that includes family members, friends, and coworkers. Chan et al. (2010) suggested that a positive attitude can be affected by the influence of the social circle. Since satisfaction is basically a positive attitude being formed over a course of time of dealing with MB services (Kim et al. 2009), we suggest that:

H5: *Social influence will positively influence customer satisfaction for using MB.*

4.4.6. Facilitating conditions (FC)

Facilitating conditions show to what extent a person perceives that the use of MB system is supported with organizational and technical infrastructure (Miltgen et al., 2013). Facilitating conditions for technological innovations, which include but not limited to help-desk support, peer support, and sufficient knowledge, can provide a strong foundation to both positive feeling and system usage. For example, when individuals are armed with the necessary resources for using MB and with a responsive assistance team, they may feel MB is highly reliable and thus would be more satisfied towards using it. A causal link between facilitating conditions and satisfaction is empirically validated in prior research in the contexts of e-government services (Chan et al., 2010) and mobile banking (Baptista and Oliveira, 2015), thus, we suggest that:

H6: *Facilitating conditions will positively influence customer satisfaction for using MB.*

4.4.7. Satisfaction (SAT), loyalty (LY), and actual use (AU)

Satisfaction reflects the affective reaction that individuals have when interacting with MB services (Cenfetelli, 2008). Satisfaction has been widely proposed as one of the most IS metric for both behavioral intention and actual system use (Delone and McLean, 2003). When banks sustain the satisfaction level among MB users, this may help to sustain the level of MB usage.

Additionally, it is most likely that individuals who have an enjoyable and pleasant experience with MB, they will develop a positive attitude and become more loyal toward using it.

Rationally speaking, users who feel they are being well-served will show a greater level of satisfaction towards MB, which in turn leads to building up their loyalty besides encouraging them to actually using it. The positive relationship between satisfaction and system usage has an empirical support in e-learning system (Mohammadi, 2015b), which overlaps with MB in key features. As proposed by Delone and McLean (2003), satisfaction is also a significant predictor of system usage. Moreover, satisfaction has been validated as a determinant of loyalty in mobile phone usability (Lee et al., 2015) and mobile platforms (Ryua et al., 2014). Hence, we propose that:

H7: *Customer satisfaction will influence positively MB loyalty.*
H8: *Customer satisfaction will influence positively MB usage.*

4.5. Methodology

Besides analyzing computer-recorded data for MB use extracted from bank log files, our method used a field survey to test the hypothesized relationships. The survey was provided through an internet link and directed to MB users, our target population. The questionnaire was developed to measure all our variables of interest.

4.5.1. Measurement instruments

All constructs items were adapted from previous research to ensure face validity. The items were measured via a seven-point Likert-scale with 7 “Strongly agree” and 1 “Strongly disagree”. Quality factors (system, information, and service) and satisfaction were adapted from Zhou (2013).

While loyalty was adapted from Zhou and Lu (2011). UTAUT factors of performance expectancy, social influence, and facilitating conditions were adapted from Chan et al. (2010). Subjective and objective MB usage were adapted from Straub et al. (1995). Subjective MB usage will reflect customers' actual usage derived from the survey while objective MB usage will reflect customers' actual usage derived from system log data (Table 4.1). The questionnaire was pilot tested with about 10 MB users and preliminary evidence had been found for scales' validity and reliability.

Table 4.1. Construct Operationalization

Construct	Item Code	Lead Questions and Item Scales	Citation
System Quality	TQ1 TQ2 TQ3 TQ4	Q1. MB quickly loads all the text and graphics. Q2. MB is easy to use. Q3. MB is easy to navigate. Q4. MB is visually attractive.	Zhou (2013)
Service Quality	SQ1 SQ2 SQ3 SQ4	Q9. MB provides me real-time services. Q10. MB provides me quick response-time services. Q11. MB provides me professional services. Q12. MB provides me personalized services.	Zhou (2013)
Information Quality	IQ1 IQ2 IQ3 IQ4	Q5. MB provides me with information relevant to my needs. Q6. MB provides me with sufficient information. Q7. MB provides me with accurate information. Q8. MB provides me with up-to-date information.	Zhou (2013)
Satisfaction	SAT1 SAT2 SAT3	Q13. I feel satisfied with using MB. Q14. I feel happy with using MB. Q15. I feel pleased with using MB.	Zhou (2013)
Performance Expectancy	PE1 PE2 PE3	Q22. Using MB enables me to access bank services more quickly Q23. Using MB makes it easier to access bank services. Q24. Using MB enhances my effectiveness in accessing bank services.	Chan et al. (2010)
Social Influence	SI1 SI2 SI3	Q28. People who influence my behavior think that I should use MB to access bank services. Q29. People who are important to me think that I should use MB to access bank services. Q30. People who are in my social circle think that I should use MB to access bank services.	Chan et al. (2010)
Facilitating Conditions	FC1 FC2	Q31. I have the resources necessary to use MB to access bank services. Q32. I have the knowledge necessary to use MB to access bank services.	Chan et al. (2010)

	FC3	Q33. I have a specific person (or group) available for assistance with difficulties using MB to access bank services.	
Loyalty	LY1 LY2 LY3	Q34. I will continue using MB. Q35. I will recommend MB to others. Q36. I will consider MB as my first choice when conducting mobile banking transactions.	Zhou and Lu (2011)
MB Use	AU1	Q34. Perception of usage frequency for transfer, bill payment, deposit, and other MB activities (survey and log data).	Straub et al. (1995)

4.5.2. Data collection and participants profile

Participants were recruited from a US mid-sized bank, headquartered in the northeastern region. We sent the survey for 5000 + online users including MB users and non-users to investigate their reasons for not using MB. The data was collected via an online survey and from system log data, particularly for the MB usage frequency. The log data had been compiled for 8 months by the bank and provided to us without any personal identifier to protect customers' privacy.

For more efficient recruiting procedure, the questionnaire had been administrated by the bank through sending an invitation email to their customers to participate in the study. The bank, also, offered an incentive for its customers for completing the survey, which helped to obtain adequate response rate. The bank primarily interacted with its customers to collect the survey and system log data.

The overall sample consisted of 1,165 responses, 760 are MB users while the remaining are non-users. Due to the removal of missing values and matching between surveyed usage and actual usage for all participants, we ended up with 472 valid respondents out of the 760 MB users. Even with such reduction in the sample, there was no big effect on its representation because demographics, explained below, reflect the population from a typical mid-sized local bank. This final sample showed no big difference between female and male representation (Figure 4.2). While most of the participants' age show to be greater than 40. For education and work, the majority of the respondents are literate and have a full-time job. This sample can help to generalize the findings to other mid-sized banks in the United States.

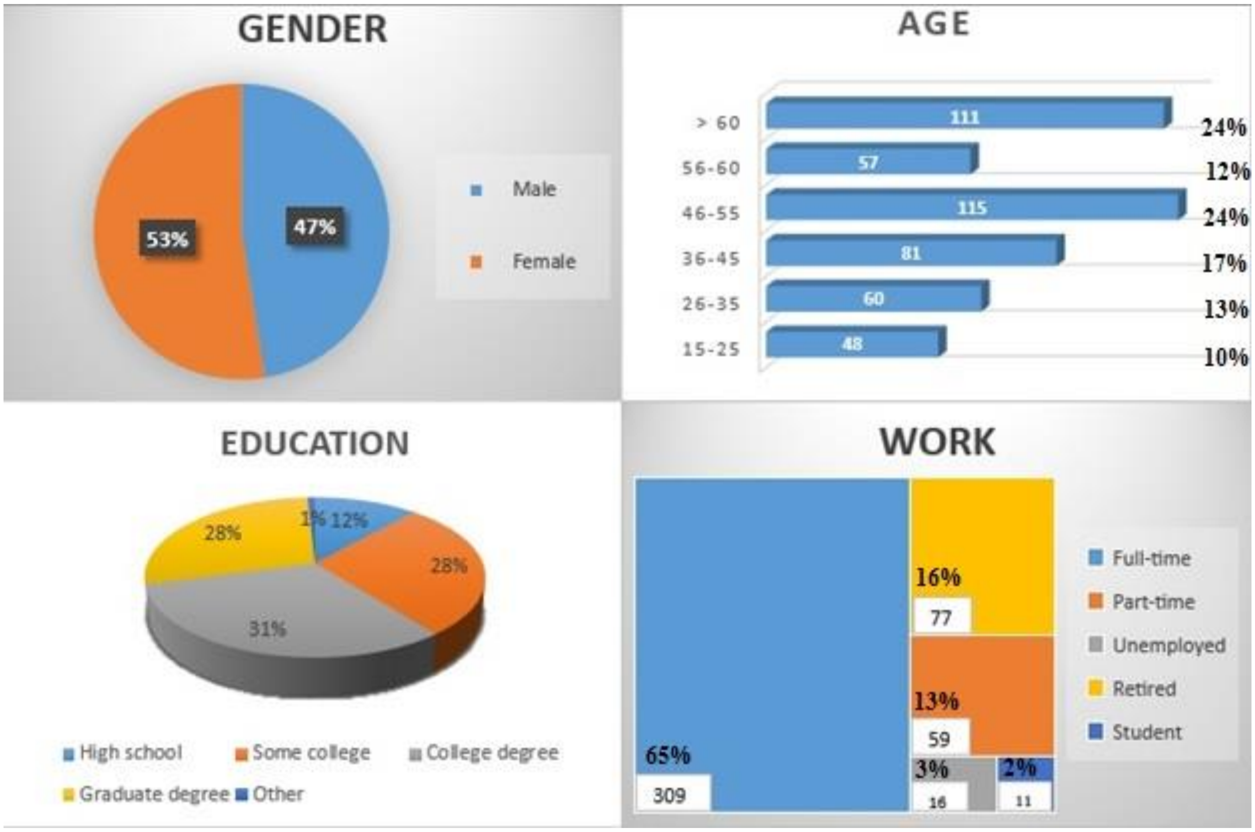

Figure 4.2. Demographic Profile for Participants

For the analysis of non-MB users, it appears that, as figure 4.3 below shows, about one-third of customers would favor using computers to access their banking services instead of MB. The second and third major reasons for not using MB are customers' concern about security measures embedded in MB app and many of these customers do not own a smartphone or tablet, respectively. Also, there is a fair group of customers doesn't trust MB and surprisingly another group isn't aware of MB. However, the major cluster of MB non-users is senior female customers who had finished their college diploma.

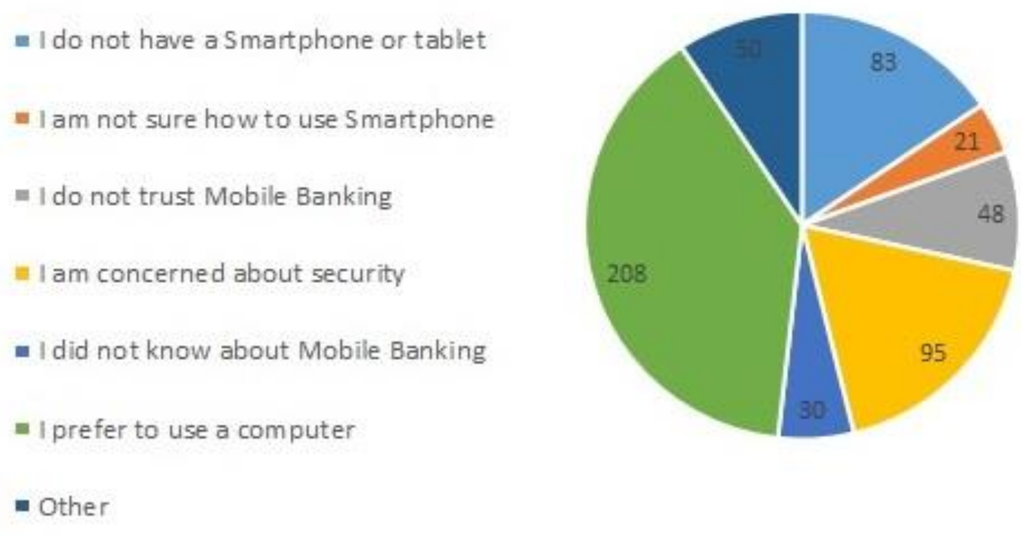

Figure 4.3. Reasons for not Using MB

4.5.3. Data analysis

Before testing the structural model, the variables were statistically described in terms of mean and standard deviation and checked for confirmatory factor analysis (CFA) (Table 4.2). Using SmartPLS, CFA helps to evaluate the validity of the model's manifest variables through factor loadings that show to what extent every item is related to its underlying latent variable.

Table 4.2. Descriptive Statistics and Factor Loadings

Factors	*Items*	*Mean*	*S.D.*	*Factor loadings*
System Quality	TQ1	5.797	1.042	0.732
	TQ2	5.981	1.054	0.909
	TQ3	5.949	1.001	0.893
	TQ4	5.436	1.287	0.767
Service Quality	SQ1	5.879	1.126	0.798
	SQ2	5.809	1.109	0.857
	SQ3	5.761	1.052	0.773
	SQ4	5.443	1.176	0.817
Information Quality	IQ1	5.850	1.030	0.873
	IQ2	5.782	1.082	0.870
	IQ3	6.242	0.782	0.815

	IQ4	6.163	0.869	0.773
Performance Expectancy	PE1	6.017	0.996	0.923
	PE2	5.928	1.127	0.953
	PE3	5.773	1.152	0.937
Social Influence	SI1	4.290	1.539	0.964
	SI2	4.358	1.535	0.966
	SI3	4.284	1.497	0.949
Facilitating Conditions	FC1	6.144	0.824	0.955
	FC2	6.239	0.701	0.806
Satisfaction	SAT1	5.869	1.168	0.956
	SAT2	5.799	1.214	0.971
	SAT3	5.809	1.181	0.965
Loyalty	LY1	6.324	0.840	0.875
	LY2	5.953	1.191	0.916
	LY3	5.801	1.360	0.887
Actual Use (Survey)	AU1	1.892	1.260	1.000
Actual Use (Log Data)	LogUsage1	1.288	0.671	1.000

As per table 4.3, Cronbach's alpha, and composite reliability were evaluated for further proof of instruments' reliability. Convergent validity was tested with average variance extracted (AVE) while collinearity between variables was assessed via variance inflation factor (VIF). As per table 4.4 and 4.5, discriminant validity was checked by comparing the square root of AVEs with other variables coefficients (Fornell-Larcker Criterion) (Fornell & Larcker, 1981) and cross-loadings criteria. Common method variance was tested through conducting a Harman's single-factor test (Zhou, 2012).

Table 4.3. Instrument Reliability and Validity

Factors	***Cronbach's alpha***	***Composite reliability***	***AVE***	***VIF***
System Quality (TQ)	0.846	0.897	0.687	2.467
Service Quality (SQ)	0.828	0.886	0.660	2.579
Information Quality (IQ)	0.855	0.901	0.695	2.520
Performance Expectancy (PE)	0.932	0.956	0.880	2.050
Social Influence (SI)	0.957	0.972	0.921	1.169
Facilitating Conditions (FC)	0.745	0.876	0.781	1.434
Satisfaction (SAT)	0.962	0.975	0.929	1.000
Loyalty (LY)	0.873	0.922	0.798	1.000

Table 4.4. Fornell-Larcker Criterion									
Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. AU	**1.000**								
2. FC	0.028	**0.884**							
3. IQ	-0.017	0.451	**0.834**						
4. LY	0.096	0.362	0.663	**0.893**					
5. PE	0.162	0.500	0.555	0.636	**0.938**				
6. SAT	0.053	0.335	0.731	0.812	0.678	**0.964**			
7. SQ	0.068	0.429	0.708	0.655	0.609	0.688	**0.812**		
8. SI	0.156	0.149	0.214	0.337	0.343	0.334	0.305	**0.960**	
9. IQ	0.093	0.354	0.692	0.743	0.604	0.770	0.688	0.307	**0.829**

Table 4.5. Item Loading and Cross Loadings									
	Actual Use	**Facilitating Conditions**	**Information Quality**	**Loyalty**	**Performance Expectancy**	**Satisfaction**	**Service Quality**	**Social Influence**	**System Quality**
AU1	**1.000**	0.028	-0.017	0.096	0.162	0.053	0.068	0.156	0.093
FC1	0.025	**0.955**	0.445	0.385	0.488	0.364	0.418	0.177	0.348
FC2	0.024	**0.806**	0.335	0.214	0.382	0.183	0.329	0.052	0.265
IQ1	0.040	0.406	**0.873**	0.617	0.549	0.718	0.630	0.250	0.687
IQ2	0.008	0.298	**0.870**	0.594	0.439	0.650	0.585	0.203	0.603
IQ3	-0.042	0.395	**0.815**	0.475	0.428	0.530	0.522	0.131	0.500
IQ4	-0.090	0.424	**0.773**	0.502	0.418	0.503	0.628	0.099	0.482
LY1	0.099	0.412	0.637	**0.875**	0.595	0.714	0.552	0.232	0.631
LY2	0.076	0.308	0.580	**0.916**	0.588	0.759	0.620	0.326	0.688
LY3	0.084	0.250	0.560	**0.887**	0.518	0.701	0.582	0.345	0.671
PE1	0.172	0.470	0.534	0.591	**0.923**	0.597	0.547	0.284	0.571
PE2	0.096	0.470	0.531	0.617	**0.953**	0.664	0.568	0.315	0.572
PE3	0.192	0.468	0.497	0.580	**0.937**	0.643	0.597	0.363	0.556
SAT1	0.034	0.321	0.703	0.789	0.654	**0.956**	0.654	0.305	0.755
SAT2	0.062	0.332	0.694	0.780	0.677	**0.971**	0.670	0.347	0.737
SAT3	0.059	0.315	0.716	0.779	0.628	**0.965**	0.665	0.313	0.734
SQ1	0.006	0.365	0.639	0.549	0.474	0.574	**0.798**	0.184	0.557
SQ2	0.037	0.372	0.639	0.579	0.513	0.576	**0.857**	0.243	0.580
SQ3	0.094	0.365	0.512	0.493	0.517	0.498	**0.773**	0.269	0.512
SQ4	0.088	0.296	0.504	0.503	0.479	0.582	**0.817**	0.298	0.580
SI1	0.142	0.153	0.238	0.361	0.353	0.361	0.330	**0.964**	0.332
SI2	0.167	0.115	0.175	0.304	0.307	0.292	0.269	**0.966**	0.259
SI3	0.143	0.159	0.197	0.299	0.321	0.299	0.272	**0.949**	0.285
TQ1	-0.015	0.345	0.513	0.493	0.441	0.497	0.481	0.218	**0.732**
TQ2	0.118	0.289	0.640	0.742	0.568	0.746	0.587	0.284	**0.909**
TQ3	0.133	0.306	0.631	0.654	0.574	0.674	0.621	0.276	**0.893**

TQ4	0.043	0.251	0.496	0.539	0.401	0.604	0.584	0.233	**0.767**

The above tables show that all factors and their respective items have values above the recommended thresholds in literature, for example, 0.7 for Cronbach's alpha (Straub, 1989), 0.5 for AVE (Henseler et al., 2009), and 0.7 for factor loading (Churchill, 1979). This indicated that instruments' reliability and validity have been established. For common method variance, the Herman's single factor test showed that the large factor explains 43.979% of the total variance. Hence, there is no dominant single factor since this percentage is less than 50%, confirming our data is not affected by common method variance.

4.6. Results

4.6.1. Structural model

Structural equation modeling – partial least square (SEM-PLS) was employed here because we were testing latent variables and several mediation terms. With the help of SmartPLS software, this technique can reveal the significant relationships with path coefficients in the tested model. We have tested the hypothesized relationships in two separate models; the first structural model uses the subjective measure for system usage (Table 4.6 & Figure 4.4) whereas the second structural model uses the objective measure for system usage (Table 4.7 & Figure 4.5) so that we can effectively compare the findings in regards to MB use.

Table 4.6. Model 1 (Subjective System Usage)

Path	Estimate	Std. Error	t-statistics	p-Value	Supported
H1: TQ → SAT	0.347	0.055	6.265***	0.000	Yes
H2: SQ → SAT	0.093	0.052	1.802*	0.072	Yes
H3: IQ → SAT	0.310	0.045	6.938***	0.000	Yes
H4: PE → SAT	0.279	0.045	6.175***	0.000	Yes
H5: SI → SAT	0.052	0.022	2.410**	0.016	Yes
H6: FC → SAT	-0.113	0.039	2.924***	0.004	Yes[a]

H7: SAT → LY	0.813	0.022	36.262***	0.000	Yes
H8: SAT → AU	0.054	0.043	1.246	0.213	No
Note: n= 472, ***p < 0.01, **p < 0.05, *p < 0.10 Explained variance in satisfaction = 73.2% Explained variance in loyalty = 66.1% [a]: this relationship is significant but with a contrary direction to the hypothesis.					

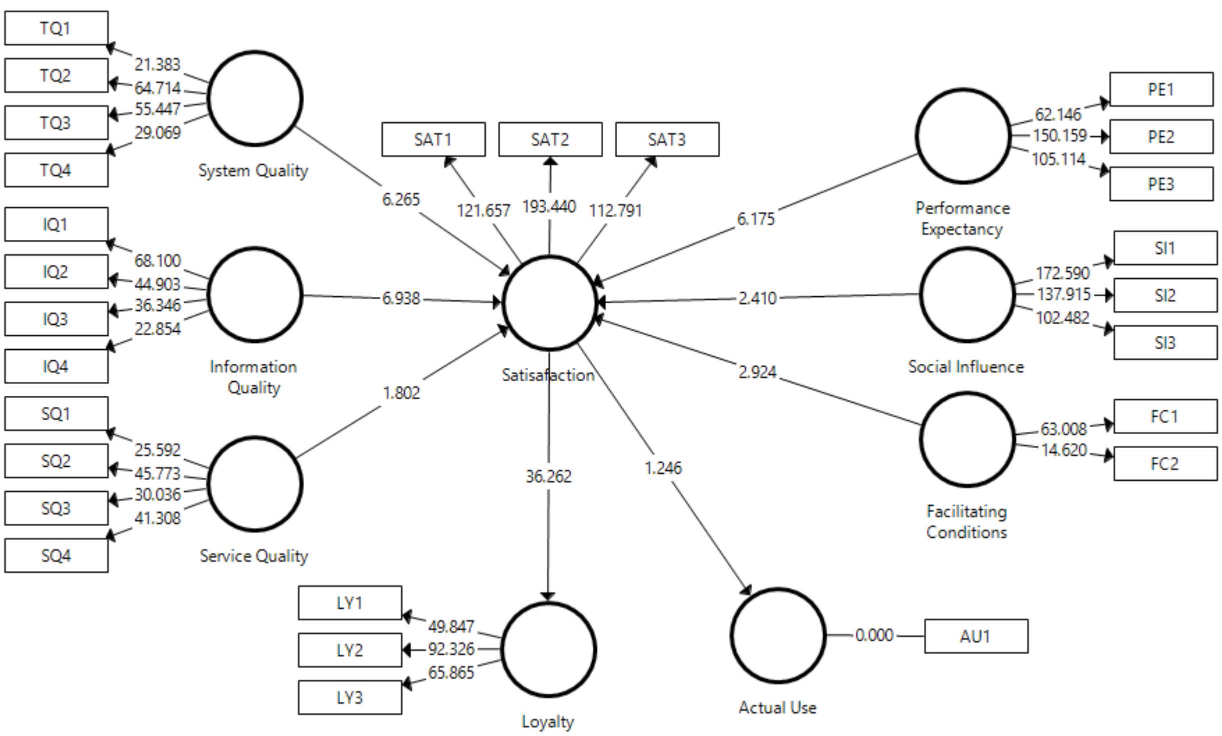

Figure 4.4. Nomological Net Model 1 for Self-Reported System Usage

Under subjective system usage, SEM-PLS results indicate that system quality (β = 0.347, p < 0.01) and information quality (β = 0.310, p < 0.01) are highly significant but service quality is not that significant (β = 0.093, p < 0.10). Also, as hypothesized, both of performance expectancy (β = 0.279, p < 0.01) and social influence (β = 0.052, p < 0.05) have a significant and positive impact on user satisfaction while facilitating conditions (β = -0.113, p < 0.01) has a significant but negative impact instead. On the other side, satisfaction is an important predictor for users' loyalty (β = 0.813, p < 0.01) but not for the perceived MB system usage (β = 0.054, p > 0.10).

Table 4.7. Model 2 (Objective System Usage)					
Path	**Estimate**	**Std. Error**	**t-statistics**	**p-Value**	**Supported**
H1: TQ → SAT	0.348	0.054	6.360***	0.000	Yes
H2: SQ → SAT	0.093	0.052	1.796*	0.073	Yes
H3: IQ → SAT	0.308	0.045	6.965***	0.000	Yes
H4: PE → SAT	0.279	0.042	6.600***	0.000	Yes
H5: SI → SAT	0.054	0.023	2.376**	0.018	Yes
H6: FC → SAT	-0.114	0.035	3.275***	0.001	Yes[a]
H7: SAT → LY	0.810	0.024	33.839***	0.000	Yes
H8: SAT → AU	0.090	0.036	2.437**	0.015	Yes

Note: n= 472, ***p < 0.01, **p < 0.05, *p < 0.10
Explained variance in satisfaction = 73.3%
Explained variance in loyalty = 65.7%
Explained variance in actual use = 0.9%
Correlation between subjective and objective system usage = 0.495
[a]: this relationship is significant but with a contrary direction to the hypothesis.

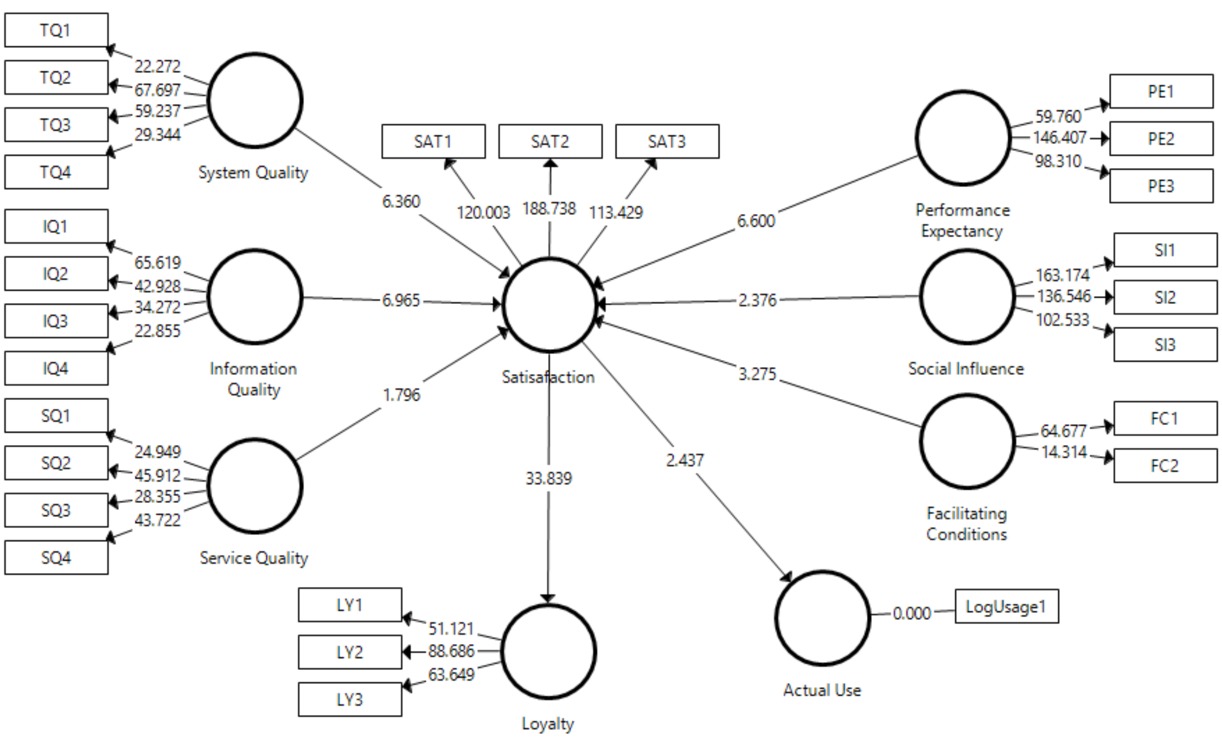

Figure 4.5. Nomological Net Model 2 for Computer-Recorded System Usage

Under objective system usage, it appears that SEM-PLS results of the significant factors in model 2 are similar for those in model 1 except for MB system usage, which turned to be significant ($\beta = 0.090$, $p < 0.05$). Hence, it is important to emphasize that MB system usage retrieved from computer-recorded data is significant but MB system usage retrieved from the survey is not. However, subjective system usage has weak correlation with objective system usage; 0.495. Those two constructs are basically the same; one is perceived use from self-reported data and the other is actual use from computer-recorded data, and accordingly they should be highly correlated. Thus, it is very unexpected to reach at such conclusion.

As per table 4.7, the integrated version of IS Success and UTAUT accounts for 73.3% of the total variance explained in user satisfaction, outperforming the standalone models (68% for IS Success and 47% for UTAUT within MB) and thus confirming the authenticity and validity of such integration. While satisfaction accounts for about 66% of the total variance explained in loyalty but surprisingly accounts for 0.9% of the total variance explained in actual system use.

4.6.2. Importance-performance map analysis (IPMA)

To complement the analysis of the relative importance of latent variables and their manifest variables (indicators) provided in Table 4.8 below, our investigation is extended to include performance of those variables by assessing an index value for each one (Table 4.9). The index value determines to what extent an endogenous variable could be improved by a set of exogenous variables, in other words, the bigger value of the index, the smaller area to improve on. Consequently, the focus for improvement should be on the factors that show higher relative importance but low performance simultaneously (Hair et al., 2014).

Fundamentally, IPMA technique enhances the current version of classical regression by helping to demonstrate not only which latent and manifest variables influence more users' satisfaction (importance) but also which ones have higher index values (performance). This analysis matrix rescales the index values to show performance level on a scale of 0 to100; the closer to 100, the better performing variable or item. For a better graphical interpretation, IPMA inverts the index values (100-index value) for the negative coefficients/estimates (Trang et al., 2016), as the case for facilitating conditions. IPMA for latent variables is depicted below in figure 4.6 while for manifest variables depicted in figure 4.7 to provide a better visualization and understanding of those two dimensions.

Since relative importance and performance are reflected by path coefficients and index values, respectively, we can determine the most needed areas to improve on by identifying the significant predictors that have higher coefficients values but low index values in regards to satisfaction. According to the matrix analysis, the results related to factors internal to the system show that system quality ($\beta = 0.347$, index value = 80.403), and information quality ($\beta = 0.310$, index value = 82.808) are very important but have high index values, which indicates minor potential for improvement. While service quality ($\beta = 0.093$, index value = 77.767) seems less important and less performing. On the other hand, the results related to factors external to the system show that both performance expectancy ($\beta = 0.279$, index value = 81.819) and facilitating conditions ($\beta = -0.113$, index value = 79.820) are very important and well-performing while social influence ($\beta = 0.052$, index value = 55.147) is important but less-performing. This means that there is much potential in improvement of social influence rather than in performance expectancy and facilitating conditions.

With regards to the manifest variables in IPMA, most of the items show high scores on performance level (>= 80), meaning that less room for improvement except for TQ4, SQ3, SQ4, FC2, SI1, SI2, and SI3. Those items are not the same on the importance level and can be ranked accordingly. For example, TQ4 shows the highest important score among them, followed by SQ4 and SQ3, while the items of social influence seem to have the lowest important scores.

Table 4.8. Importance of Latent Variables and their Manifest Variables (Items)		
	Latent Variables	**Manifest Variables**
System Quality	0.347	
TQ1		0.082
TQ2		0.123
TQ3		0.111
TQ4		0.099
Service Quality	0.093	
SQ1		0.029
SQ2		0.030
SQ3		0.026
SQ4		0.030
Information Quality	0.310	
IQ1		0.111
IQ2		0.101
IQ3		0.082
IQ4		0.078
Performance Expectancy	0.279	
PE1		0.093
PE2		0.103
PE3		0.100
Social Influence	0.052	
SI1		0.021
SI2		0.017
SI3		0.018
Facilitating Conditions	-0.113	
FC1		-0.085
FC2		-0.043

Table 4.9. Performance of Latent Variables and their Manifest Variables (Items)		
	Latent Variables	**Manifest Variables**
System Quality	80.403	
TQ1		79.944
TQ2		83.016
TQ3		82.486
TQ4		73.941
Service Quality	77.767	
SQ1		81.321
SQ2		80.155
SQ3		75.212
SQ4		74.047
Information Quality	82.808	
IQ1		80.826
IQ2		79.696
IQ3		84.831
IQ4		86.052
Performance Expectancy	81.819	
PE1		83.616
PE2		82.133
PE3		79.555
Social Influence	55.147	
SI1		54.838
SI2		55.968
SI3		54.732
Facilitating Conditions	79.820	
FC1		82.881
FC2		74.647

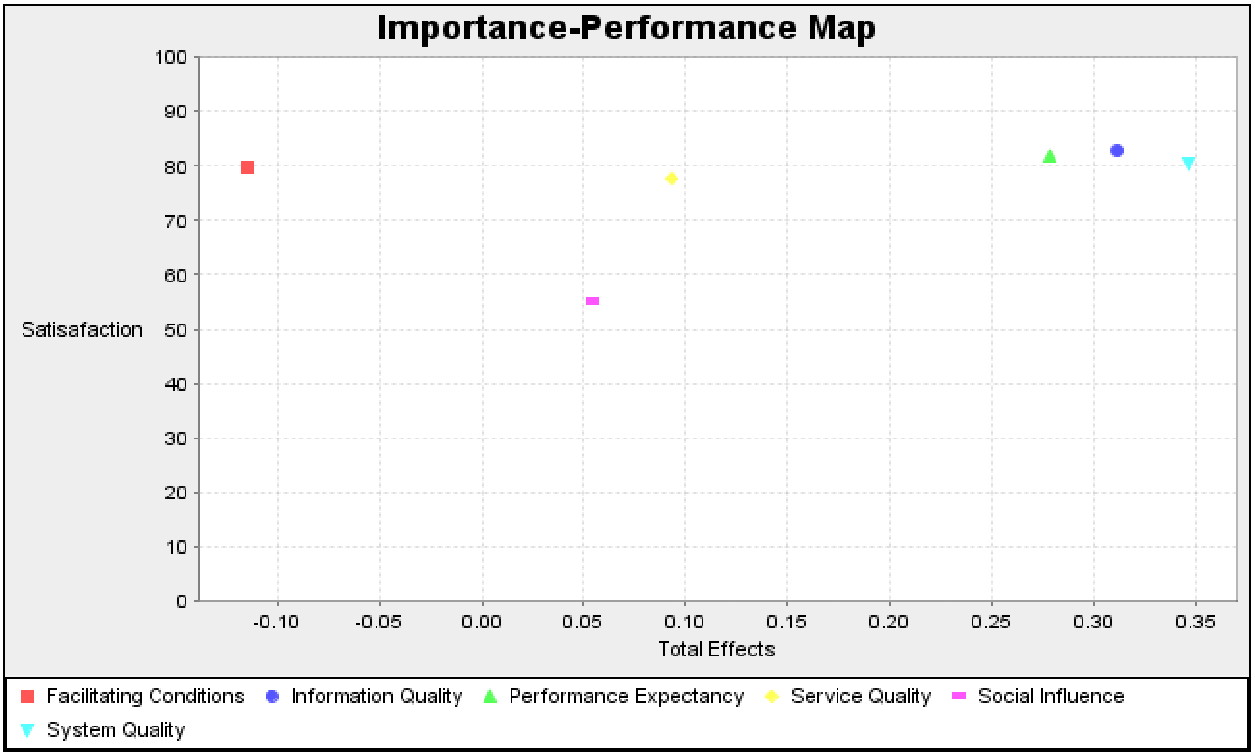

Figure 4.6. High and Low Performing Latent Variables

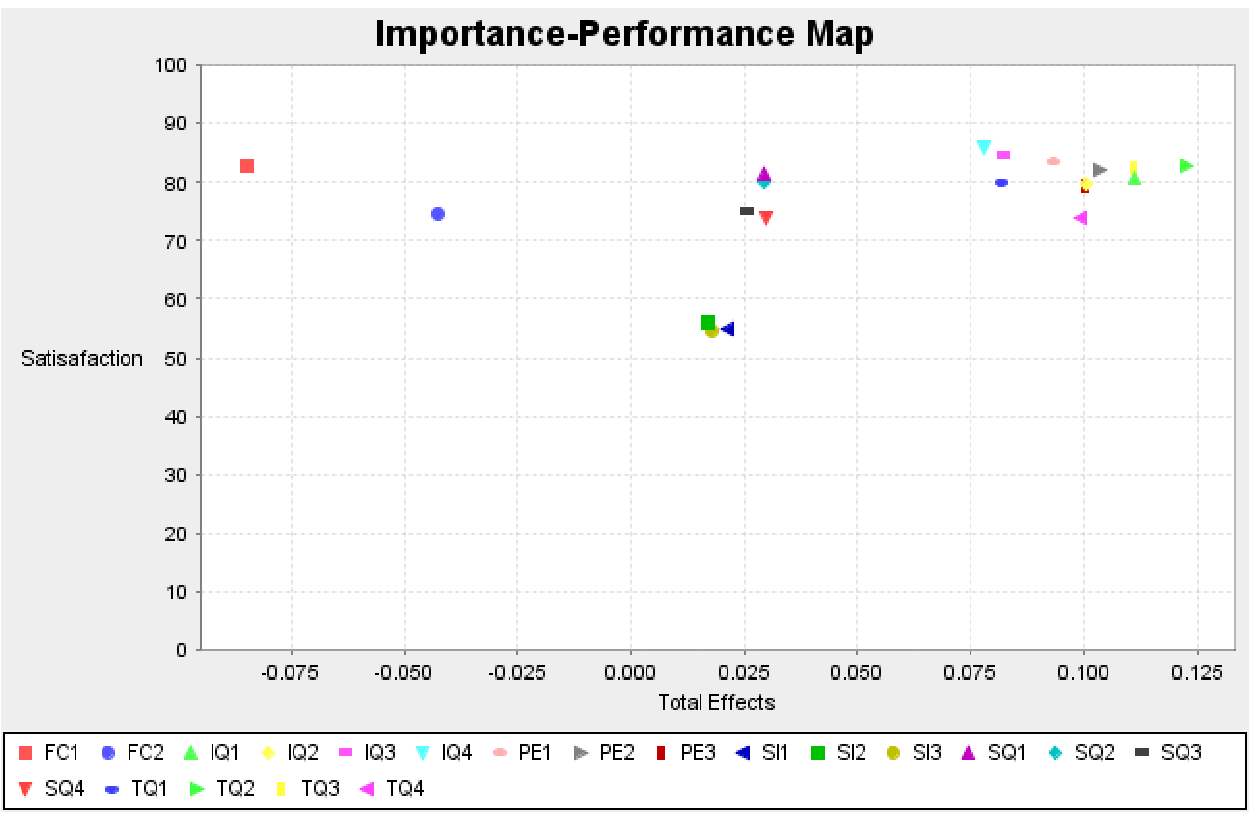

Figure 4.7. High and Low Performing Manifest Variables (Items)

4.7. Discussion

4.7.1. Major findings

Most of our hypothesized relationships are found to be significant and hence consistent with prior IS research. Quality factors (system quality, service quality, and information quality) are positively significant and in line with results reached by Xu et al. (2013) and Zhou (2013). Performance expectancy and social influence are also important predictors of user satisfaction and supported by IS studies of Brown et al. (2008) and Chan et al. (2010).

While the factor of facilitating conditions shows to be significant, consistent with Chan et al. (2010) and Baptista and Oliveira (2015), it is unexpectedly associated with a negative sign. This negative direction may be attributed to the friendly-to-use interface and services exhibited in MB, which makes most users do not need to access further resources to interact with MB.

4.7.2. Theoretical implications

Based on SEM-PLS analysis, it seems that subjective system usage does not strongly correlate with objective system usage, opposing the fact that they are literally the same. Additionally, objective system usage shows to be significantly predicted by satisfaction while subjective system usage does not. This means that many MB users underestimate their MB usage and perceive themselves as light users but they are not as indicated by their actual use retrieved from system log data.

This leads us to argue about the authenticity of subjective systems usage used as a dependent variable in prior IS research (Mohammadi, 2015; Hou, 2012; Zhou et al., 2010). Due to the flaw in human judgment, this perceived construct may not reflect the actual state of system usage among system users and could involve self-reported bias (Collopy, 1996; de Reuver and

Bouwman, 2015), which may drive scholars to draw false conclusions. Moreover, the lack to validate the correlation between subjective and objective system usage has augmented this concern. As a result, it is plausible to infer that many of past IS studies employing self-reported system usage had been implicated and resulted in providing an inadequate measure for this construct. Therefore, it is very important to shift into the objective measurement of system usage by obtaining computer-recorded data for the system usage. This would help to lift this concern and to enhance the reliability of the reported results.

On the other hand, this study has theoretically proved to enable a greater cognitive understanding of MB usage behavior through user satisfaction. Integrating IS Success's factors, that are internal to the system with UTAUT's factors, that are external to the system helps to increase the boundaries of these two models and accordingly contribute to advance the theoretical knowledge of this area. In addition, this integrative model has outperformed the two standalone models and provided higher explanatory power, leading us to back our argument that they complement each other. Thus, this holistic framework can be established as a robust theoretical base model to examine MB system usage in future studies.

4.7.3. Practical implications

This study can be of a great help to the banking industry as it highlights not only the key factors in need to be addressed but also their respective indicators, taking into account the study findings are generalized to US mid-sized banks. Using IPMA, both dimensions of importance and performance are analyzed to evaluate the ranking of the factors and their indicators. Accordingly, it enables us to provide deeper insights and to inform on the most important and needed areas to take a specific action.

On the variable-level, practitioners should pay close attention to the following areas since they are important and exhibit more potential for improvement:

1. Increasing the quality of the services embedded in MB app, for example, banks should look for ways to enhance the responsiveness of those service and provide timely feedback on the conducted transactions.
2. Working on getting MB users to influence their social circle (e.g., family, friends, colleagues, etc.) toward increasing their positive attitude and actual engagement to MB services. Hence, banks must leverage the word-of-mouth marketing strategy so that their MB users would become informal marketing agents.

On the indictor-level, there are several needed areas where practitioners should divert their resources into improving them, for instance:

1. MB users are mostly affected by the look of the MB services, meaning that the users would be more pleased when interacting with visually attractive services. Thus, banks should look to provide dynamic, interactive, and good-looking interface and services.
2. Users get more satisfied when they interact with MB services that exhibit professionalism, reflected by trust and credibility. Hereby, banks must work hard on security and privacy aspects of their MB app.
3. The level of satisfaction among MB users gets very high when they are provided with personalized services based, for example, on their usage, age, gender, and education. This should push banks to study their users' profiles and employ data

analytics techniques to figure out the best approach for giving MB users a personalized experience.

4. The level of users' satisfaction increases towards MB when the surrounding individuals start talking about how good MB services are and most importantly recommending MB to their social network. This type of viral marketing where should banks heavily invested on.

It is critical to note that all the significant variables are important but the highlighted factors and indicators are the most needed areas to consider first and should be given a special attention in the process of designing, refining and implementing MB services. This would help to increase user satisfaction and system usage. Once customers' satisfaction is sustained, banks would be able to transform those customers into loyal. loyalty, which is an ultimate goal for banks, can lead to increase retention rate and thus make banks stay in competition or even ahead of it.

7.8. Contribution and Conclusion

This study contributes to the theory and practice by 1) incorporating system-oriented factors (IS Success) with non-system-oriented factors (UTAUT) and evaluate the robustness of this theoretical framework in a MB context. Since the integrative model has been found to provide a greater predictive power compared to the standalone models of IS Success and UTAUT, it can be established as a substantial theoretical grounding to guide future research in mobile banking and to move towards a deeper understating of this phenomenon; 2) using subjective and objective measures for MB system usage; such measurement approach has not been yet employed in MB research. Accordingly, this paper provides insightful feedback based on the comparable findings between the subjective and objective usage and their correlation. This helps us to advise on reliability and validity aspects of previous IS studies that have employed self-reported system usage; and 3) revealing the significant results highlighted by importance-performance matrix that provides valuable remarks for the banking industry, which should be used accordingly to address the emphasized important aspects and improve them to increase the level of satisfaction and loyalty among MB users. In particular, for software vendors, the embedded services should be given more attention and so enhanced in the design and refinement process in terms of personalization and attractiveness. For banks, the MB should be promoted with stronger campaigns that spread awareness of MB app and its new enhanced features. As well, marketing channels should be increased and conducted at a larger scale so that MB users tap on this role and start to recommend the app informally to their social circle.

This paper is an attempt to increase our understating about MB by exploring actual system use among MB users. Our integrated theoretical framework of IS Success and UTAUT enables us to be informed about the critical aspects influencing satisfaction, MB usage, and loyalty on two levels; variable and indicator. While the objective measurement of system usage helps to uncover critical insights and disclose some research clues for future studies.

Chapter 5. Third Paper: Privacy and Personalization in Continued Usage Intention of Mobile Banking: An Integrative Perspective

This chapter presents the third research paper that investigates the existing paradox between privacy and personalization and its impact on continued usage intention of MB.

5.1. Introduction

Approximately 75.8% of the U.S. population owns a smartphone today (Lella, 2015). Smartphone ownership has been growing steadily over the last decade since the introduction of iPhone. This growth, combined with a surge in mobile commerce (m-commerce), has driven the demand for mobile banking (MB). MB focuses on connecting users to the bank from their smartphones to conduct interactive transactions such as account information, fund transfer, bill payment and others (Crowe et al., 2015). The same report finds that 78% of U.S. banks currently offer MB and another 16% plan to offer within the next year. MB is considered a strategic service by banks today to build customer loyalty and increase customer retention. Multiple studies from the banking industry (Fiserv, 2014; Fiserv, 2012) show a meteoric rise of MB services, with roughly 35% of bank interactions in the U.S. and 30% of bank interactions globally are conducted through MB - a surge of 19% from 2013. MB has, thus, become a dominant method for customers to interact with their banks. Today, more bank interactions are handled through MB than ATM or bank branches due to the tremendous economic benefits. Digital transactions cost about 17 cents each, compared with 85 cents for ATM transaction, and $4 for a branch transaction (Fiserv, 2014).

Prior studies on mobile technology have shown that both adoption and usage increase with higher levels of ease of use and customer satisfaction (Hong et al., 2006). Although the primary focus of academic research has been on MB adoption (Lin, 2011; Huang et al., 2011; Chang, 2010; Shen et al., 2010; Zhou, 2012) rather than on continued usage intention of mobile banking (CUMB), banking research shows more strategic and economic value for continued usage. Payoffs are higher when customers interact frequently and stay loyal to the bank, as they purchase more services, thereby generating more revenue for banks (Fiserv, 2014). Usefulness and ease of use have been widely used in MB adoption research with the use of technology acceptance model

(TAM) (Chung and Kwon, 2009). However, because the focus of the mentioned studies are on initial adoption and not continued usage intention, they have not explored the influence of privacy issues or personalization on mobile banking. Post-adoption studies on mobile technology have shown that privacy and personalization tend to either decrease or increase satisfaction and continued usage intention (Park, 2014; Sutanto et al., 2013; Xu et al., 2011).

Privacy is about individual rights to protect personal information from service providers. Customers have cited privacy as a major reason for not using mobile payment and mobile commerce systems (Zhang et al., 2013). For example, 70% of banking institutions have considered security concern as the biggest barrier to MB adoption while customer privacy protection, identity theft, malware and data breaches as top concerns for improving MB security (Crowe et al., 2015: p. 43-44). Privacy fears affect customers behavior when using mobile devices with real-time tracking features (Keith et al., 2013) and are major inhibitor in their acceptance by consumers (Xu et al., 2011). Banks that address privacy concerns with better communication and awareness will have higher MB usage (Fiserv, 2014) but they would strive to sustain such level of usage. Thus, it is important to study the influence of customers privacy on CUMB.

Personalization involves customizing the user interface and graphics to customers' need. Research shows that apps with personalization capability increase customer satisfaction, loyalty, continued usage and provide a higher return on investment for the banks (Fiserv, 2012). Personalized MB applications require the use of customer profile, customer preferences, prior usage data of MB service and social media data. Personalization increases adoption and can sustain continued usage of IT due to the increase of user satisfaction (Park, 2014). However, information collection process can restrain usage of IT as users feel an invasion of their privacy (Dhar and Varshney, 2011), which creates a conflict between personalization and privacy. This personalization-privacy paradox is a prominent phenomenon in usage studies (Xu et al., 2011). Mobile location-tracking services are great resource for personalized service but privacy restrictions limit sharing personal information with third parties (Sutanto et al., 2013). This suggests both personalization and privacy could have a reverse impact on customer satisfaction and in turn on CUMB.

Our study focuses on the post-adoption behavior of users on mobile banking. The main contribution is to extend TAM by examining the impact of two important but contradictory factors (privacy and personalization) on user satisfaction and continued usage intention with MB services. The rest of this paper is organized as follows; the next section provides related work on, TAM, mobile continued usage intention, and CUMB followed by our research model, hypotheses development, and research method, then data analysis, results, and discussion. The last section highlights the study conclusion.

5.2. Related Work

5.2.1. TAM

TAM has been a very popular model for IT adoption studies since its introduction by Davis (1989). TAM's main objective is to determine users' intention to accept new systems based on its' perceived usefulness and ease of use. Due to its parsimonious and simplicity, TAM is preferred over the Theory of Planned Behavior (TPB) (Hong et al., 2006). Both TAM's elements of perceived usefulness and perceived ease of use, which are deeply rooted in Theory of Reasoned Action (TRA) (Davis et al., 1989), have been considered the most popular two factors employed in examining mobile technology adoption. In a MB context, perceived usefulness assesses to what extent MB can improve conducting banking services, while perceived ease of use assesses to what extent MB can be perceived as a user-friendly app) Davis, 1989).

Many studies have extended TAM to study continued usage intention, the post-adoption stage that comes after actual usage (Boakye et al., 2012; Chong, 2013; Thong et al., 2006). Hong et al. (2006), also, emphasizes that TAM has been used extensively to examine the intention of experienced users to continue using IT applications. In addition, the Expectation-Confirmation Model for IT (ECM-IT) has shown that TAM constructs; perceived usefulness and ease of use, can be used to determine user satisfaction, which is a significant predictor of continued usage intention (Bhattacherjee, 2001; Chong, 2013; Hong et al., 2006; Lee and Park, 2008). Therefore, we believe TAM constructs would be good predictors for measuring MB user satisfaction and continued usage intention in our study.

5.2.2. Continued usage intention of mobile technology

Prior research has regarded continued usage intention of mobile technology as a crucial outcome to determine the success of such technology because it is cheaper to retain current customers and highly-rewarded to shift them into loyal (Chen, 2012; Dai et al., 2014). Both, Chong (2013) and Lu (2014) examine mobile commerce and propose that when customers perceive mobile commerce to be useful, and easy to use, along with having an enjoyable interaction, they become more satisfied and willing to continue using it. Zhou in 2013 and 2014 examines post-adoption of mobile payment and similarly suggests that both satisfaction and continued usage increase when users perceive trust, flow, usefulness and productivity.

Prior studies on post-adoption have combined TAM with other models such as, ECM-IT, to provide a better prediction power (Hong et al., 2006) for continued usage intention across mobile and non-mobile technologies (Boakye et al., 2012; Hong et al., 2006; Thong et al., 2006). Besides TAM and ECM-IT, self-developed mode (i.e., value-based) predicts usage of mobile users through using IS behavior-habit, which is an input construct to continued usage intention (Setterstrom et al., 2013). Another value-based model shows a strong prediction of continued usage in a mobile service context (Dai et al., 2014).

5.2.3. CUMB

CUMB is defined as the intent to continue using MB after the initial adoption (Bhattacherjee, 2001) or after the actual use. While flow theory and task-technology fit (TTF) model have been employed to study CUMB through satisfaction, ECM-IT, besides TAM, plays more significant role in predicting CUMB (Chen, 2012; Yuan et al., 2014; Zhou and Liu, 2014). ECM-IT was developed and advocated by Bhattacherjee (2001) after being adapted from Expectation-Confirmation Theory (ECT); a well-known theory in the literature of consumer behavior. Although ECM-IT is considered the dominant model in determining CUMB, it does not account for the impact of either personalization and privacy. Such constructs are substantially related to a MB context.

In sum, while there is a greater economical value associated with CUMB (Chen, 2012), prior research has given it limited attention (Table 5.1) and not emphasized the role of privacy and personalization. Both of these factors are of a great importance and manifested to be relevant determinants of satisfaction and MB continued usage intention as well as have been significantly underlined in IS literature (Chang et al., 2011; Tong et al., 2012; Wang et al., 2006). Also, with their paradoxical underlying nature, privacy and personalization can help extend the theory from one side and assist industry to understand the mechanism of their interaction in MB from another side.

Table 5.1. Prior Work on Continued Usage Intention of Mobile Banking			
Authors	**Theoretical Lens**	**Main Findings**	**Sample Analyzed**
Yuan et al. (2014)	TAM, ECM-IT, and TTF	Satisfaction, perceived usefulness, perceived task-technology fit, and perceived risk are the main significant factors to CUMB	434 participants
Zhou and Liu (2014)	ECM-IT and flow theory	Perceived usefulness, satisfaction, and flow can determine continuance intention of MB	194 participants
Chen (2012)	ECM-IT	Satisfaction and trust predicts continued usage intention of MB and worked as mediators to technology readiness and service quality	390 participants
Rejikumar (2012)	TAM	Satisfaction and perceived risk are major influencers of CUMB	184 participants

5.3. Research Model and Hypotheses Development

TAM, when integrated with other models, can explain a higher variance of continued usage intention (Hong et al., 2006). Accordingly, our research model incorporates two factors - satisfaction, and personalization - from the Park model (Park, 2014). While privacy is found to play a crucial role in satisfaction (Chang et al., 2011), Sutanto et al. (Sutanto et al., 2013) propose there is a paradox between personalization and privacy of IS usage. As this study attempts to understand this hypothetical paradox in MB, privacy is incorporated into the research model.

Drawing on prior research (Bansal et al., 2008; Thongpapanl and Ashraf, 2011; Wang and Groth, 2014), we indicate that both privacy and personalization can show a positive moderating role on satisfaction, which in turn serves as a mediating factor to CUMB (Hong et al., 2006). Thus, our conceptual model shows usefulness and ease of use as independent variables, privacy, and personalization as independent and moderating variables, while satisfaction and continued usage intention of MB as dependent variables (Figure 5.1).

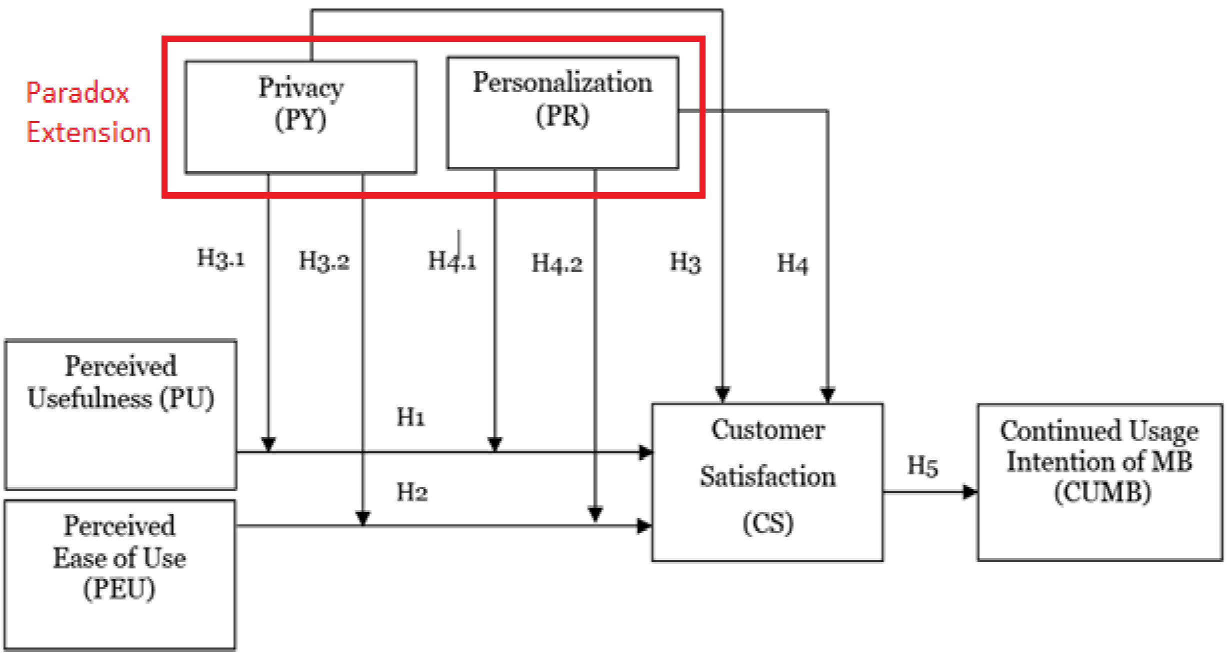

Figure 5.1. Research Model

5.3.1. Perceived usefulness (PU) and perceived ease of use (PEU)

TAM is based on TRA (Davis et al., 1989) and is often used by IS researchers to determine behavioral intention and actual use based on PU and PEU (Taylor and Todd, 1995). These two factors are found to play a major role in determining satisfaction in contexts similar to MB, for example, online banking (Bhattacherjee, 2001), mobile internet (Hong et al., 2006), online university (Joo et al., 2011), and mobile technology (Lee and Park, 2008). Thus, we hypothesize that:

H1: *Perceived usefulness is positively related to customer satisfaction in MB.*

H2: *Perceived ease of use is positively related to customer satisfaction in MB.*

5.3.2. The role o f privacy (PY)

Privacy refers to what extent an individual has control over his/her personal information when interacting with MB (Hong and Thong, 2013). Mobile users usually show their privacy concerns when interacting with online products or services (Sutanto et al., 2013), thus, privacy could be perceived an important factor to satisfaction of MB users. When MB is associated with good measures of privacy, it can generate trust and satisfaction, which in turn leads to continued usage intention of MB (Wang et al., 2006; Zhou, 2012). Other empirical studies find a support for the association between privacy and satisfaction (Chang et al., 2011; Dharmesti and Nugroho, 2013). However, privacy has been regarded as a moderating factor in a number of different milieus, including but not limited to the usage of e-commerce and health system)Bansal et al., 2008; Xu et al., 2011). Customers like to have a greater protection on their personal information so they may show a higher level of satisfaction when privacy is reinforced for a productive and easy-to-use MB app. Thus, we believe privacy can be a predictor and moderator:

H3: *Privacy is positively related to customer satisfaction in MB.*

- ***H3.1:*** *The higher level of privacy, the greater positive relationship between perceived usefulness and customer satisfaction.*
- ***H3.2:*** *The higher level of privacy, the greater positive relationship between perceived ease of use and customer satisfaction.*

5.3.3. The role o f personalization (PR)

Personalization considers providing tailored services to MB users based on their behaviors and preferences (Xu et al., 2011). Personalized services can increase efficiency to conduct MB services. For instance, MB users who are always checking their balance would like to have a single authentication to do so. Hence, once MB provides such personalized experience, they would show a higher satisfaction towards it. Expanding on that, providing more personalized MB services may lead to improving the system's usefulness and easiness to predict users' satisfaction. For example, with increasing personalization, MB can enhance users' productivity to conduct banking services (usefulness) and improve users' usability and flexibility to these services (easy to use), which in turn may increase their satisfaction level. Past studies have shown that personalized services predict satisfaction among Internet banking users (Tong et al., 2012), and also moderate their level of satisfaction (Thongpapanl and Ashraf, 2011; Wang and Groth, 2014). As MB is an extension of internet banking, those relationships most likely will hold in this context. Accordingly, we hypothesize that personalization can be a predictor and moderator:

H4: *Personalization is positively related to customer satisfaction in MB.*

H4.1: *The higher level of personalization, the greater positive relationship between perceived usefulness and customer satisfaction.*

H4.2: *The higher level of personalization, the greater positive relationship between perceived ease of use and customer satisfaction.*

5.3.4. Customer satisfaction (CS)

In our study context, satisfaction refers to what extent a person feels satisfied towards MB services (Bailey and Pearson, 1983). Consumer satisfaction, as mentioned in extant research, has a significant influence on continued usage intention of IT (Park, 2014). Satisfaction is a critical antecedent of continued usage intention due to consumers' sensitivity towards switching cost in online commerce (Hsu, 2014). Therefore, consumers that are satisfied with existing MB services will not switch to competing services according to the rational decision-making perspective (Kim and Gupta, 2009). According to Delone and Mclean (2003), customer satisfaction plays a major role in determining IS usage. Bhattacherjee (2001), also, validates empirically the relationship between customer satisfaction and continued usage intention of online banking. Thus, we hypothesize that:

H5: *Customer satisfaction is positively related to CUMB.*

5.4. Research Method

Our study data was collected from customers of a local bank in the U.S. via an online survey. A 7-point, Likert-scale was implemented to measure the survey items with a range of 1, “strongly disagree” to 7, “strongly agree”. Survey participation was voluntary with an incentive from the bank to donate $1000 to a charity organization for completing the survey. Our data collection approach was successful with a 16% response rate (939 customers) but due to critical missing data, our sample got reduced to 851 valid respondents. We included both users and non-users of MB, but our research question is concerned primarily with MB users only (486 participants). System log data of MB services was included to compare actual usage and perceived usage.

The survey items were assessed for content validity first by subject matter experts and later for face validity and reliability through an online pilot survey with 130 internal bank customers. Pilot survey respondents were asked to provide any remarks on clarity and understandability of the questions. Pilot study helped us revise the survey and making it more clear and understandable before the final survey was sent to all online customers of the bank.

Our survey constructs and items (Table 5.2) were adapted from literature in a comparable area. Perceived usefulness and perceived ease of use were adapted from Davis (1989). These two factors showed to have a composite reliability of 0.94 and 0.89, respectively. Privacy was adapted from Hong and Thong (2013) and personalization was adapted from Xu et al. (2011). Privacy and personalization showed to have a composite reliability of 0.88 and 0.93, respectively. Customer satisfaction was adapted from Fornell et al. (1996) and Thong et al. (2006) while continued MB usage intention was adapted from Bhattacherjee (2001) and Hong et al. (2006). Satisfaction and continued usage intention showed to have composite reliability of 0.92 and 0.85, respectively.

Table 5.2. Construct Operationalization

Construct	Item	Citation
Perceived usefulness (PU)	PU1: Overall, I find MB to be useful PU2: Using MB improves my performance in conducting financial transactions PU3: Using MB enables me to process financial transactions quickly PU4: Using MB enhances my productivity with financial transactions	Davis (1989)
Perceived ease of use (PEU)	PEU1: Overall, I find MB to be easy to use PEU2: MB is easy for doing what I want to do PEU3: My interactions with MB are clear and understandable PEU4: Interaction with MB app is flexible (on any device) PEU5: It is easy to become skillful at using MB	Davis (1989)
Privacy (PY)	PY1: I am concerned that when I give personal information to MB for some reason, the bank would use the information for other reasons PY2: I am concerned that my information could be breached when using MB PY3: I am concerned that my information could be shared or sold when using MB	Hong and Thong (2013)
Personalization (PR)	PR1: MB provides me with personalized services tailored to my needs PR2: MB provides me with more relevant information tailored to my preferences PR3: MB provides me with more convenient services that I like	Xu et al. (2011)
Customer satisfaction (CS)	CS1: Overall, I am satisfied with my MB experience. CS2: MB experience meets my expectations.	Fornell et al. (1996) & Thong et al. (2006)
Continued usage intention of MB (CUMB)	CUMB1: I intend to continue using MB services in the future. CUMB2: I intend to continue to use Enterprise Bank's MB rather than seek out other banks for a better mobile experience.	Bhattacherjee (2001) & Hong et al. (2006)

	CUMB3: I intend to increase my use of various services provided by MB in the future.	

5.4.1 Participants profile and usage comparison

Participants' demographics (Table 5.3) were divided into three groups (full sample, MB-users, and non-users). Our main focus is on MB-users sample, which shows that the majority group of the respondents is full-time employed females who aged between 56 and 65 and have a college degree while the minority group is part-time employed males who aged less than 25 years and have associate degree "2-year diploma".

Table 5.3. Demographic Information

	Full (n = 831)		MB-users (n = 466)		Non-users (n = 365)	
Demographics	**Freq.**	**Perc.**	**Freq.**	**Perc.**	**Freq.**	**Perc.**
Gender						
Male	381	45.8%	216	46.4%	165	45.2%
Female	450	54.2%	250	53.6%	200	54.8%
Age						
<25	43	5.2%	40	8.6%	3	0.8%
25-35	82	9.9%	69	14.8%	13	3.6%
36-45	86	10.3%	65	13.9%	21	5.8%
46-55	189	22.7%	121	26%	68	18.6%
56-65	231	27.8%	109	23.4%	122	33.4%
> 65	200	24.1%	62	13.3%	138	37.8%
Education						
High school	183	22%	105	22.5%	78	21.4%
Associate degree	149	17.9%	87	18.7%	62	17%
College degree	271	32.6%	149	32%	122	33.4%
Graduate degree	228	27.4%	125	26.8%	103	28.2%
Work Status						
Unemployed	175	21.1%	68	14.6%	107	29.3%
Full-time	405	48.7%	268	57.5%	137	37.5%
Part-time	95	11.4%	43	9.2%	52	14.2%
Self-employed	156	18.8%	87	18.7%	69	18.9%

Note: Freq: Frequency and Perc: Percentage (%)

The bank gave us an access to actual usage data of MB services (system log file). This data was collected during the period of our survey and then averaged on a weekly basis so that we can compare it with survey responses (Figure 5.2). MB usage survey questions were designed to collect the same data provided by the log file to enable a valid and insightful comparison.

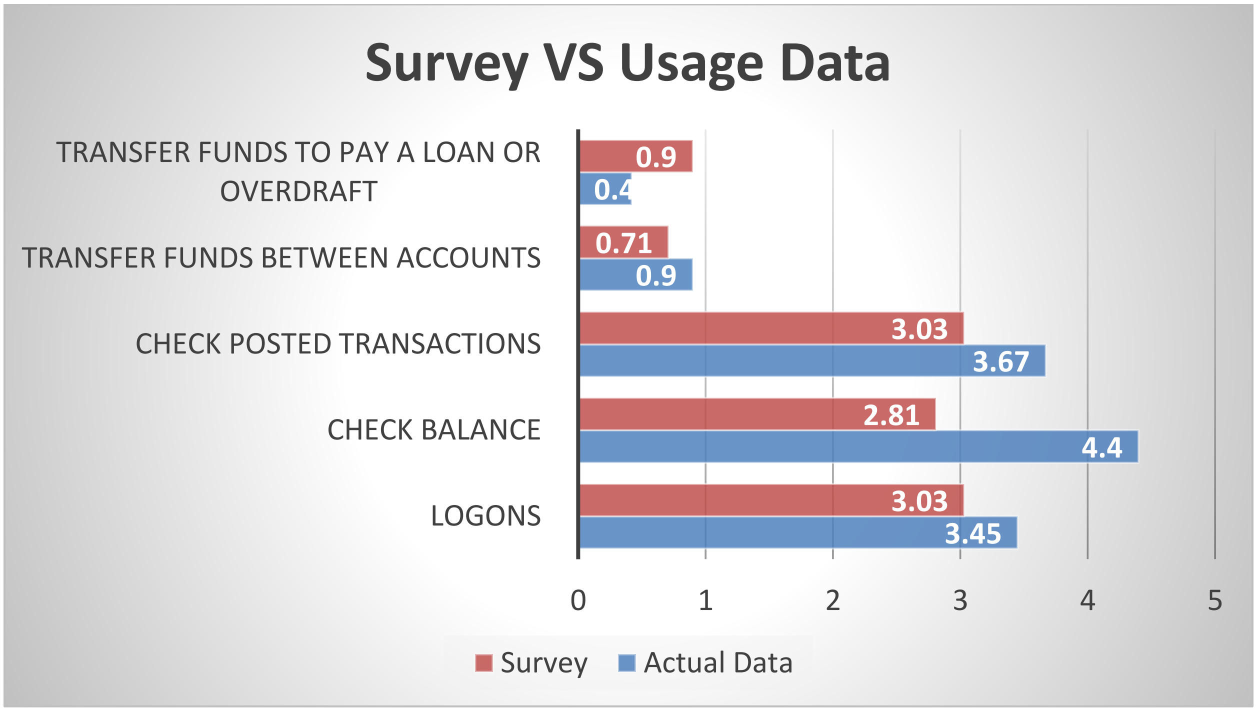

Figure 5.2. Comparison between Survey and Archival Data of MB

As per figure 5.2, it is evident that customer actual usage of MB exceeded their perception (survey) in all the categories above except for "Transfer funds to pay a loan or overdraft", where the gap between actual usage data and survey is not significant. This conclusion was supported with t-test (p-value = 1.079). Therefore, we can infer that responses on the usage of MB services provided by participants were reliable.

5.5. The Measurement Model

The measurement model shows no high correlation among the variables (Table 5.4). While the square root of AVE (average variance extracted) for each factor has a greater value than other correlation coefficients of the same factor. Hence, discriminant validity is acceptable.

Table 5.4. Correlations of Latent Variables and Square Root of AVE (bold in diagonal)						
Construct	**PU**	**PEU**	**PY**	**PR**	**CS**	**CUMB**
PU	**0.904**					
PEU	0.792	**0.903**				
PY	-0.200	-0.201	**0.901**			
PR	0.654	0.684	0.189	**0.750**		
CS	0.729	0.805	0.136	0.613	**0.980**	
CUMB	0.666	0.738	0.215	0.493	0.677	**0.840**

Data was, also, analyzed for convergent validity to determine to what extent the items are reflecting their relevant constructs. Table 5.5 below shows factor loading for each item, communality (COM), composite reliability (CR), AVE, internal consistency (Cronbach's alpha) and variance inflation factor (VIF) for the constructs and their items. All item loadings are good (0.6 or greater) on their corresponding factor. This suggests that the items are relevant, non-redundant and form independent constructs. Communality for each item is greater than 0.5, which denotes that items share common features except for CUMB3, which is about 0.5. All CRs and AVEs are greater than 0.7 and 0.5, respectively, which indicates a good convergent validity. Alpha values are greater than 0.7 for each factor, while the total Cronbach's alpha is 0.914. Thus, all factors confirm good reliability (Zhou, 2013). VIF for all factors is smaller than 5, which indicates there is no collinearity between variables.

Table 5.5. Reliability and Validity Indicators							
Construct Measurement	**Number of Items**	**Factor Loadings**	**COM**	**CR**	**AVE**	**Alpha Value**	**VIF**
Perceived usefulness	4			0.947	0.816	0.925	2.828
PU1		0.899	0.736				
PU2		0.924	0.618				
PU3		0.888	0.641				
PU4		0.902	0.703				
Perceived ease of use	5			0.956	0.815	0.942	3.025
PEU1		0.948	0.833				

PEU2		0.923	0.811				
PEU3		0.940	0.811				
PEU4		0.800	0.555				
PEU5		0.896	0.724				
Privacy	3			0.928	0.811	0.884	1.049
PY1		0.899	0.780				
PY2		0.868	0.787				
PY3		0.934	0.872				
Personalization	3			0.920	0.794	0.871	2.009
PR1		0.898	0.737				
PR2		0.895	0.807				
PR3		0.880	0.704				
Customer satisfaction	2			0.980	0.961	0.960	1.000
CS1		0.981	0.798				
CS2		0.980	0.781				
Continued usage intention of MB	3			0.877	0.706	0.794	N/A
CUMB1		0.902	0.618				
CUMB2		0.875	0.507				
CUMB3		0.733	0.479				

Note: n = 486, Total Cronbach's alpha of all constructs = 0.914

5.6. The Structural Model

Using SmartPLS, which is immune to violation of normality assumption, the structural model was tested through structural equation modeling-partial least square (SEM-PLS). We have four independent variables: PU, PEU, PY, and PR; two moderating variables: PY and PR; and two dependent variables: CS and CUMB.

As per table 5.6 and Figure 5.3, perceived usefulness ($\beta=0.274$, $p<0.05$) and perceived ease of use ($\beta=0.582$, $p<0.01$) are significant predictors of satisfaction, while privacy ($\beta=0.027$, $p>0.05$) and personalization ($\beta=0.002$, $p>0.05$) are not. Thus, H1 and H2 are supported while H3 and H4 are not. For the interaction effects, privacy was found significantly moderating both perceived usefulness ($\beta=-0.109$, $p<0.05$) and perceived ease of use ($\beta=0.095$, $p<0.05$), whereas personalization was found to have no significant effect. Thus, both H3.1 and H3.2 are supported but both H4.1 and H4.2 are not supported. Privacy showed a negative sign because the question code wasn't reversed. Customer satisfaction is positively related to continued usage intention of MB (β=0.677, p<0.01), thus, H5 is supported. This model appears to explain higher variance in satisfaction (69.3%), compared to Park model that does not account for privacy.

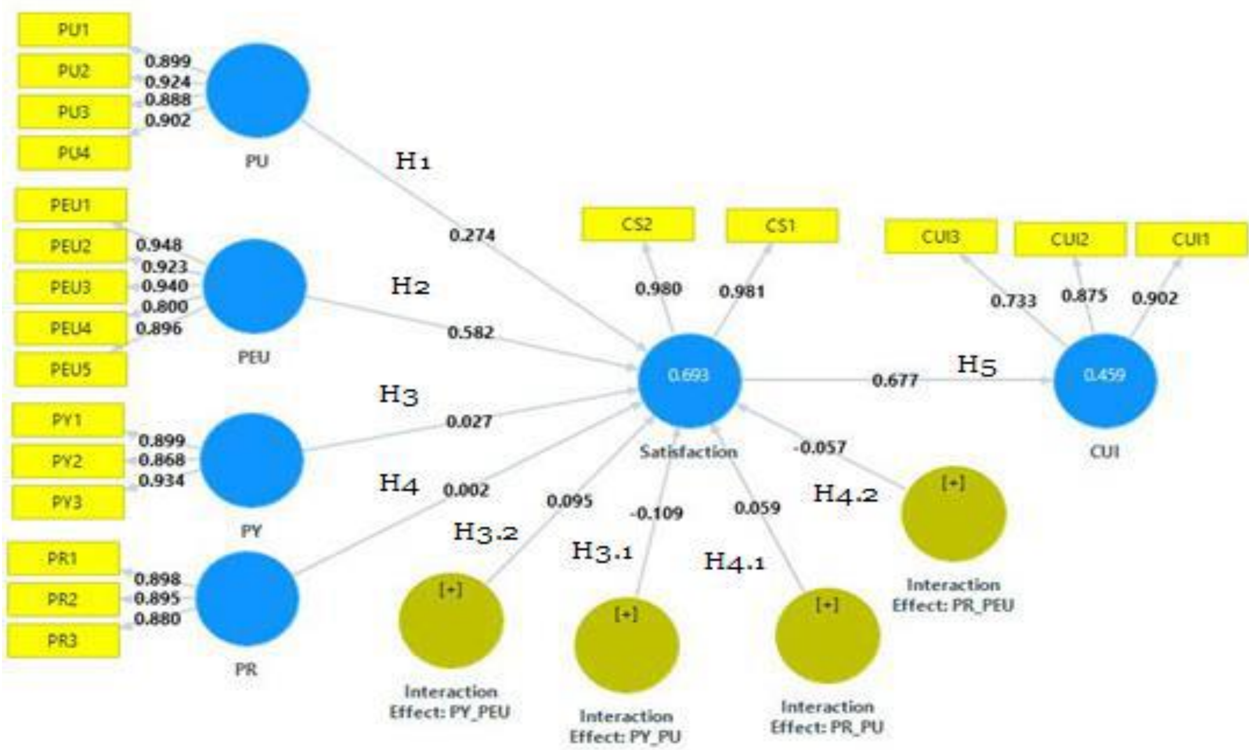

Figure 5.3. Structural Tested Model

Table 5.6. Structural Model Results				
Structural Paths	**Sign**	**PLS Path coefficient**	**t-Statistics**	**p-Value**
H1: PU → CS	+	β = 0.274	2.563*	<0.05
H2: PEU → CS	+	β = 0.582	6.023**	<0.01
H3: PY → CS	+	β = 0.027	1.086	ns (p>0.05)
H3.1: PY Moderator → CS	-	β = 0.109	2.146*	<0.05
H3.2: PY Moderator → CS	+	β = 0.095	2.109*	<0.05
H4: PR → CS	+	β = 0.002	0.055	ns (p>0.05)
H4.1: PR Moderator → CS	+	β = 0.059	1.071	ns (p>0.05)

H4.2: PR Moderator → CS	-	β = 0.057	1.155	ns (p>0.05)
H5: CS → CUMB	+	β = 0.677	16.431**	<0.01

n = 486 – ns: not significant
P*<0.05, P**<0.01

Variance explained: CS = 69.3%
Variance explained: CUMB = 45.9%

5.7. Discussion

5.7.1. Summary of findings

Consistent with prior research (Joo et al., 2011; Lee and Park, 2008) , our findings indicate that perceived usefulness and perceived ease of use are significant determinants of satisfaction. Privacy and personalization do not have an impact on satisfaction directly; this relationship is supported in a few studies (Alawneh et al., 2013; Tomovska–Misoska et al., 2014; Thongpapanl and Ashraf, 2011; Wang and Groth, 2014), but not supported in other studies (Chang et al., 2011; Dharmesti and Nugroho, 2013; Park, 2014). While personalization seems not to have a moderating effect on satisfaction, privacy does have it. This moderating effect of privacy is confirmed in (Bansal et al., 2008; Xu et al., 2011). Our conclusion regarding satisfaction, as an important predictor to CUMB, is consistent with the findings of Bhattacherjee (2001) and Hong et al. (2006).

A number of reasons can be considered for our results on privacy and personalization. First, although privacy is well addressed in the bank's MB app, some customers are still concerned about their information accessed or shared by a third party. Second, the surveyed customers have not been provided with any options to personalize their MB experience. This may contribute to make personalization a weak or insignificant determinant of satisfaction. Lastly, both privacy and personalization may have not been given a considerable attention by the customers because being relatively a mid-sized bank, users must have a higher level of trust. In other words, participants of our study focused on the efficient and flexible performance of their banking interactions without giving much thought to the aspects of privacy and personalization. Nonetheless, we do consider that both of these could be important factors in the long-run with mature usage of MB services.

5.7.2. Implications for theory

The area of mobile technology is rich with opportunities for IS researchers who want to examine either adoption or post-adoption through refining the existing theoretical models. TAM is considered a well-established model in predicting IS usage)Davis, 1989; Davis et al., 1989), but it focuses on two specific beliefs, which limits its underlying theoretical framework for providing a sufficient explanation and greater understanding of this phenomenon. Our study attempts to extend TAM framework with relevant cognitive factors from other models, like ECT-IT and Park, to improve its theoretical contribution in the MB continued usage context. Our research has empirically validated the extended model, helping to further the understanding of MB usage. Specifically, TAM does not account for the customers' perception of privacy and personalization of IS services. And when integrate these factors to TAM, its analytical power considerably increases. This indicates that TAM is developed with an embedded capability to explain various types of IT innovations, including MB.

Considering the paradox of privacy and personalization proposed by Xu et al. (2011), this study taps on this aspect and shows such paradox may exist in mobile technologies (e.g., MB). According to our analysis, MB users tend to have a very high level of privacy, which in turn influences personalized services to be at the minimum (reverse impact). This confirms that there is a trade-off between those two factors (Xu et al., 2011). However, the main goal achieved by the study is revealing the moderating role of both privacy and personalization in a MB context and communicating that to the research community. This contribution is added to the existing MB theoretical base and so advancing the knowledge to understand IT innovations.

5.7.3. Implications for practice

Our study finds that customers who perceive the current MB services to be convenient, helpful, effective, easy, and effortless show a higher level of satisfaction, which results in a higher tendency to continue using MB in the future. Our focus about the relationship between privacy, and personalization and CUMB is central to our discourse, but satisfaction, affected by the level of privacy, is very important to understand customers as it can impose a strong impact on their loyalty and retention (Fornell et al., 1996).

In the light of these findings, we can state that mid-sized banks should address their MB services by focusing on; 1) enhancing the aspects of productivity and performance to reflect usefulness, 2) increasing flexibility and agility to reflect easiness, and 3) augmenting their privacy level with better security approaches against data breaches and stronger policies against data sharing. Hence, MB strategies initiated by banks should integrate the above recommendations into their business plan in order to increase customers' retention rate, reflected by a high intention to continue using MB services. Banks can also increase MB usage by developing a special and personalized campaign to MB minority groups, such as, the male customers less than 25 years old who have a part-time job and 2-year diploma as the demographics shows.

5.8. Conclusion

Exploring MB continued usage is of utmost importance, particularly for banking institutions because it can provide valuable insights about the most significant stage of customers' usage behavior. Study contributions are two-fold. First, it reveals the direct and indirect effect of both privacy and personalization on continued usage intention of MB. This area is important and very relevant to a MB context, yet has never been investigated before. Hence, it has enriched MB literature with a new theoretical perspective. Second, the study unfolds practical implications on how to improve MB services; for instance, it is by more privacy, less personalization or more personalization, less privacy. Understanding such paradox would lead to increased customer loyalty and sustained usage, which ultimately nets more profits to the banks.

Chapter 6. Overall Contributions, Limitations, and Conclusion

This chapter presents the synthesized contributions of this research theoretically and practically, provides limitations and future research directions, and concludes with insightful inferences.

6.1. Theoretical and Practical Contributions

Shedding light on MB from various angles can help to disclose novel contributions for both theory and practice. In broad and brief, targeting MB behavioral intention with a multi-analytical approach reveals the most influential factors affecting this phenomenon, detects non-linear relationships, and provides deep insights about user experience in system adoption research. Second, integrating IS Success and UTAUT helps to evaluate and authenticate its theoretical foundation as a holistic and robust framework to examine system usage in a MB context. Such integrative model would analyze the subjective and objective MB usage to reduce the bias generated from self-reported data and to inform academia on validation aspects related to their measurement and correlation. Third, extending TAM with privacy-personalization paradox to explore users' continued usage intention towards MB is a significant addition to the literature because this paradox has been a centric topic in IS research. Thus, it is necessary to know whether such paradox can be generalized to mobile technologies (e.g., MB).

Practically, both the multi-analytical approach and integrative framework can allow the banking industry to have a wider and more comprehensive picture of the significant factors that increase customers' satisfaction, usage, and loyalty. For example, through IPMA matrix, not only the significant factors are revealed but also their respective indicators, giving a further layer of analysis and so a further layer of understanding. This understanding can promote a better mechanism to interact with those factors and their composing elements by deliberately ranking and so managerially prioritizing for enhancement by MB development team.

6.2. Limitations and Future Research

Our study has some limitations that can be transformed into future research opportunities. First, although we have a good sample size, it had been obtained from one bank at a single point of time (cross-sectional sample), which limits our scope to interpret the results even though they could be extended to other US mid-sized banks with similar customers. Thus, we recommend further research in this area by including banks of different sizes and various geographic regions to enhance the external validity. Second, this study suggests association rather than causality or cause-effect; the causal relationship should be addressed in future research through a longitudinal study. For instance, longitudinal studies can use the same multi-analytical approach to identify causality and establish stronger theoretical and practical implications. Third, the employed self-reported data may convey unnoticed bias. For example, some customers may be pleased with bank services or staff; hence, they give the highest scores for all asked items. Also, although we conclude that using subjective system usage could provide unreliable or invalid results, one study can't confirm such extreme conclusion. Accordingly, further research should be conducted to confirm this concern and suggest additional remedies. Fourth, even the integrative framework has proved its high analytical power, its validity to other IT innovations other than MB has not been yet established. Thus, future IS research is needed to verify the model validity and its extension to other emerging technological innovations.

Lastly, it is important to note that our study has been conducted from a customer's perspective; how to leverage the level of satisfaction and loyalty among bank customers. While a bank's perspective is as important as a customer's perspective, there have been a few studies conducted in this area, leading to a lack of understanding. Most importantly, there are still some financial institutions are hesitant to move towards adopting MB despite its realized benefits. Therefore, it would be valuable to study the organizational factors affecting a bank decision to adopt this new technology.

6.3. Conclusion

MB is an evolving phenomenon, which directs the eyes, specifically those of banks and software vendors to look for areas for further improvement in a way to increase its adoption, actual use, and most importantly continued usage intention. The importance of continuance intention is attributed to its significant tie to not only satisfaction but also to loyalty and word-of-mouth marketing strategy, which is considered a vital element to help increasing bank market share. In the practical sense, this research study assists practitioners to adopt effective techniques for improving MB services while using efficiently their organizational resources.

Overall, this study does not examine MB usage behavior as a static object but as a three-object life cycle that starts with the behavioral intention (the first stage of acceptance), goes through system actual use, and ends with continued usage intention. Every object is being investigated via a different conceptual framework, which gives the study an enriched dimension of a multi-theoretical perspective. This examination can help to expand our knowledge in MB area and lend opportunities for future research.

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Biographical Sketch of Author

Mousa Albashrawi is a PhD candidate in the area of Management Information Systems (MIS) at University of Massachusetts Lowell. Mr. Albashrawi earned his M.S. degree in Information Systems (Healthcare Technology Management Track) from University of Colorado Denver. His research interests include, but not limited to, mobile technologies, entrepreneurial intention, and information privacy. He has worked as a lecturer at King Fahd University of Petroleum and Minerals, KSA. Mr. Albashrawi reviewed research papers for various journals and conferences, for example, *Computer and Human Behavior*, *Information and Management*, *AMCIS, and ICIS*. His papers are accepted and published in different good conferences, AMICS, Western DSI, Eastern Academy of Management, Pre-ICIS, ACM, and HICSS. Also, his paper of fraud detection is published in *Journal of Data Science* while another paper is going under review in *Information Systems Frontier*.