BEHAVIORAL INTENTION OF USING MOBILE BANKING: A MODEL COMPARISON APPROACH

A. A. D. P. Bandara[1,*] and R. M. G. H. N. Ratnayake[2]

[1]Department of Accountancy & Finance, Faculty of Management Studies, Rajarata University of Sri Lanka, Mihintale, Sri Lanka
[2]Department of Business Management, Faculty of Management Studies, Rajarata University of Sri Lanka, Mihintale, Sri Lanka

*Corresponding author (email: bandaraaadp@gmail.com)

INTRODUCTION

The evolution of technology has dramatically impacted human lives. As a result, the banking sector has experienced a growth in mobile banking, which has proven to be an integral part of customer access to banking services (Nawaz & Yamin, 2018). Mobile banking can be identified as a new method in this process. Mobile banking has become a popular method of banking among users worldwide within a short time of its launch, offering customers an easy and fast way to experience banking services from anywhere at any time (Ravichandran & Madana, 2016). The past few years have significantly seen some growth in mobile banking in Sri Lanka, as many commercial banks have facilitated their customers to conduct banking transactions through mobile banking applications (Central Bank of Sri Lanka, 2019).

Most studies on mobile banking adoption or behavioural intention (Aboelmaged & Gebba, 2013; Kumar et al., 2020) have been limited to examining models derived from theoretical and empirical models or testing existing theoretical models. Although the research takes place in the same context, the output may vary depending on the data set used. However, suppose different models can be compared with the same data set in the same context. In that case, it is helpful in decision-making, especially in cross-sectional quantitative studies of business and marketing. In the context of the behavioural intention of mobile banking by customers of Sri Lankan banks, only a few published works compare different conceptual models. Therefore, conducting a model comparison of behavioural intention to use mobile banking in the context of Sri Lankan bank customers is worthwhile to bridge the existing research gap. This study aimed to compare the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and the derived model with a combination of TAM and TPB in the context of behavioural intention to use mobile banking among bank customers in Sri Lanka.

METHODOLOGY

This study adopted a quantitative research design and used a standard structured questionnaire as the research instrument. Those were distributed via the internet for data collection purposes. The study population was Sri Lankans with an active bank account in any commercial bank using a smartphone or portable smart device.

Due to the non-availability of the sampling frame, the sample was selected using convenience sampling, a non-probability sampling technique. Based on the previous studies in a similar background, the statistical tool and estimation technique employed, as well as model complexity, targeted 500 responses and collected 579 accurate records within four weeks of questionnaire distribution. The conceptual model of the research is shown in Figure 1 and was developed with a combination of constructs derived from TAM and TPB.

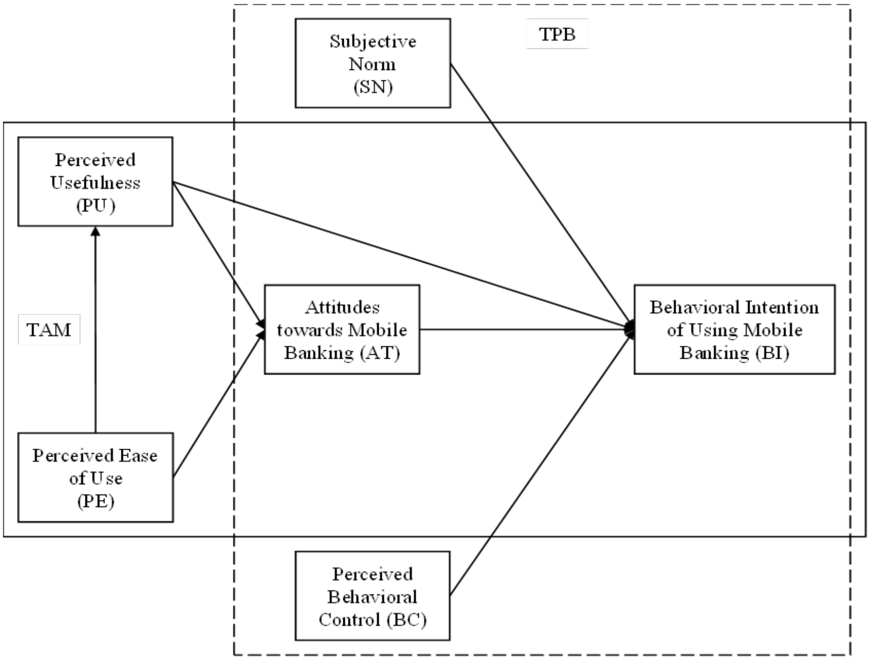

Figure 1 Conceptual Framework

Previous studies have shown that Covariance-Based Structural Equation Modeling (CB-SEM) is best suited to confirm key factors and compare theoretical or empirical models (Hair et al., 2019). Therefore, the CB-SEM approach was applied using IBM SPSS Amos 21.0 software package for data analysis and model evaluation. The data distribution has not achieved multivariate normality, although it satisfied conditions for univariate normality. Therefore, structural model analysis in the present study was conducted by adopting the bootstrapping technique. The validity of the measurement model was assessed by establishing acceptable goodness-of-fit levels and considering construct validity. It was observed that the measurement model fitted the data well while achieving convergent and discriminant validity. In comparing models, goodness-of-fit indices, the explanatory power of each model, as well as the significance and strengths of individual paths, were taken into account.

RESULTS AND DISCUSSION

The observed chi-square value for the derived model was 1446.669 with 447 degrees of freedom. Meanwhile, the chi-square values for TAM and TPB were 763.553 and 653.229, respectively, with corresponding degrees of freedom of 219 and 200. The probability levels for the chi-square were significant for all models, implying that the predictions do not closely match the actual data. Since significant probability values are generally accepted when the number of observations is more significant than 250 (Hair et al., 2019), there was no need to worry about the above output and checked other goodness-of-fit indices.

Table 1 shows the values obtained for the goodness-of-fit indices for the models.

Table 1 Comparison of Goodness-of-Fit Indices

Goodness-of-Fit Index		Derived Model	TAM	TPB
Absolute fit indices	CMIN/DF	3.033	3.487	3.266
	AGFI	0.837	0.864	0.880
	SRMR	0.045	0.032	0.042
	RMSEA	0.059	0.066	0.063
Incremental fit indices	TLI	0.943	0.953	0.955
	CFI	0.948	0.959	0.961
	RFI	0.917	0.935	0.937
	NFI	0.925	0.944	0.945
Parsimony fit indices	PGFI	0.732	0.708	0.716
	PRATIO	0.903	0.866	0.866
	PNFI	0.836	0.817	0.818
	PCFI	0.857	0.830	0.832

Generally, the overall goodness-of-fit is said to be good when the CMIN/DF value is less than 5.000 (Hair et al., 2019). Among the models considered, the derived model reported the lowest CMIN/DF value, while TPB and TAM reported low values. The minimum acceptable value for AGFI is 0.800, and values close to 1.000 indicate a good fit. TPB reported the highest value for AGFI, followed by TAM and the derived model. The SRMR should be less than 0.080 (Hair et al., 2019) and all three models conformed to this criterion, while TAM recorded the lowest value. Values below 0.080 are generally acceptable for RMSEA and indicate a good fit when the observed value is small (Hair et al., 2019), so the derived model is superior in terms of RMSEA. Based on the observed values for the absolute fitness indices, it can be said that the three models are competitive in the overall goodness of fit.

Values above 0.900 are recommended for incremental fit indices (Meyers et al., 2016), and observed values for TLI, CFI, RFI, and NFI of all models considered in this study appeared to meet these criteria. When studying the observed values for the incremental fit indices, it was found that TPB is superior while TAM is better than the derived model. The recommended minimum value for the parsimony fit indices considered in this study is 0.500 (Meyers et al., 2016) and all observed values exceeded this limit. Based on the values obtained for the parsimony fit indices, the derived model is the best, followed by TPB and TAM, respectively. The squared multiple correlation coefficients of each model and internal endogenous constructs are depicted in Table 2.

Table 2 Explanatory Power of the Models

Explanatory Power	Derived Model	TAM	TPB
R^2_{BI}	0.789	0.725	0.803
R^2_{AT}	0.849	0.849	-
R^2_{PU}	0.726	0.726	-

When considering the explanatory power of each model, it can be observed that TPB is superior in explaining the behavioural intention of using mobile banking. In contrast, the derived model is better than TAM. However, all three models have shown a significant potential to explain the behavioural intention of using mobile banking in the context of Sri Lankan bank customers.

The observations for the path coefficients for each model and their significance are shown in Table 3.

Table 3 Comparison of Significance and Strengths of Individual Paths

Path	Derived Model		TAM		TPB	
	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value
BC → BI	0.367	0.001	-	-	0.365	0.001
SN → BI	0.090	0.003	-	-	0.089	0.001
PU → BI	0.152	0.011	0.204	0.003	-	-
AT → BI	0.416	0.008	0.667	0.002	0.561	0.001
PU → AT	0.405	0.001	0.410	0.001	-	-
PE → AT	0.552	0.001	0.547	0.001	-	-
PE → PU	0.852	0.001	0.852	0.001	-	-

Notes: The results reported in this table is based on bootstrapping method using 2000 subsamples.

The only path common to all models considered in the present study was the path from attitudes to behavioural intention, which was significant in all three models. However, the path coefficients of this path differed in the three models, and TAM reported the highest path coefficient, followed by TPB and the derived model. Furthermore, in all three models, attitudes were the primary factor influencing behavioural intention. This finding is consistent with the results of several recent studies (Aboelmaged & Gebba, 2013; Chaouali et al., 2017). The path from the subjective norm to behavioural intention was familiar to the derived model and the TPB and was significant in both models with nearly identical path coefficients. This finding matches the results of several previous studies (Puschel et al., 2010; Kumar et al., 2020) conducted in a similar background. Similarly, the path from perceived behavioural control to behavioural intention common in the derived model and the TPB was positive and significant, with almost identical and high coefficients. This finding is in harmony with the results of the studies by Chau and Hu (2001) and Puschel et al. (2010) but was not aligned with the findings of Aboelmaged and Gebba (2013). The path from perceived usefulness to behavioural intention was common to both TAM and the derived model and was positive and significant. However, this effect was slightly greater in TAM than in the derived model. This result is in harmony with the findings of Nawaz and Yamin (2018) and Kumar et al. (2020).

Meanwhile, the paths from perceived usefulness and perceived ease of use to attitudes common to the derived model and TAM reported nearly identical coefficients, consistent with Lule et al. (2012). Among the paths common to both the derived model and TAM, the highest path coefficient was reported for the path from perceived ease of use to perceived usefulness, which was similar in both models. This result is consistent with several studies (Aboelmaged & Gebba, 2013; Chang et al., 2017).

CONCLUSIONS AND IMPLICATIONS

The observed values for the goodness-of-fit indices of the three structural models indicated that all three models fit well with the data. In most cases, this is obvious when the measurement model has been shown to fit the data well. Although the three models have shown significant potential to explain the behavioural intention to use mobile banking, it can be observed that TPB is superior, and the derived model is slightly better than TAM. When considering the strength and significance of common paths in the three models, the results showed that all common paths in at least two of the compared models were positive and significant. Furthermore, almost all the significant paths exhibited relatively high levels of statistical significance. The comparison concludes that all three models can be recommended for examining the behavioural intention to use mobile banking in the context of Sri Lankan bank customers. Convenience sampling was used to select the sample; therefore, the study's results should be interpreted cautiously when drawing generalizations. Moreover, the questionnaire was distributed using online methods only, and if there is any possibility of collecting data using online and offline methods, it is worth it. To the best of our knowledge, this study is the first attempt to compare models in the context of behavioral intention to use mobile banking by bank customers in Sri Lanka. These findings provide new perspectives for the research community in planning their future studies.

Keywords: Behavioral intention, mobile banking, model comparison

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