ASIA MARKETING JOURNAL

Volume 23 | Issue 4 Article 3

February 2022

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Yun Kyung Oh
Dongduk Women's University Seoul, Korea, ykoh1@dongduk.ac.kr

Jung-Min Kim
Business School, University of Seoul Seoul, Korea, kimjm2016@uos.ac.kr

Recommended Citation

Oh, Yun Kyung and Kim, Jung-Min (2022) "What Improves Customer Satisfaction in Mobile Banking Apps? An Application of Text Mining Analysis," *Asia Marketing Journal*: Vol. 23 : Iss. 4 , Article 3.
Available at: https://doi.org/10.53728/2765-6500.1581

What Improves Customer Satisfaction in Mobile Banking Apps? An Application of Text Mining Analysis☆

Yun Kyung Oh [a], Jung-Min Kim [b,*]

[a] Department of Business Administration, Dongduk Women's University, Seoul, South Korea
[b] Business School, University of Seoul, Seoul, South Korea

Abstract

Consumer-generated reviews reflect consumers' experiences and perceptions toward a product or service. In this context, we propose a text mining approach to identify factors that improve customer satisfaction in the mobile banking app service. To do so, we collect 96,140 mobile app reviews for four U.S. banks: Bank of America, Capital One, Chase, and Wells Fargo. Using the Latent Dirichlet Allocation (LDA) topic model, we first derive the critical quality dimensions such as ease of use, convenience, security, and customer support. Analysis of weekly panel data shows that positive responses to the security and convenience of mobile banking apps improve app ratings. However, increased comments about insecurity, negative customer support experiences, discomfort, and complexity lower user ratings. Overall, the empirical results support that security is the most influential factor in customer satisfaction with mobile financial services.

Keywords: Mobile banking application, Financial services, Customer satisfaction, Text mining, Customer reviews

1. Introduction

COVID-19 has accelerated digital transformation in all industries around the world. When it comes to using financial services, customers become reluctant to visit bank branches due to concerns about the infection. Instead, a growing number of customers use Internet banking or mobile banking as an alternative. Experts in the financial sector estimate that the pandemic dramatically accelerated digital banking technology adoption (Mondres 2020). Before the pandemic, retail banks had gradually adopted non-face-to-face channels such as ATMs and online banking to increase customer convenience and efficiency. As the need for non-face-to-face transactions proliferates, traditional banks face the challenges of increasing consumer satisfaction and loyalty through mobile banking services (Shankar, Tiwari, and Gupta 2021). Conventional and online-only banks should find ways to improve their customer experience and alleviate technical issues using mobile banking applications (hereafter, apps). In this context, understanding which quality dimensions facilitate or hinder user satisfaction with mobile banking apps is an important research question.

Mobile banking is one of the latest digital technologies that combine mobcommunication technology and financial services. Customers can perform various financial transactions through mobile apps that financial institutions provide. Customers can conveniently execute financial transactions such as balance inquiry, account transfer, and bill payment in real-time using smart devices (Shaikh and Karjaluoto 2015). Existing studies identify the factors affecting the acceptance intention of mobile banking based on the technology acceptance model (hereafter, TAM). Customers using mobile banking apps generally consider security, ease of use, and convenience are essential (Sampaio, Ladeira, and Santini 2017).

☆ This work was supported by the 2021 Research Fund of the University of Seoul.

Received 23 December 2021; accepted 30 December 2021.
Available online 3 February 2022.

* Corresponding author.
E-mail addresses: ykoh1@dongduk.ac.kr (Y.K. Oh), kimjm2016@uos.ac.kr (J.-M. Kim).

https://doi.org/10.53728/2765-6500.1581

Laukkanen (2007) studies the differences in customer value perception between the Internet and mobile banking, suggesting that efficiency, convenience, and safety determine the main differences. Prior studies explore the quality dimensions that determine mobile banking service user satisfaction (Arcand et al. 2017; Jun and Palacios 2016; Sampaio, Ladeira, and Santini 2017).

Consumers can leave reviews about their positive or negative experiences with mobile banking apps. The vast amount of online reviews provide sources to understand reasons for customer reactions (Jeon et al. 2019; Leem and Eum 2021; Proctor 2021; Shankar, Tiwari, and Gupta 2021). Shankar, Tiwari, and Gupta (2021) conduct exploratory research by analyzing mobile banking app reviews. They identify the critical success factors for mobile banking: privacy/security, navigation, customer support, convenience, and efficiency. Although recent literature explores the major quality dimensions of mobile banking, no research examines how those quality dimensions affect user ratings. This study derives the quality dimensions of mobile banking from a large scale of unstructured text reviews. Furthermore, we examine which factors significantly impact changes in user ratings. In particular, we analyze how the perception changes in the quality dimensions are related to the changes in customer satisfaction.

The remainder of this paper is structured as follows. The following section provides the theoretical background and hypotheses on the quality dimensions in the mobile banking service based on the prior literature. We then explain the data and text mining analysis process. Next, we describe the empirical model and report the hypothesis test results. Finally, we suggest the implications of the main results and discuss limitations and further research.

2. Theoretical background

2.1. Mobile banking adoption

The technology acceptance model (TAM) based on Fishbein and Ajzen's (1977) theory assumes that users' beliefs and attitudes lead to behavioral intentions. TAM has been widely used to understand the main factors that affect mobile banking acceptance (Gu, Lee, and Suh 2009; Sharma 2019). TAM theory argues that perceived usefulness and ease of use are fundamental determinants of system adoption and use. Previous studies on mobile banking acceptance identify influencing factors based on TAM. For example, Luo et al. (2010) show that perceived risks to mobile banking negatively affect consumers' intention to accept mobile banking. Shaikh and Karjaluoto (2015) study the literature related to the acceptance of mobile banking and conclude that perceived usefulness and compatibility with an individual's lifestyle are the main drivers of mobile banking acceptance.

2.2. Service quality dimensions of mobile banking

Prior studies explore the quality dimensions that explain customer satisfaction with mobile banking apps. For example, Jun and Palacios (2016) identify mobile banking application quality and find that convenience, accuracy, diversity in features, ease of use, and continuous improvement are significant influencers. Arcand et al. (2017) investigate the multidimensional concept of mobile banking and find that utilitarian features such as security and practicality affect customer satisfaction mediated by customer trust. In addition, Sampaio, Ladeira, and Santini (2017) conduct survey research on the benefits offered by mobile banking apps and find that the consequences of satisfaction with mobile banking are trust, loyalty, and positive word-of-mouth. Thus, the previous studies on the service quality of mobile banking emphasize that a bank should prioritize the customers' perception of service value.

3. Conceptual framework and hypotheses

Fig. 1 provides an overview of our conceptual framework to explain how customer satisfaction changes in mobile banking apps. The selected quality dimensions of the mobile banking service are ease of use, convenience, security, and customer support. We expect that changes in the occurrence rate of service quality keywords will affect changes in user satisfaction. Next, we discuss the related literature and develop hypotheses.

3.1. Ease of use

Many researchers reveal that perceived usefulness and ease of use are the critical components for accepting new IT-based services (Alalwan et al. 2016; Davis 1989; Gu, Lee, and Suh 2009; Kekre, Krishnan, and Srinivasan 1995; Sharma 2019). Gu, Lee, and Suh (2009) propose that self-efficacy affects mobile banking adoption through perceived ease of use. They suggest that banks develop a user-friendly interface and quickly provide professional guidelines for mobile banking apps. Therefore, user satisfaction will increase as more users easily navigate and access various financial services in mobile banking apps. Conversely, reduced perceived ease of use due to the complexity of mobile app interfaces can reduce user satisfaction.

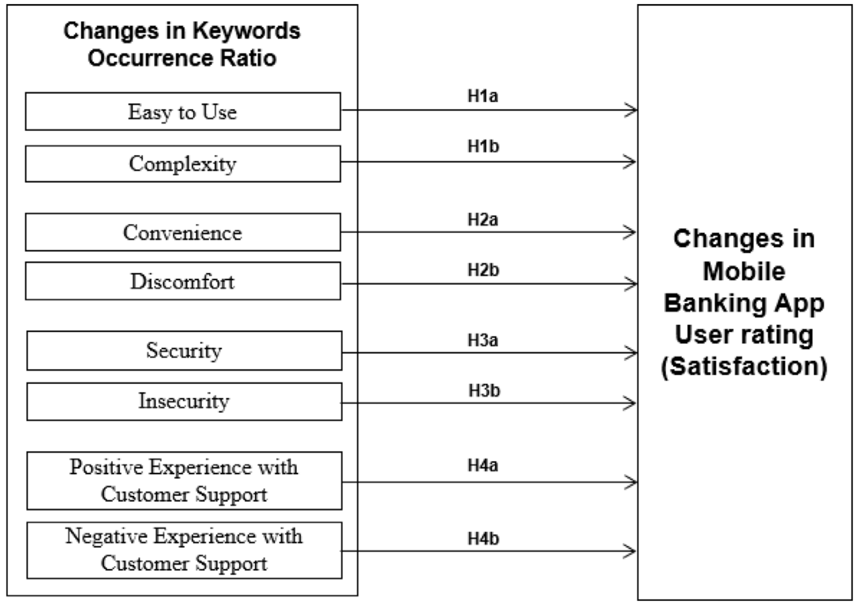

Fig. 1. Conceptual framework.

H1a. An increase (decrease) in the occurrence rate of perceived ease of use in mobile banking app reviews will be positively related to an increase (decrease) in user satisfaction.

H1b. An increase (decrease) in the occurrence rate of perceived complexity in mobile banking app reviews will be negatively related to an increase (decrease) in user satisfaction.

3.2. Convenience

Service convenience refers to the characteristics of using the service with a minimum of time and effort (Benoit, Klose, and Ettinger 2017). Convenience in mobile banking refers to the ability to conveniently use the necessary financial services through the app anytime, anywhere (Shankar, Tiwari, and Gupta 2021). Consumers can transfer accounts using the mobile banking app without visiting a branch or finding an ATM. In addition, mobile banking app users can receive notifications about bill payments to avoid overdue fees. Jebarajakirthy and Shankar (2021) analyze the effect of multi-dimensions of convenience on mobile banking acceptance intention. They reveal that access, transaction, search, and benefit conveniences are critical influencers on mobile banking service adoption. Therefore, convenience is one of the essential factors for the positive evaluation of mobile banking apps.

In contrast, technical errors in a mobile banking app make it challenging to use banking services. In particular, a high level of complaints may arise if technical mistakes in the app cause delayed payment. Hence, technical problems such as crashes or connection errors related to using the mobile banking app are likely to cause significant discomforts to customers.

H2a. An increase (decrease) in the occurrence rate of perceived convenience in mobile banking app reviews will be positively related to an increase (decrease) in user satisfaction.

H2b. An increase (decrease) in the occurrence rate of perceived inconvenience in mobile banking app reviews will be negatively related to an increase (decrease) in user satisfaction.

3.3. Security

Security is one of the critical attributes valued by customers conducting financial transactions through mobile banking apps (Sreejesh, Anusree, and Amarnath 2016). Customers may be sensitive to security issues, such as whether their personal and financial transaction information is safe from hacking. Perceived security concerns can be an essential reason users avoid financial transactions through online (Chang and Chen 2009). Recently, many banks have introduced personal identification technologies such as fingerprint recognition and facial authentication into mobile apps to enhance customer access convenience. Biometric authentication is fast and straightforward, but it is also vulnerable to hacker attacks. Therefore, banks should balance customer convenience with security.

H3a. An increase (decrease) in the occurrence rate of perceived security in mobile banking app reviews will be positively related to an increase (decrease) in user satisfaction.

H3b. An increase (decrease) in the occurrence rate of perceived insecurity in mobile banking app reviews will be negatively related to an increase (decrease) in user satisfaction.

3.4. Customer support

Traditional banks have managed the quality of face-to-face customer service to respond to various needs related to customers' use of financial services. However, as the demand for non-face-to-face banking services increases, it is necessary to respond to customer needs arising from new channels. Specifically, banks should provide good customer support services that suggest solutions to customer inquiries related to mobile banking because financial services often offer very intensive decisions such as money management (Jun and Palacios 2016; Shankar, Tiwari, and Gupta 2021).

When consumers solve problems through seamless communication, they can build trust in mobile apps and banks. Customer support related to mobile banking apps includes answering questions about financial services and troubleshooting technical errors such as mobile app crashes. However, consumers can discredit banks when they experience delayed contact with customer support or an unfriendly attitude. Unpleasant experience with the customer support team may lead to dissatisfaction and low ratings of the mobile banking apps.

H4a. An increase (decrease) in the occurrence rate of pleasant customer support experience in mobile banking app reviews will be positively related to an increase (decrease) in user satisfaction.

H4b. An increase (decrease) in the occurrence rate of unpleasant customer support experience in mobile banking app reviews will be positively related to an increase (decrease) in user satisfaction.

4. Empirical analysis

4.1. Data

We collect online reviews generated from February 2019 to October 2021 to understand what causes the changes in consumer evaluation of mobile banking apps. Our data contains online review ratings and text data available at the Apple App Store and Google Play Store. As of October 2021, the apps ranked by DAU (daily active users) are in the following order: Capital One, Chase, Bank of America (BoA), and Wells Fargo. Capital One operates as a specialized online bank without an offline branch. The other three banks are traditional banks that operate physical offices and provide Internet and mobile banking services.

We select the reviews with 20 or more characters to identify the reasons for user satisfaction or dissatisfaction. By doing so, the final sample includes 96,140 reviews. Table 1 presents descriptive statistics for mobile app review characteristics for each bank. Capital One has the highest number of reviews ($n = 35{,}616$) and the highest average rating (4.11 out of 5) during the sample period. BoA and Chase have lower mean ratings, higher standard deviations, longer review lengths, and a higher ratio of negative opinions (1 or 2 points) than the other two banks. In particular, the high variability of customer ratings suggests that user ratings are changing rather than static during the analysis period. These results support the notion that achieving high levels of customer satisfaction is a moving goal in the financial services industry (Krishnan et al. 1999).

We illustrate the changes in the monthly ratio of positive reviews (5 out of 5) and negative reviews (1, 2 out of 5) in Fig. 2. In early 2019, Capital One's mobile banking app had the highest favorable reviews and the lowest negative reviews compared to the other three banks. However, the percentage of positive (negative) reviews on Capital One decreases (increases) over time. Over the same period, three traditional banks (BoA, Chase, and Wells Fargo) appear to improve mobile banking service quality, closing the gap with the online-only bank (Capital One). Next, we apply the text mining technique to understand which factors improve/deter customer satisfaction with mobile banking apps.

4.2. Text mining analysis

Text mining analysis of review data is similar to exploratory analysis of responses to open-ended questions (Allenby 2012). Our study uses the text mining approach in the following three steps: natural language processing, topic model application, and explanatory variable construction. We then test the role of the identified components in

Table 1. Descriptive statistics of mobile banking app review characteristics.

Company	Obs.	Rating (mean)	Rating (stdev)	Review Length	Positive_Ratio (Rating = 5)	Negative_Ratio (Rating = 1,2)
BoA	16,184	3.17	1.80	189	0.44	0.42
CapitalOne	35,616	4.11	1.50	126	0.69	0.19
Chase	13,583	3.11	1.80	187	0.42	0.44
WellsFargo	30,757	3.97	1.58	126	0.66	0.23
Total	96,140	3.77	1.67	145	0.60	0.28

either promoting or degrading mobile banking user ratings.

Step 1. Application of natural language processing

In the preprocessing stage, we remove stop words and derive the words with high frequency: "bank," "account," "payment," "money," "deposit," "credit," and "card." Except for the commonly appeared banking terminologies, words that frequently appear in positive reviews are "love," "easy," "convenient," "user friendly," "helpful," "simple," and "fast." For the negative reviews, "update," "fix," "issue," "crash," "error message," and "white screen" appear frequently.

Step 2. LDA topic modeling

This study applies the LDA (Latent Dirichlet Allocation) topic model (Blei, Ng, and Jordan 2003), a type of unsupervised machine learning. The topic model is a technique that extracts various topics composed of a combination of specific words using the frequency of words appearing in the document. The topic model helps researchers extract key quality dimensions reflected in a large scale of unstructured text data (Tirunillai and Tellis 2014). Recent studies widely adopted the topic model to extract latent topics in online reviews and elicit in-depth customer insights (Guo, Barnes, and Jia 2017; Leem and Eum 2021; Shankar, Tiwari, and Gupta 2021; Zhang 2019).

We apply the topic model to the reviews of positive (Rating = 5) and negative (Rating = 1,2) separately. Then we identify the topics and top words that contain attributes related to mobile banking in word combinations. Among the topics presented through unsupervised learning, we recognize the words that appear in the topics related to ease of use, convenience, security, and customer support. Previous studies have also suggested that these variables are important for adopting mobile banking services (Alalwan et al. 2016; Gu, Lee, and Suh 2009; Jebarajakirthy and Shankar 2021; Shankar, Tiwari, and Gupta 2021; Sharma 2019; Sreejesh, Anusree, and Amarnath 2016). Table 2 summarizes the results of applying the topic model and related literature.

Step 3. Construct explanatory variables for mobile banking app user rating

Next, we measure the occurrence of mobile banking service quality terms for each review. However, the terms might have opposite meanings if the selected keywords appear with negators (e.g., not, never, no, doesn't, isn't) in a phrase. To split the text into phrases, we separate texts using punctuation marks (./,/:/;/ !/ ?) and conjunctions (e.g., and, because, but, so) following the prior literature (Büschken and Allenby 2020; Oh and Yi 2021). Then we exclude the phrases containing the selected keywords and negators simultaneously. Table 2 also shows the occurrence rate and sample content of the constructs in the reviews for mobile banking apps.

4.3. Model estimation

We create a dummy variable indicating the occurrence of selected keywords in a review after deriving quality dimensions for mobile banking apps. A total of 44,141 reviews with at least one quality dimension are used for model estimation. Then we build a weekly, bank-level panel data set by taking the average of variables. Table 3 reports the descriptive statistics and correlation matrix for the difference-in-difference of variables.

The sample dataset has a cross-sectional and time-series format. Thus, we control for unobserved bank-level heterogeneity by modeling the impact of changes in mobile banking quality dimensions on changes in user ratings (Luo and Homburg 2008; Luo, Homburg, and Wieseke 2010) as follows:

$$\Delta Rating_{it} = \alpha + \beta_1 \Delta easytouse_{it} + \beta_2 \Delta convenience_{it} + \beta_3 \Delta security_{it} + \beta_4 \Delta CS\_PE_{it} + \beta_5 \Delta complexity_{it} + \beta_6 \Delta discomfort_{it} + \beta_7 \Delta insecurity_{it} + \beta_8 \Delta CS\_NE_{it} + \epsilon_{it} \quad (1)$$

where $\Delta Rating_{it}$ are changes in the mean rating of bank i during week t. $\Delta easytouse_{it}$, $\Delta convenience_{it}$,

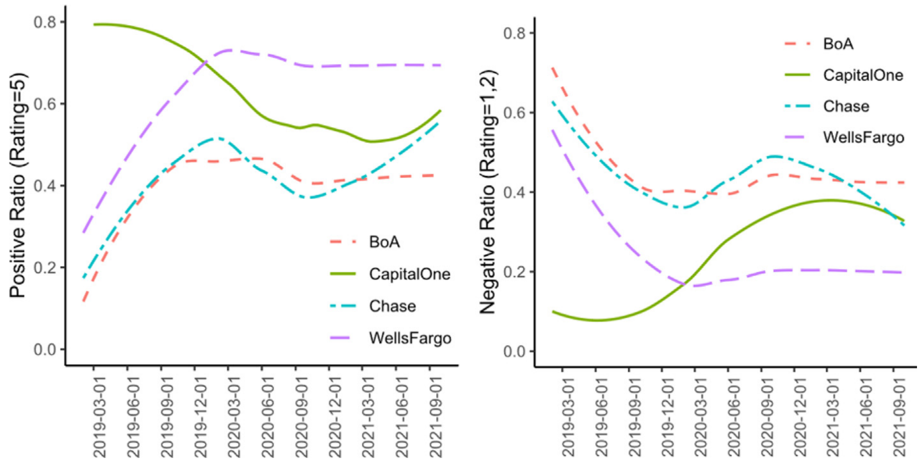

Fig. 2. Changes in positive and negative review ratio over time.

$\Delta security_{it}$, and ΔCS_PE_{it} are changes in the occurrence rate of positive experience in ease of use, convenience, security, and customer support for bank i during week t, respectively. $\Delta complexity_{it}$ $\Delta discomfort_{it}$, $\Delta insecurity_{it}$ and ΔCS_NE_{it} are changes in the occurrence rate of negative experience in ease of use, convenience, security, and customer support for bank i during week t. ϵ_{it} is a residual term with variance σ^2_ϵ.

Additionally, we model the impact of changes in mobile banking quality dimensions on the ratio of positive ratings (5 out of 5) and negative ratings (1,2 out of 5) as follows:

$$\Delta PosR_{it} = \alpha + \beta_1 \Delta easytouse_{it} + \beta_2 \Delta convenience_{it} + \beta_3 \Delta security_{it} + \beta_4 \Delta CS\_PE_{it} \quad + \beta_5 \Delta complexity_{it} + \beta_6 \Delta discomfort_{it} + \beta_7 \Delta insecurity_{it} + \beta_8 \Delta CS\_NE_{it} + \epsilon_{it} \tag{2}$$

$$\Delta NegR_{it} = \alpha + \beta_1 \Delta easytouse_{it} + \beta_2 \Delta convenience_{it} + \beta_3 \Delta security_{it} + \beta_4 \Delta CS\_PE_{it} \quad + \beta_5 \Delta complexity_{it} + \beta_6 \Delta discomfort_{it} + \beta_7 \Delta insecurity_{it} + \beta_8 \Delta CS\_NE_{it} + \epsilon_{it} \tag{3}$$

where, $\Delta PosR_{it}$ ($\Delta NegR_{it}$) are changes in the ratio of positive (negative) ratings of bank i during week t.

5. Results

Table 4 shows the estimation results of the fixed effect model (level) and the first difference model (change) for the weekly panel data. In the fixed-effect model, all constructs of mobile banking have significant effects on the customer's overall rating (*Rating*) and the ratio of positive ratings (*PosR*) in the expected directions. In the negative ratio ratings (*NegR*) model, all explanatory variables show expected and significant effects except positive experience in customer support (*CS_PE*). The parameter estimators in the fixed-effect model demonstrate that our constructs using the text mining approach have content validity to explain the aggregated customer rating in mobile banking apps.

We estimate the first difference model using Eq. (1) to investigate the factors that lead to changes in customer response for mobile banking apps. We find that the increases in *convenience* and *security* are associated with increases in *Rating*, *PosR*, and decreases in *NegR*. In addition, increases in *complexity*, *discomfort*, *insecurity*, and negative experience with customer support (*CS_NE*) lead to declines in *Rating*, *PosR*, and increments in *NegR*. Our estimation results imply that changes in some positive quality dimensions (*easytouse* and *CS_PE*) may not affect changes in customer reactions. However, increasing complaints regarding the key quality of mobile banking can hurt the overall ratings by increasing negative feedback from customers. Our findings align with prior literature on the customer's asymmetric reactions to service quality (Arbore and Busacca 2009; Oh and Yi 2021).

Further, we apply the first difference model to the bank subsample to examine what factors improved or deterred the mobile banking app user experience during the sample period. Estimation results (Table 5) imply that the improvements in Wells Fargo rating are mainly attributable to the increase in *security*, *convenience*, and *easytouse*. On the other hand, Capital One, which has the highest overall mean rating, experiences adverse reactions due to customer complaints regarding *insecurity*, *CS_NE*, *discomfort*, and *complexity*. The bank-level analysis shows that the quality dimensions of mobile banking apps have differential impacts on customer response from bank to bank.

Table 2. Text mining analysis of major quality dimensions in mobile banking.

Construct		Topic Terms	Occurrence (%)	Content Sample	Related Studies
Ease of use	PE	easy to use, simple, straightforward, user-friendly, intuitive	66.15	• The app is very easy to use. • This app gives me simplicity in reviewing my account to check balances and pay off bills.	(Alalwan et al. 2016; Davis 1989; Gu, Lee, and Suh 2009; Sharma 2019)
	NE	hard, difficult, complicate	4.25	• I am unsure why paying bills with the app got so difficult two weeks ago after the latest version or update. • Most apps like this are so difficult and sensitive for security.	
Convenience	PE	convenient, track, notification, anytime, anywhere, fast, quick, instant	26.02	• Like how I can track and get payment alerts from text messages for approval as to payment pending. • Love the way I am instantly notified when a charge is posted to my account by a merchant.	(Benoit, Klose, and Ettinger 2017; Jebarajakirthy and Shankar 2021; Shankar, Tiwari, and Gupta 2021)
	NE	inconvenient, slow, crash, won't work, error, freeze, can't get, white screen, please fix	18.17	• A lot of crashes upon opening the app with several of these latest updates. • I can't believe they still can't fix pay bills on the mobile app.	
Security	PE	security, secure	6.72	• I feel totally secure using it to pay my payment. • I have touch id set up for the app, which helps with security.	(Arcand et al. 2017; Chang and Chen 2009; Shankar, Tiwari, and Gupta 2021; Sreejesh, Anusree, and Amarnath 2016)
	NE	insecure, hacking, fraud, privacy, concern	1.06	• I had fraudulent charges on my card. • Constantly signing on today and it's making me leary if someone is hacking my information.	
Customer Support	PE	{customer service, customer support, staff, call} and {good, great, excellent, best, helpful, friendly,polite}	3.61	• Every time I talk to a customer service rep they are polite and very helpful. • Customer service wait time is reasonable they are very friendly and helpful.	(Jun and Palacios 2016; Shankar, Tiwari, and Gupta 2021)
	NE	{customer service, customer support, staff, call} and {poor, worst, horrible, rude}	0.81	• Their customer service people are rude and don't know the first thing about true customer service. • I've been a long time customer and have had the worst customer service over the years.	

Note: PE(NE) stands for positive(negative) user experience for the given construct.

Table 3. Descriptive statistics and correlation matrix.

	ΔRating	*ΔPosR*	*ΔNegR*	*Δeasytouse*	*Δconvenience*	*Δsecurity*	*ΔCS_PE*	*Δcomplexity*	*Δdiscomfort*	*Δinsecurity*	*ΔCS_NE*
ΔRating	1.00										
ΔPosR	0.91***	1.00									
ΔNegR	−0.95***	−0.79***	1.00								
Δeasytouse	0.30***	0.30***	−0.30***	1.00							
Δconvenience	0.29***	0.28***	−0.26***	−0.06	1.00						
Δsecurity	0.31***	0.28***	−0.30***	−0.06	−0.05	1.00					
ΔCS_PE	0.12***	0.12**	−0.10*	−0.08	−0.08	0.01	1.00				
Δcomplexity	−0.12***	−0.17***	0.11**	−0.20***	−0.14***	0	−0.06	1.00			
Δdiscomfort	−0.65***	−0.64***	0.59***	−0.38***	−0.32***	−0.25***	−0.18***	−0.04	1.00		
Δinsecurity	−0.15***	−0.13**	0.15***	−0.09*	−0.04	−0.02	0.10*	−0.01	−0.12**	1.00	
ΔCS_NE	−0.12***	−0.11**	0.10*	−0.10*	0.04	0.01	0.07	−0.01	−0.08*	0.01	1.00
Mean	0.004	0.001	−0.001	−0.0002	0.0004	0.0001	0.0004	0.0003	−0.001	0.0002	0.0001
SD	0.44	0.12	0.12	0.1	0.09	0.05	0.04	0.05	0.12	0.03	0.03

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table 4. Factors for improving and deterring mobile banking app user rating.

	Fixed Effect (Level)				First Difference (Change)		
	Rating	*PosR*	*NegR*		*ΔRating*	*ΔPosR*	*ΔNegR*
easytouse	0.50***	0.12**	−0.12**	*Δeasytouse*	0.10	0.01	−0.06
	(0.18)	(0.05)	(0.05)		(0.15)	(0.04)	(0.04)
convenience	0.91***	0.21***	−0.21***	*Δconvenience*	0.45***	0.09*	−0.12**
	(0.21)	(0.06)	(0.06)		(0.17)	(0.05)	(0.05)
security	2.14***	0.54***	−0.57***	*Δsecurity*	1.37***	0.29***	−0.38***
	(0.33)	(0.10)	(0.09)		(0.27)	(0.08)	(0.08)
CS_PE	0.77**	0.30***	−0.14	*ΔCS_PE*	0.53	0.12	−0.10
	(0.38)	(0.11)	(0.10)		(0.34)	(0.10)	(0.10)
complexity	−2.56***	−0.85***	0.58***	*Δcomplexity*	−1.04***	−0.41***	0.25***
	(0.30)	(0.09)	(0.08)		(0.26)	(0.07)	(0.08)
discomfort	−2.94***	−0.85***	0.72***	*Δdiscomfort*	−2.29***	−0.65***	0.55***
	(0.16)	(0.05)	(0.04)		(0.15)	(0.04)	(0.04)
insecurity	−3.18***	−0.79***	0.82***	*Δinsecurity*	−3.33***	−0.87***	0.84***
	(0.54)	(0.16)	(0.15)		(0.45)	(0.13)	(0.13)
CS_NE	−3.55***	−0.97***	0.89***	*ΔCS_NE*	−3.08***	−0.80***	0.69***
	(0.61)	(0.18)	(0.17)		(0.50)	(0.14)	(0.15)
Bank Fixed Effect	Controlled			*Constant*	0.004	0.001	−0.001
					(0.012)	(0.004)	(0.004)
Obs.	569	569	569		565	565	565
R^2	0.80	0.78	0.77		0.55	0.53	0.47
Adj-R^2	0.80	0.78	0.76		0.54	0.52	0.46

Note: *p < 0.1; **p < 0.05; ***p < 0.01, Standard errors are in parentheses.

Table 5. Factors for improving and deterring mobile banking app user rating by banks.

	Capital One			Bank of America			Chase			Wells Fargo		
	ΔRating	*ΔPosR*	*ΔNegR*	*ΔRating*	*ΔRating*	*ΔPosR*	*ΔRating*	*ΔPosR*	*ΔNegR*	*ΔRating*	*ΔPosR*	*ΔNegR*
Δeasytouse	0.33	0.09	−0.02	0.25	0.03	−0.13	−0.57	−0.09	0.15	0.49*	0.03	−0.21***
	(0.24)	(0.08)	(0.07)	(0.31)	(0.09)	(0.09)	(0.35)	(0.09)	(0.11)	(0.26)	(0.08)	(0.07)
Δconvenience	0.53**	0.12	−0.14*	1.04***	0.30***	−0.22*	−0.26	−0.04	0.14	0.56**	0.06	−0.21***
	(0.24)	(0.08)	(0.07)	(0.39)	(0.11)	(0.11)	(0.37)	(0.10)	(0.11)	(0.25)	(0.07)	(0.07)
Δsecurity	0.55*	−0.05	−0.29***	2.91***	0.59***	−0.84***	0.77	0.32**	−0.05	0.79*	0.18	−0.28**
	(0.33)	(0.11)	(0.10)	(0.66)	(0.19)	(0.19)	(0.60)	(0.15)	(0.18)	(0.42)	(0.12)	(0.11)
ΔCS_PE	0.37	−0.06	−0.14	1.48	0.32	−0.29	0.22	0.17	0.05	−0.55	−0.15	0.16
	(0.40)	(0.14)	(0.12)	(0.95)	(0.27)	(0.28)	(0.65)	(0.17)	(0.20)	(0.63)	(0.19)	(0.17)
Δcomplexity	−2.07***	−0.63***	0.49***	−0.52	−0.24*	0.21	−1.67***	−0.72***	0.26	0.01	0.05	0.07
	(0.39)	(0.14)	(0.12)	(0.50)	(0.14)	(0.15)	(0.56)	(0.14)	(0.17)	(0.55)	(0.16)	(0.15)
Δdiscomfort	−2.80***	−0.79***	0.72***	−2.03***	−0.62***	0.44***	−2.20***	−0.52***	0.58***	−2.36***	−0.70***	0.56***
	(0.22)	(0.08)	(0.07)	(0.28)	(0.08)	(0.08)	(0.36)	(0.09)	(0.11)	(0.28)	(0.08)	(0.08)
Δinsecurity	−4.48***	−0.91***	1.14***	−2.99***	−0.84***	0.64**	−3.32***	−0.90***	0.93***	−3.63***	−1.16***	0.79***
	(0.59)	(0.20)	(0.18)	(1.01)	(0.29)	(0.29)	(0.88)	(0.23)	(0.27)	(1.04)	(0.31)	(0.28)
ΔCS_NE	−4.23***	−0.96***	1.12***	−2.68**	−0.92***	0.41	−3.84***	−0.76***	1.08***	−0.13	−0.06	−0.37
	(0.69)	(0.24)	(0.21)	(1.04)	(0.30)	(0.30)	(0.99)	(0.26)	(0.30)	(1.35)	(0.40)	(0.36)
Constant	0.0003	0.0000	−0.0002	0.004	0.0001	−0.001	0.01	0.002	−0.003	0.01	0.002	−0.001
	(0.01)	(0.005)	(0.004)	(0.03)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)	(0.005)
Obs.	136	136	136	143	143	143	143	143	143	143	143	143
R^2	0.78	0.68	0.73	0.63	0.61	0.53	0.39	0.43	0.29	0.66	0.60	0.67
Adj-R^2	0.77	0.66	0.71	0.60	0.59	0.51	0.35	0.40	0.25	0.64	0.58	0.65

Note: *p < 0.1; **p < 0.05; ***p < 0.01, Standard errors are in parentheses.

6. Conclusions

6.1. Summary

This study examines the factors to improve customer satisfaction in mobile banking services. To do so, we collect 96,140 mobile app reviews for four U.S. banks: Bank of America, Capital One, Chase, and Wells Fargo. We first extract quality dimensions using the LDA topic model and interpret the factors as ease of use, convenience, security, and customer support based on the prior literature. We then conduct panel data analysis to investigate how changes in each factor affect user ratings. Our estimation results show that user ratings get improved as positive responses to security and convenience increase. However, user rating declines as reactions to insecurity, negative experience with customer support, discomfort, and complexity accumulate. Overall, we find that security is the most influential factor that affects user ratings. Moreover, analysis results for each bank suggest that the effect of each factor on customer satisfaction may differ from bank to bank.

6.2. Theoretical implications

This study contributes to the existing literature in the following two aspects. First, this study applies text mining analysis to online reviews to explain users' satisfaction with mobile banking services. As the importance of mobile platforms increases, many recent studies have investigated mobile app reviews to understand the motives of consumer behavior (Liu et al. 2019; Verkijika and Neneh 2021). However, only a few recent studies explore major quality dimensions of mobile banking app with customer-generated reviews (Leem and Eum 2021; Shankar, Tiwari, and Gupta 2021). Our study extends the prior research by identifying major quality dimensions using natural language processing and machine learning methods.

Second, this study is the first paper to study how the factors extracted through text analysis on online reviews affect users' satisfaction. Existing studies related to mobile banking acceptance intention primarily conduct a survey approach and identify influencing factors at a certain point in time. Unlike prior studies, we establish weekly panel data using large-scale reviews to investigate the dynamic effect of service quality factors on customer satisfaction.

6.3. Managerial implications

The results of this study have the following implications. Security has the most significant influence on user satisfaction. In online reviews, words related to ease of use or convenience are left 4 to 10 times more than words related to security. However, user satisfaction with security has a greater impact on user ratings. These results suggest that banks need to pay special attention to security to increase customer satisfaction when designing mobile banking apps.

Currently, banks face increasingly fierce competition to provide a better mobile services experience (Shankar and Jebarajakirthy 2019). Thus, increasing user satisfaction with mobile banking apps is essential to retain loyal consumers and prevent customer churn. In particular, reducing complaints due to poor customer support and technical errors is critical. Therefore, banks should utilize marketing intelligence systems to monitor changing customer reactions reflected in user-generated reviews.

6.4. Limitations and future research

It is challenging to determine whether a phrase with negators means positive or negative until reading the actual review. Hence, this study constructs and analyzes samples after removing phrases containing negators. However, the number of sample reviews will increase if advanced text mining techniques correctly classify sentences with negators. In such a case, the accuracy of detecting positive/negative perceptions of mobile banking service quality is also likely to increase.

This study does not examine banking-related functions such as deposit, money transfer, bill payment, and credit score management. In contrast, this study focuses on the four quality dimensions of mobile banking service: ease of use, convenience, security, and customer support. With the merit of rich consumer-generated text data, a future study can analyze how users' evaluation of each functional element affects mobile banking app satisfaction. Research on customer response using online reviews and text mining can provide in-depth insights into consumer behavior towards financial services.

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