The Impact of Subjective and Objective Experience on Mobile Banking Usage: An Analytical Approach

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Abstract

This paper aims to investigate mobile banking (MB) usage through the theoretical lens of UTAUT model with its four pillars. The research model will be tested via a hybrid neural networks-based structural equation modeling (SEM-NN) to reveal significant factors. Universal structural modeling (USM) will be then utilized to find the hidden paths and nonlinearity in our research model. To the best of our knowledge, this is the first study to examine the role of subjective and objective experience on MB usage using a multi-analytical approach. Neural network (NN) and USM can identify the most significant determinants and hidden interaction effects, respectively. Thus, both techniques would help to complement SEM and increase our understanding of the influential factors on MB usage. Preliminary results are presented and discussed. Potential contribution and conclusion are communicated to both academia and industry.

1. Introduction

Mobile Banking (MB) enables bank customers to access a wide array of banking services including balance check, money transfer, and mobile deposit. This emerging technology provides a ubiquity advantage when compared to the traditional banking; it can be accessed anytime and anywhere using a web-enabled mobile device. MB has been adopted on a large scale due to the sharp increase in using smartphones [6]. However, it is associated with some constraints, such as small screens, inconvenient input and slow responses [30] that may hinder its usage.

Extant research has drawn on various IS theories and acceptance models to examine MB adoption, for example, unified theory of acceptance and use of technology (UTAUT) and task-technology fit (TTF) [29], technology acceptance model (TAM) [17], and innovation diffusion theory [14]. Actual system use has a greater value than behavioral intention (adoption) because it is a key to determine information system success and can provide a better indication of satisfaction [7]. Hence, there has been an important call to shift IS research from intention stage to actual use [26]. Although with the significance of this outcome object, very few studies attempt to go beyond behavioral intention and focus on MB actual use [21]; [10]. This indicates that MB research still remains sparse in this area. In addition, MB research has focused only on identifying the significant factors but not the most important ones that drive system usage. As the complexity of decision-making process towards intention to use various types of information systems has been overlooked in IS research through investigating only the linear relationships [22], it is critical to employ a technique (i.e., universal structural modeling (USM)) that accounts for hidden patterns of nonlinearity in the data. While experience has not been given much attention in MB. This has motivated us to address such research gaps using a multi-analytical approach and through our research question: does the impact of subjective and objective experience differ and which factors affecting MB usage have the most influence? These questions will be addressed via the theoretical lens of UTAUT, which has been established as a high-order model that can explain the highest amount of variance in user behavior [24].

This study contributes to theory and practice by 1) highlighting the role of 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 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 significant determinants but also the most important ones that influence MB usage. Second, USM technique would disclose hidden nonlinearity and not theoretically suggested paths. Both of these techniques can allow a deeper analysis and understanding of the factors impacting MB usage

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The rest of this paper is organized as follows: section 2 describes UTAUT, neural network, and USM in details 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 preliminary results. Section 6 explains the future steps to be done while section 7 concludes with discussion, potential contribution, and conclusion.

2. Related work

In this section, we elaborate on the unified theory of acceptance and use of technology (UTAUT) and its uses in IS literature, define neural network and illustrate its applications in the two streams of IS research, show the importance of universal structural modeling, and then browse works that combine adoption behavior and SEM-NN analysis.

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) in order to improve predictability power [24]. 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. [11] adapted UTAUT to predict Facebook acceptance among college students. While in a mobile context, Zhou et al. [29] used convenience sample to collect data and analyzed it via UTAUT to explain mobile banking user adoption. Baptista and Oliveira [1] 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 mining tool that can enhance its nomological validity in the context of mobile banking. 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 model.

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" [4: p. 516]. NN seems like a human brain but it is composed of artificial neurons (nodes) that have the ability to learn from its environment and obtain new knowledge [5]. 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 data structure [8].

NN has been mostly applied in decision science research to address a specific business problem, for example, re-constructing gene regulatory networks [15] and detecting financial fraud [16]. However, few behavioral studies have utilized NN to estimate probabilities in consumer choice [9] and to explain behavior towards web and traditional stores [4]. According to Tan et al. [22], 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 usage.

In our study, to employ NN, we will use a multilayer perceptron algorithm that builds a network of linear classifiers. Each node computes a weighted sum of inputs and uses a threshold function on the results. We have deployed a non-linear threshold function, commonly used sigmoid function:

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

We will be building a model 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.

2.3. Universal structure modeling

Buckler and Hennig-Thurau [2] introduce a new innovative tool 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 tool 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 [2]:

- Hidden paths: USM, besides identifying the proposed hypotheses in the research model, can detect unsuggested and not theoretically supported paths in the model. This feature has been considered a valuable tool for theory development.
- Hidden interactions: CVSEM and PLS help a researcher to test a hypothesized interaction effect (a moderating variable) by multiplying the constructs’ items 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 relations and identify those relations whether proposed or not proposed by the model. In other words, it can detect systemic and non-systemic moderating effects.
- Hidden nonlinearity: CVSEM and PLS can recognize only linear relationships in the measurement model. While USM can account for nonlinearity due its Bayesian neural network estimation technique.

Mathematically speaking, USM specifies the structural model with $\hat{y}^j$ as the endogenous latent variable defined by functions of one or more other latent variables y that can be exogenous or endogenous. Formally, $\hat{y}^j$ is estimated through y^j 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.

However, most studies that have sought to examine MB adoption or behavioral intention are based on a traditional statistical analysis [1]; [29]. Such analysis is limited by observing only linear relationships in the conceptual model. These linear relationships over-simplify the complexity associated with IT adoption decisions [22]. USM can overcome such limitation by finding the hidden nonlinearity patterns in the data. Also, it would find any hidden direct or indirect paths not suggested by the conceptual model, which helps to inform further insights about MB usage.

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

2.4. Adoption behavior and SEM-NN

Few studies have employed a conjoint analysis approach, i.e. SEM-NN, to examine the impact of usage intention. Scott and Walczak [20] investigated students’ intention to use an ERP training tool by employing both SEM and NN. Leong et at. [13] explored the acceptance of near field communication (NFC)-enabled mobile credit card system via using the same conjoint analysis method on various-industry sample in Malaysia. Chong [5] utilized a multi-analytical (SEM-NN) approach to measure mobile commerce adoption among college students. Yadav et al. [27], similar to Chong [5], measured mobile commerce adoption using the same approach among postgraduate students. Tan et al. [22] 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 being regarded as a key to determine information system success [7]. Second, most studies have sampled on students. Considering the generalizability issue associated with a 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 [13] and to study its impact on system usage. Fourth, no a single study has examined the highest-impact predictors in a MB context using a multi- sophisticated technique. Fifth, no a single study, also, has attempted to account for nonlinearity that may exist in customers' decisions to adopt MB or to actually use it.

3. Research model and hypotheses

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

3.1. Research model

Each context has some differences when compared to others. Such differences make it necessary to research usage behavior in its specific environment [11]. Accordingly, we plan to investigate usage behavior in a MB context via UTAUT because of its high analytics power. This model is visualized in Figure 1. It posits that UTAUT's four pillars are predictors to 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 survey and objectively via log data.

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" [24: p. 447]. Since this construct had been developed from TAM's perceived usefulness [24], it simply indicates maximizing efficiency. Individuals normally like to adopt technologies that increase their productivity and enhance their effectiveness in accessing and dealing with 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 a considerable empirical support in a MB context [1]; [28]; [29], thus, we hypothesize that:

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

3.3. Effort expectancy (EE)

Effort expectancy is defined as "the degree of ease associated with the use of the system" [24: p. 450]. Since this factor had been developed from TAM's perceived ease of use, MPCU's complexity, and IDT's ease of use [24], 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 to be more interested to start using MB. The positive relationship between effort expectancy and behavioral intention has been validated in MB research [28], hence, we hypothesize that:

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

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 [16]. 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.

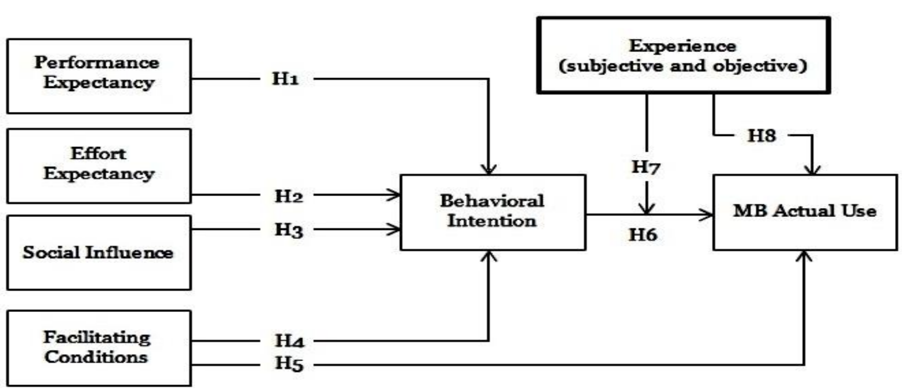

Figure 1. Research model

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 literature supporting this association [11]; [28]; [29], we hypothesize that:

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

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 [16]. MB is facilitated by various resources. Such resources that include 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 [1]; [28]; [29]. 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.*

3.6. 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'' [23: p. 484]. Psychological theories argue that individuals' behavioral intention is linked to the actual use [1]. Thus, individuals with a high intention to use a MB system will break the ceiling and start using it. In addition, various studies in IS literature support this causal link [11], and specifically in a MB setting [1]. Thus, we hypothesize that:

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

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." [25: p. 161]. Experience helps to build up individuals' competence when utilizing a specific system, which in turn sustains 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 [12] 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 [19].

Experience helps to decrease uncertainty and increase the sense of control over a MB system. Therefore, 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 [23]. With increasing MB experience, individuals reinforce their habit of using the system and therefore this behavior becomes automatic [25]. Automatic behavior could enhance the level of system use. For example, individuals who have a long experience at using various MB services would 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.*

4. Research method

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 donate $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 516 participants due to the removal of missing values.

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

4.2. Survey instrument

Survey was designed as closed-ended structured questions. It has two parts. The first part askes demographic questions like age, gender, education, and work status. The second part asks questions about our variables of interest (research questions).

The survey was pre-tested with a pilot of 10 bank customers using 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 revise the survey and make it more clear and understandable before sending it to the full sample.

4.3. Measurement

Constructs' items have been adapted from literature and modified to a MB context (Appendix 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. [3]. Both behavioral intention and actual use are adapted from Venkatesh et al. [25]. Experience is measured in months as suggested by Venkatesh et al. [25].

4.4. Data analysis

4.4.1. Participants' demographic profile

As per table 1, the sample shows more female representation in the data; 54.07%. In terms of age, senior customers (> 60) constitute the majority group while young customers (15-25) constitute the minority group. Regarding the education level, degree holders are considered to be more than half of the sample (about 61% had obtained a bachelor degree or higher). For work status, the regular employees dominated the survey with 64.34% and about 28 multiple of the student size.

4.4.2. Descriptive statistics, validity, and reliability

As per table 2, the mean, standard deviations, and factor loadings are presented for every item. All loadings are good as their values are greater than 0.60 except for FC3, which had been removed from the data.

As per table 3, data was analyzed for various indicators of validity and reliability. The data shows a good convergent validity because composite reliability (CR) and average variance extracted (AVE) for all factors are greater than 0.7 and 0.5, respectively. The measured factors, also, have a good reiability since their Cronbach's alpha values are higher than 0.70. Lastly, variance inflation factor (VIF) shows acceptable levels (< 5), which indicate no collinearity between variables.

Table 1: Demographic profile for participants

Variable	Frequency	Percentage
Gender		
Male	237	45.93
Female	279	54.07
Age		
15-25	51	9.88
26-35	64	12.21
36-45	84	16.28
46-55	124	24.03
56-60	62	12.02
> 60	132	25.58
Education		
High school	57	11.05
Some college	141	27.33
College degree	164	31.78
Graduate degree	149	28.88
Other	5	0.97
Work Status		
Full-time	332	64.34
Part-time	64	12.40
Unemployed	17	3.29
Retired	91	17.64
Student	12	2.33

Table 2: Descriptive statistics

Variables' Items	Mean	Standard Deviation	Factor Loadings
PE1	5.98	1.03	0.94
PE2	5.90	1.13	0.95
PE3	5.74	1.19	0.94
EE1	5.84	1.15	0.90
EE2	5.94	1.02	0.94
EE3	5.92	0.98	0.91
SI1	4.34	1.52	0.96
SI2	4.40	1.53	0.97
SI3	4.33	1.49	0.95
FC1	6.11	0.84	0.90
FC2	6.19	0.77	0.89
BI1	6.25	0.90	0.80
BI2	5.46	1.36	0.88
BI3	5.61	1.30	0.93

Table 3: Validity and reliability indictors

Variables	CR	AVE	Alpha	VIF
PE	0.96	0.88	0.93	2.83
EE	0.94	0.84	0.90	2.96
SI	0.97	0.92	0.96	1.13
FC	0.89	0.80	0.75	1.54
BI	0.90	0.76	0.84	1.30

Note: CR: composite reliability, AVE: average variance extracted, VIF: variance inflation factor.

5. Preliminary results

We have performed partial analysis on the collected data, time and space permitting. The analysis is limited to SEM and USM and based on the survey data only.

5.1. Hypotheses testing (SEM)

As per table 4, the hypothesized relationships are tested using SEM-PLS technique, which does not require the data to be normally distributed. The testing had been conducted on two phases. Phase one or model 1 includes only independent variables and their impact on dependent variables (i.e., behavioral intention and actual use). Phase two or model 2 includes the independent variables and interaction effect (i.e., experience). SmartPLS software was utilized to analyze the data.

Table 4: Hypotheses testing

Model 1			
Path	**Estimate**	**t-statistics**	**Remark**
PE > BI	0.50	9.39**	Supported
EE > BI	0.26	3.92**	Supported
SI > BI	0.12	3.56**	Supported
FC > BI	0.03	0.69	Not supported
FC > Actual Use	0.05	0.98	Not supported
Experience > Actual Use	-0.11	2.73**	Supported
BI > Actual Use	-0.45	8.15**	Supported
Model 2 (with interaction effect)			
Path	**Estimate**	**t-statistics**	**Remark**
PE > BI	0.50	9.01**	Supported
EE > BI	0.26	3.83**	Supported
SI > BI	0.11	3.46**	Supported
FC > BI	0.03	0.73	Not supported
FC > Actual Use	0.05	0.87	Not supported
Experience > Actual Use	0.33	1.50	Not supported
BI > Actual Use	-0.29	2.71**	Supported
Experience*BI > Actual Use	-0.51	2.04**	Supported

Note: n = 516
** $p < 0.01$ Variance explained in BI = 61.4%
* $p < 0.05$ Variance explained in Actual use = 22.1%

SEM results of model 1 indicate that all of the performance expectancy, effort expectancy, and social influence affect behavioral intention significantly and positively. On the contrary, facilitating conditions do not impose any effect either on behavioral intention or MB actual use. Experience and behavioral intention, on the other hand, seem to influence MB actual use significantly but negatively.

SEM results of model 2 show the interaction effect and suggest that experience moderates the relationship between behavioral intention and MB actual use significantly but not positively as being proposed. This means that with more experience, the impact of behavioral intention will be less on actual use. Also, all significant relationships in model 1 appear to be significant in model 2 except for experience. However, the amount of explained variance accounted by the predictors on behavioral intention is about 61% and on actual use is about 22%.

5.2. Hypotheses testing (USM)

USM, conducted by Neusrel software [2], had been applied to compare and complement SEM results. USM analysis is restricted here to illustrating the non-linear relationships while revealing the hidden paths and interaction effects will be deferred to future analysis.

USM results suggest that there are two nonlinearity relationships exist in the data. The first relationship occurs between effort expectancy and behavioral intention. Figure 2 shows that effort expectancy increases with behavioral intention but after a specific point, it stops increasing and forms an inverted half U-shape. The second relationship occurs between behavioral intention and actual use. Behavioral intention starts with a very slight increase then goes for a significant decrease forming an inverted U-shape with actual use.

According to the nonlinearity relationships found, it is possible to say that the increase of effort expectancy does not always lead to the increase of intention to use MB. While the increase of this intention may start with an increase of actual use but does not last and even decreases within time. However, USM shows approximately the same amount of explained variance for behavioral intention as SEM but shows higher explained variance for actual use (39%). This suggests that USM has a better prediction than SEM.

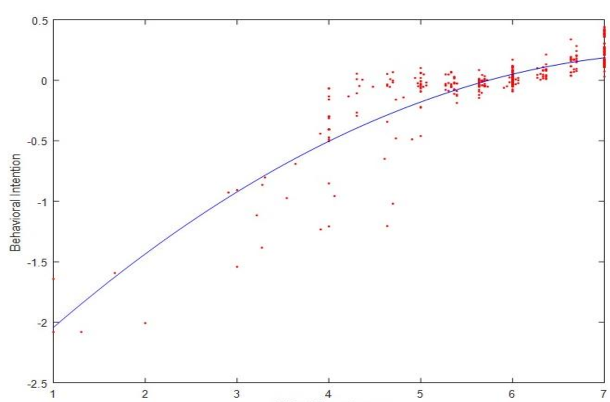

Figure 2: Nonlinearity between EE and BI

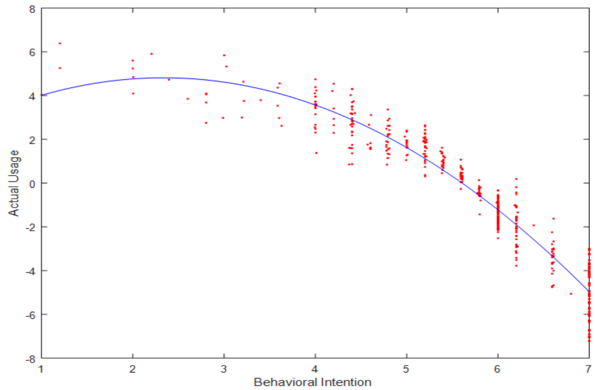

Figure 3: Nonlinearity between BI and actual use

6. Future work

Objective experience generated from the system log data will be examined to find its impact on the actual use and compare this finding with subjective experience. Second, the significant determinants, which are revealed by SEM analysis, they will be used as input variables in the input layer of NN, while behavioral intention and actual use will be used as output variables in the output layer. Such approach can handle the model overfitting issue associated with NN [5] and rank the significant factors influencing MB usage form the most important to the least important with the help of sensitivity analysis. Third, USM will be contributing on a larger scale to find the non-hypothesized paths whether direct or indirect.

7. Discussion, conclusion and potential contribution

The first three pillars of UTAUT (performance expectancy, effort expectancy, and social influence) appears to be significant and so consistent with previous research [28]; [29]. While facilitating conditions do not influence both behavioral intention and MB actual use. These results are anticipated because the investigated customers do not feel that the bank provides them with the expected resources to obtain further knowledge about MB. Also, they think they do not need to contact the help desk a lot. Thus, they overlook this factor. Experience and behavioral intention, on the other hand, determine actual use but negatively. It is in contradiction to the hypothesized relationship but justifiable. Taking a close look at the data, it appears that most of our survey participants are elder people who pay the least attention to their usage level. Hence, those people are experienced with the intention to use but do not consider themselves on an increasing curve of usage. Experience as moderator goes against what is being proposed, meaning that with more experience, the impact of behavioral intention will be less on actual use. There is a plausible interpretation of this finding. Increasing experience enhances the routine behavior and make it more automatic which, may decrease rather than increase actual use [25] as the attention decreases.

This study has 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 less attention to their usage behavior towards MB because they developed a cognitive lock-in. Also, the experience impact is considered be more pronounced on elder users as their experience is usually transformed into a habit. As a result, they do not show a considerable engagement to their MB usage. Second, it would be valuable to measure experience using self-reported data and computer-recorded data (future analysis). This will help to validate both impact and correlation; which in turn enable us to benchmark experience factor with prior IS research and develops a compelling theoretical-discursive case. Third, as USM provides an evidence of nonlinearity in the data, it gives us a more insightful view about effort expectancy, behavioral intention, and actual use. It seems that providing easy-to-use MB service does not always lead to increase the customer's usage intention. Specifically after a while, the impact of effort expectancy stops. While the usage intention may increase the customers's actual commitment to MB services first but it shrinks significantly afterward. From a methodological perspective, the study contributes to MB research by developing 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 (future analysis). Additionally, it may disclose undetected interaction effects (future analysis). As a result, banks and software vendors may be able to rank the influential factors on MB usage from the most important to the least important. This will assist them to allocate their efforts 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. However, it can lend opportunities for future research. For example, scholars can employ this hybrid (SEM-NN) method to reveal the highest-impact factors on various segmentations of customers. Customers can be whether segmented by age: young generation, mid-aged generation, and senior generation;

or by education: associate degree holders, bachelor degree holder, and M.S. & PhD holders; or by work: full-employed, self-employed, and student. Also, one limitation of this study is collecting the data at a single point of time but it can be converted to a future research opportunity. Longitudinal studies can use the same multi-analytical approach to identify causal relationships and establish stronger theoretical and practical implications.

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Appendix 1:

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. [2]
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. [2]
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. [2]
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. [2]
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. [24]
MB system usage	SU1	Q16. Perception of own usage on a monthly basis (light, moderate and heavy).	Venkatesh et al. [24]