Using text mining to measure mobile banking service quality

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Abstract

Purpose – The purpose of this study is to propose a method of measuring service quality as well as suggesting to detect customer complaints through analysis of customer online reviews of mobile bank, which is unstructured data.

Design/methodology/approach – This study uses text mining approach for customer online reviews analysis. The research procedure includes: (1) extracting users' reviews for Kakao Mobile Bank, (2) pre-processing of the extracted review data, (3) analyzing the sentiment of each review, (4) measuring the service quality score of each dimension by analyzing keyword frequency and network for each polarity, (5) evaluating total score for mobile bank service quality, and (6) detecting customer complaints on online reviews.

Findings – There are some findings. First, from the customer's point of view, it was possible to see which factors are important among the various dimensions of service quality and which factors should be managed well in mobile banking setting. Second, by periodically finding customer complaints, service failures can be prevented early, and service quality and customer satisfaction can be improved.

Practical implications – From a practical point of view, mobile bank managers should pay more attention to the service quality dimensions of practicality and enjoyment. In addition, the results mean that the app design and aesthetics with the most negative reviews should be reviewed from the user's perspective rather than from the company's point of view. Second, it is possible for them to establish a systematic complaint management system that can prevent service failure in advance by detecting customer complaints early. Third, it is possible for them to make quick decisions regarding service quality with the help of real-time customer response through dashboard construction.

Originality/value – This paper is a pioneer study measuring service quality with sentiment analysis, one of the text mining applications, using customers' reviews of a mobile bank.

Keywords Text mining, Sentiment analysis, Mobile bank, Service quality

Paper type Research paper

1. Introduction

These days, sustainable businesses depend on the degree of value they co-create with their customers. A major challenge facing many companies is the transformation of value co-created with their customers into assets. An example of this is the transformation of the vast amount of unstructured data available as knowledge and assets (Davenport, 2013).

These changes in business are rapidly moving from online websites to mobile applications. Focusing on the huge platforms such as Apple Store and Google Play, customers and companies are creating huge amounts of big data through interactions and creating value as assets. Mobile applications have now become an integral part of our lives.

The global mobile app market is estimated to be $581.9 billion (by 2020) and is projected to be $935.2 billion by 2023 (Iresearch, 2020). The mobile app market is expected to record an average annual growth rate of 29% from 2014 to 2023. As such, the mobile app market is growing in scale, and consumers are experiencing everyday life through mobile apps. This growth in mobile apps has also extended to banking services. In particular, in the context of COVID-19 pandemic, mobile banking is further developing and used by many consumers.

Mobile bank apps enable clients to make financial transactions on a mobile device (cell phone, tablet, etc.). This activity can be as simple as a bank sending fraud or usage activity to

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a client's cell phone, or as complex as a client paying bills or sending money abroad. The advantage of mobile banking includes the ability to bank anywhere and at any time. Mobile banking is very convenient in the modern digital age, with many banks offering impressive apps. The abilities to deposit a check, pay for merchandise, transfer money to a friend and find an ATM instantly are the reasons why people choose to use mobile banking. However, disadvantage can be security concerns and a limited range of capabilities when compared to banking in person or on a computer. In other words, establishing a secure connection before logging into a mobile banking app is important, or else a client might risk their personal information being compromised.

In the mobile banking environment, customer complaint management is becoming increasingly important. Customer complaint management is the beginning of customer satisfaction and is also an important factor in service quality management. Online reviews of complaints left by customers negatively affect the quality of service as well as the purchasing behavior of potential customers. Since such customer complaints are the most important cause of service quality and failure, it is very important to detect and resolve them at the earliest. Such customer complaints can be managed by periodically extracting and analyzing reviews left by customers.

Therefore, if a company responds to customers by measuring the service quality of mobile banks at the moment of usage, company can create a quick response to any potential risks due to the unique nature of mobile apps. To this end, a rapid response can be achieved when service quality is measured based on the data that companies and customers interact with through the mobile banking platform. This is made possible through text mining approach, such as sentiment analysis and topic modeling of reviews left by customers based on service experience. Thus, this study proposes a method for measuring the service quality and for finding customer compliant of mobile banks through sentiment analysis based on customer reviews.

This paper is organized into five sections. Section 2 describes the theoretical background and the literature review of this study. In particular, text mining, sentiment analysis and service quality using text mining are described. Next, Section 3 explains the research method of how to collect and analyze the data for this study, and then the result is discussed in Section 4. Finally, the conclusions and limitations are presented in Section 5.

2. Theoretical background and literature review

2.1 Mobile analytics

Today, mobile applications (apps) are becoming an increasingly important part of our lives. Apps are special-purpose software developed to perform specific tasks on the go. Each app has precise features and runs on certain mobile devices such as smartphones, tablet computers, or smart watches. Mobile devices use particular types of operating systems called OSs, which include Android, iOS and Windows Phone OS. Most apps can be downloaded online from app stores such as the Apple Store, Google Play and Amazon App Store. According to http://www.statista.com/, as of June 2017, there were five million apps available to download from the Apple Store and Google Play alone. App stores also provide opportunities for users to comment on and rate apps (Khan, 2018).

Generally, there are two kinds of mobile analytics: mobile web analytics and app analytics. Mobile web analytics aim to capture the characteristics, actions and behaviors of the visitors to a mobile company's website. These are very similar to conventional website analytics which collect and analyze a variety of user data, including views, clicks, demographic information and device-specific data (Khan, 2018). These days, all company websites must be mobile compatible. If a company cannot create a mobile-friendly website environment, it is likely to lose customers and business.

Mobile app analytics focus on understanding and analyzing the characteristics, actions and behaviors of a mobile app's users (Khan, 2018). Today, most organizations, big or small, use mobile apps to drive sales, improve brand affinity and enable purchases requiring just a few swipes. Most customers search for, book, and purchase what they want through mobile apps on their smartphone. Their experiences in the app are also logged. Therefore, a company needs to thoroughly understand the characteristics of a customer by analyzing the opinions left by the customer to secure a competitive advantage. In this context, this study focuses specifically on mobile app analytics using text mining.

2.2 Text mining approach

Text mining deals with the extraction and analysis of business insights from textual elements, such as comments, reviews, tweets and blog posts. It is mostly used to understand users' sentiments or identify emerging themes and topics (Khan, 2018). Organizations use text mining techniques to extract hidden valuable meanings, patterns and structures from user-generated reviews for business intelligence purposes. Text analytics, for example, are useful for gaining a quick and accurate understanding of the emotion and sentiment expressed over an online channel related to a brand or a new product launch. Text analytics has evolved into a well-established field with roots in a variety of domains including data mining, machine learning, natural language processing, knowledge management and information retrieval. Through natural language processing and machine learning technology, text mining can extract, analyze and interpret hidden business insights from unstructured textual elements of social media contents or online reviews.

Sentiment analysis, another application of text mining, focuses on the automatic extraction of positive or negative comments from text data (Pang and Lee, 2004). Because text is often a mixture of positive and negative sentiment, it is generally useful to identify the polarity of a text's sentiment (positive, negative, or neutral) and the intensity of that expressed sentiment (Thelwall *et al.*, 2011; Pang and Lee, 2004). Sentiment analysis can be used to scan and monitor online information to identify important situations, major problems and new events (Kaiser *et al.*, 2011; Levy *et al.*, 2013).

The most commonly used sentiment analysis algorithms are SVM (Support Vector Machine), Naive Bayes, Maximum Entropy and Matrix Factorization, which are used to classify text into positive or negative categories (Pang and Lee, 2004; Li and Wu, 2010). The interest of researchers in sentiment analysis has increased with the substantial growth in the amount and value of online texts. Shoppers read posted reviews on a regular basis before choosing a product, hotel, or a restaurant, and better reviews help generate higher profits. For example, Luca (2016) found out that the addition of another star on Yelp yields 5–9% more profit for a restaurant.

As mentioned above, in many service management fields, there have been several studies measuring service quality using sentiment analysis, but there has been no study measuring the service quality of mobile banks using sentiment analysis. Therefore, in the next chapter, this study proposes a method for measuring the service quality of mobile banks through sentiment analysis using text data.

2.3 Mobile bank service quality

From the traditional service industry to the mobile service industry, service quality is an important topic in marketing, and it has been broadly studied in traditional service settings. In one example, Parasuraman *et al.* (1988) explained that the SERVQUAL model is widely used as a tool to measure the service quality of traditional service settings. They proposed the five dimensions of tangible, reliability, responsiveness, assurance and empathy. SERVQUAL currently remains the most widely used instrument for measuring and operationalizing service quality (Choudhury, 2013). However, this initial conceptualization of service quality evaluation is inadequate for virtual environments (Parasuraman and Grewal, 2000; Bauer *et al.*, 2006), where customers interact with technology rather than with people based on a self-service logic.

In response to this problem, Parasuraman *et al.* (2005) later developed a multiple-item e-service quality scale, E-S-QUAL model, to measure the service quality delivered by websites. Unlike traditional e-commerce service quality assessments, E-S-QUAL defines the degree to which a website allows for effective and efficient shopping as well as product or service delivery. The basic E-S-QUAL scale comprises 22 items in four factors: efficiency, fulfillment, system availability and privacy (Parasuraman *et al.*, 2005).

Today, with the development of mobile technology, m-commerce, which provides unique values to consumers, is emerging as a new channel. In the m-commerce environment, service quality has been considered to be an expansion of the e-commerce environment, and E-S-QUAL has been expanded and used, but recently research has begun on M-S-QUAL about it being suitable for the mobile service environment. Huang and Lin *et al.* (2015) developed five dimensions for measuring m-commerce service quality: Contact, Fulfillment, Privacy, Efficiency and Responsiveness. Shankar *et al.* (2019) stated that the service quality measurement tools of SERVQUAL or E-S-QUAL are not suitable for the mobile banking environment. They also suggested dimensions to be applied in the mobile banking environment: Reliability, Assurance, Empathy, Efficiency, Fulfillment and Privacy. Sagib and Zapan (2014) and Jun and Palacios (2016) explored seven dimensions of mobile banking service quality as an expansion of SERVQUAL or E-S-QUAL. In a different study, Arcand *et al.* (2017) presented a dimension of service quality measurement in a mobile environment considering utilitarian (Security/Privacy, Practicity) and hedonic values (Design/Aesthetics, Sociality, Enjoyment) based on user experience. Puriwat and Trijopsker (2017) then empirically analyzed the relationship between mobile bank usage intentions using the service quality dimension.

This studies reviewed above have focused on measuring service quality measures through surveys employing a questionnaire using a predefined measurement tool of a mobile bank's service quality. The limitation of this survey-based service quality measurement study is that a lot of time and money must be invested first. In other words, this means that it is less effective than the time and effort for obtaining samples. Second, service quality measurement by questionnaire survey lacks accuracy due to the lack of continuous periodic measurement and does not play the role of manager's dashboard. In other words, it does not help with immediate and active decision-making. Therefore, this study proposes a new service quality measurement method that complements the shortcomings of such existing survey-based method.

Recent advances in machine learning and natural language processing technology have made it possible to complement traditional service quality measurement using customer online reviews. In particular, in fields of service such as retail (He *et al.*, 2018), hotels (Duan *et al.*, 2013), and airlines (Martin-Domingo *et al.*, 2019; Korfiatis *et al.*, 2019), some researchers have recently applied sentiment analysis to measure service quality. Therefore, this study extracts the measurement attributes of the five dimensions of mobile banking proposed by Arcand *et al.* (2017) and Puriwat and Trijopsker (2017) to measure the service quality of mobile banking. This two studies have developed and proposed dimensions of service quality of mobile banks based on a questionnaire survey, and this study presents a method of measuring service quality using the mobile bank service quality dimensions proposed by them.

3. Research method

3.1 Research design

The goal of this study is to measure the service quality of a mobile bank using sentiment analysis and keyword analysis. This study used the Naive Bayes and supervised learning methods as a classifier for sentiment analysis, and frequency analysis and network analysis for keyword analysis. To achieve this goal, we identify the sentiment of the mobile bank app review, calculate the accuracy of the sentiment identifier, and measure the service quality using sentiment identification.

User reviews can include negative or positive polarity. For example, one review might include a positive sentiment of "Thank you Kakao. This app helps you do easy banking" while another review might include the negative sentiment of "I want to use Kakao Bank, but since I'm a foreigner, it is really difficult." In this way, machine learning performs tests on user review data based on the trained data to obtain the sentiment polarity along with the level of accuracy of the sentiment analysis.

3.2 Research method

This section describes how to measure service quality with the help of user reviews left for Kakao Mobile Bank apps. The research procedure includes: (1) extracting users' reviews for Kakao Mobile Bank, (2) pre-processing the extracted review data, (3) analyzing the sentiment of each review, (4) measuring the service quality score of each dimension by analyzing keyword frequency and network for each polarity, and (5) evaluating the total score for mobile bank service quality. The research procedure is presented in Figure 1. Specialized applications for text mining, Netminer 4.0 and TEXTOM, are respectively used for text mining and sentiment analysis.

Netminer 4.0 is a social network analysis and unstructured text data extraction and analysis tool developed by CYRAM. This tool is used by 771 universities in 61 countries and 147 companies in 35 countries, and can be seen as suitable for text data analysis in this study (Cyram, 2020). TEXTOM 3.0 was used as a tool to support Korean language by providing a function of sentiment analysis of machine learning techniques through Baysian classifier (The IMC, 2020).

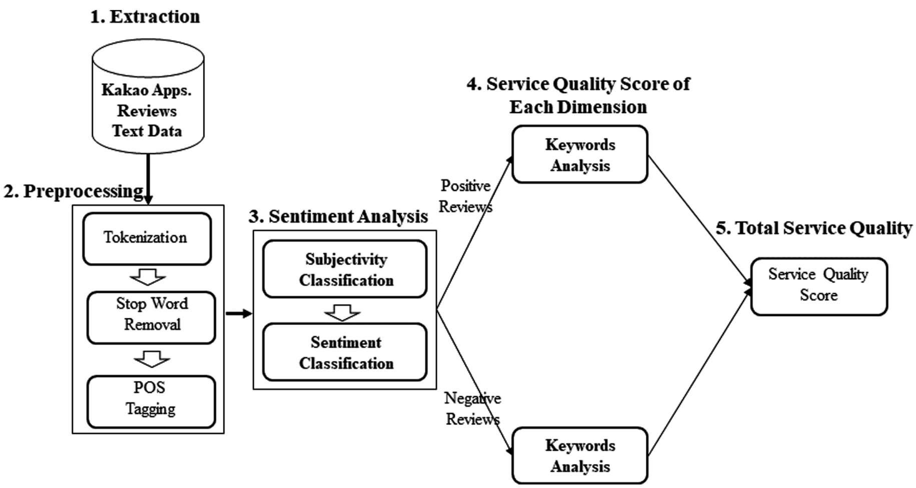

Figure 1.
Service quality measurement process using text mining

3.2.1 Data collection. We collected data from the Google Play Store for app reviews for Kakao Mobile Bank using WebHarvy, a specialized crawling tool for extracting text data from online reviews. From January 1, 2019 to December 31, 2019, 3,900 user reviews were collected in total. The extracted data includes the reviewer, the reviewer's address, the date of the review, and the review contents. After removing duplicate and advertising reviews, 3,359 reviews were analyzed. For data cleaning, we imported these collected data into Netminer 4.0.

3.2.2 Data pre-processing. In this study, filtering was performed to remove irrelevant data such as advertisements, spam or simple duplicate messages from newly collected raw data. Since the quality of the training data greatly influences the polarity classification accuracy of the sentiment analysis, the pre-processing involved converting unstructured data into structured data and removing unnecessary data variables. Therefore, data pre-processing was performed in three steps as shown in Figure 1.

The data pre-processing began with a tokenization process that first decomposed the documents extracted from the mobile apps of Kakao Bank and classified the sentences into meaningful tokens. The second step eliminated the stop words that were not worth considering in the study. The third step classified the decomposed tokens into parts of speech. This study classified the extracted words into nouns, adjectives, and adverbs that represent mobile banking service images.

3.2.3 Sentiment analysis. For sentiment analysis, we first needed to classify whether the document represented objectivity or subjectivity. The polarity of a document classified as subjective is calculated in terms of the sentence polarity. Thus, the document was first decomposed into sentences, and then the polarity of the sentences was determined. There are two main methods for classifying subjectivity and polarity: machine learning and dictionary-based approach. The machine learning approach can be further divided into the supervised machine learning method and the unsupervised machine learning method. This study classified subjectivity and polarity using supervised machine learning methods based on training data. In this study, a ratio of 70:30 was used to divide the collected data into training data and test data sets. We used TEXTOM software to detect the polarity of the sentiment in review documents.

After classifying the sentiment polarity, we tested the accuracy of the model that classified Kakao Bank users' sentiments based on the Naive Bayes. Accuracy refers to the degree of accurate predictions from all observations. Precision is the ratio of sentiments predicted by TEXTOM that were actually classified as true. Recall refers to the proportion of real sentiments that TEXTOM predicted to be true. Finally, the F-score is obtained from the harmonic mean of precision and recall. In general, the F-score is more than 70%, the social science approach is acceptable (TEXTOM, 2019).

3.2.4 Service quality dimension score. This study extracted the measurement attributes (keywords) of five dimensions – security/privacy, practicity, design/aesthetics, sociality and enjoyment – proposed by Arcand *et al.* (2017) and Puriwat and Trijopsker (2017) to measure the service quality of a mobile bank. First of all, we extracted the measurement keywords using WordNet 2.1, developed by Princeton University, for each dimension according to the service quality dimension of a mobile bank proposed by Arcand *et al.* (2017). The mobile bank service quality comprises the utilitarian (security/privacy, practicity) and the hedonic dimensions (design/aesthetics, sociality and enjoyment) with the measurement keywords shown below in Table 1.

After keywords are determined for each service quality dimension, we can analyze the frequency and network for keywords using Netminer 4.0. At this time, keyword frequency and network analysis are performed for each sentiment polarity.

3.2.5 Total service quality score. After the polarity is determined by using the supervised learning method and the Naive Bayes classifier in TEXTOM, we can calculate the total service quality scores of mobile bank using the formula below (Duan *et al.*, 2013).

Dimension	Definition	Measurement items
Security/ Privacy	Security is no longer an afterthought in anyone's software design and development process; rather, it is a fundamental dimension for driving Internet banking and mobile banking adoption. Prior to adopting mobile banking services, banking clients have to consider security and safety. Mobility increases the threat to security and privacy since there is more perceived risk in mobile banking given both remote connectivity and potential loss or theft of the mobile device	I think that the personal information that I provide on mobile is well protected I think that online transactions carried out on mobile are secure I think that the confidentiality and privacy of my personal information is assured when I do mobile banking
Practicity	In the human computer interaction field, the term practicity refers to "the use oriented and supports interactivity to enhance self-efficacy with the medium"	The productivity of my banking activities is improved on mobile The effectiveness of my banking activities is enhanced on mobile On mobile, it is easy to find what you are looking for
Design/ Aesthetics	Design is defined as the aesthetics of the content and function presented in a mobile device. In the context of mobile commerce, design and aesthetics indirectly impact user loyalty intentions toward mobile services	The design (e.g. colors, font size, graphics, animations, etc.) of the mobile application/ site is professional The design of the mobile application/site is creative Overall, the design of the mobile application/ site is visually appealing
Sociality	Sociality is defined as the social benefits derived from interacting with others (such as banking clients and representatives) via a mobile device. In the context of mobile banking, sociality does not occur among friends but rather with customer representatives and other customers. In the mobile banking services environment, connectedness allows users to chat online with a customer service representative whenever they need	I can chat online with a customer service representative of the institution when I need it on my mobile The institution offers relevant customers' testimonials on mobile
Enjoyment	Enjoyment is defined as perceived intrinsic motivation based on the pleasure or fun experienced when using an electronic device. The emotional and experiential value derived from perception of enjoyment play a positive significant role in motivating the adoption and/or use of innovative technologies, including the adoption of mobile banking platforms	Mobile banking is fun Mobile banking is pleasant Mobile banking is enjoyable

Note(s): *Arcand *et al.* (2017) and Puriwat and Trijopsker (2017)

Table 1.
Dimensions and definitions for mobile banking service quality

$$S_i = \frac{N_{Pi} - N_{ni}}{N_{Pi} + N_{ni}}$$

where S_i denotes the service quality score in dimension "i", N_{Pi} the number of positive documents in dimension "i", and N_{ni} the number of negative documents in dimension "i".

4. Results

4.1 Term frequency

Among the 3,359 words to be analyzed from Kakao Bank's app reviews from 2019, 200 words with a word length of two or more letters and TF-IDF (Term Frequency – Inverse Document Frequency) of 0.5 or more were extracted and summarized as listed in Table 2. The most common word was "good," with 940 mentions, and other words such as "comfort," "convenience," "usage" and "easy" were also common. These are all positive words. However, there were also negative words such as "no," which was the fourth-most common word. Next, Figure 2 visualizes the word network reflecting the frequency of these words and the frequency of co-occurrence of the words. The blue square is a node, and its size represents the frequency: the larger the size, the more frequent the words are, "good," "comfort," "convenience," "usage," etc. The black line connecting a word with another word refers to a relationship and is called a link or edge. The thickness of the line means the frequency of co-occurrence; the thicker the line, the higher the frequency of co-occurrence.

4.2 Sentiment analysis

The sentiment analysis of 3,359 reviews of Kakao Bank showed that 78.2% (2,628 reviews) of users had a positive sentiment while 17.1% (574 reviews) of users expressed a negative sentiment for this app. This means that while using the mobile bank app, most users are satisfied with the Kakao App service and provide a positive response in the form of a positive review. However, the fact that user reviews with negative polarity account for 17.1% of all reviews may lead to negative word of mouth effects.

To determine how well the sentiment polarity was classified in the above sentiment analysis, we calculated the accuracy, precision, recall and *F*-score using the formula in Table 3. Accuracy and recall were high at 86.4 and 100%, respectively, while precision was

Table 2.
Term frequency

Word	Frequency	Word	Frequency
good	940	inconvenience	53
comfort	397	easy	52
convenience	376	event	51
No	255	name	50
usage	247	error	50
Bank	166	plenty	46
account	142	install	44
Kakao Bank	141	confirm	44
best	122	Kakao	42
update	117	regards	41
fees	117	bank book	41
kabang	106	annoying	38
transfer	105	card	38
used	105	delete	37
make	78	safe box	36
fast	73	need	34
function	68	bank salad	33
ID	65	use well	33
certification	64	benefit	33
applications	62	linkage	33
money	60	remittance	33
use	59	identity	32
people	55	opened	32
savings	53	appreciation	32

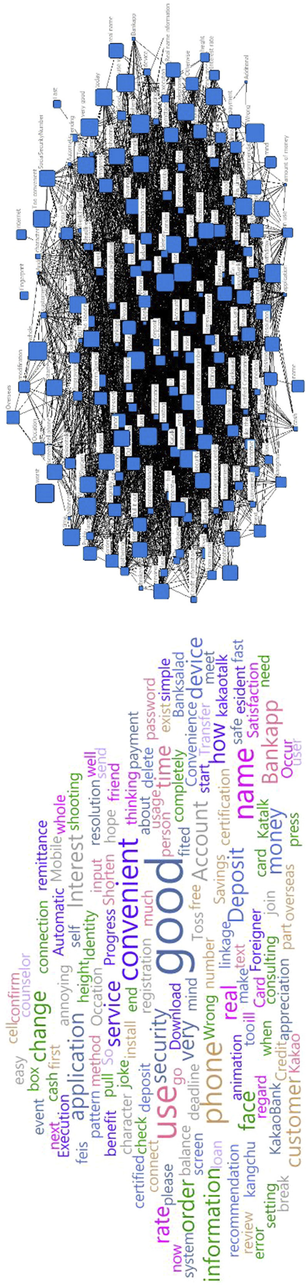

Figure 2.
Word cloud and word network

low at 54.5%. However, since the F-score was 70.6%, this sentiment classification model was adopted.

After conducting sentiment analysis, topic modeling was performed on 547 negative reviews (17.1%) to find out customer complaints. In this study, we used topic modeling developed by Blei *et al.* (2003) and extracted topic by applying the most widely used LDA (Latent Dirichlet Allocation) algorithm (Calheiros *et al.*, 2017; Guen and Juyoung, 2018). We set TF-IDF to 0.5 or more and word length to 2 or more to increase word frequency and word importance, and used alpha 8.33 and beta 0.02 for accurate topic extraction. In addition, Gibbs sampling was repeated 1,000 times using the MCMC (Monte Carlo Markov-chain) algorithm. (Steyvers and Griffiths, 2007). As a result of topic modeling, we summarized customer complaints in terms of technology (29%), interaction (25%), customer convenience (23%) and process (22%). The following Table 4 shows the extracted four customer complaints and key words.

4.3 Service quality measurement

Keyword groups for each service quality dimension were developed as shown in Table 5 to calculate the frequencies of those keywords. These keywords were extracted as shown in Table 6 based on the definition of each dimension, related research (Arcand *et al.*, 2017; Puriwat and Trijopsker, 2017), and WordNet 2.1 developed by Princeton University. Then, the frequency of the extracted keywords was calculated for each polarity analyzed in Section 4.2.

First, the keywords for the security/privacy dimension are “ID,” “authentication,” “fingerprint,” “security,” “pattern” and “safety,” and the frequency of each keyword for each of the groups of positive, negative and neutral reviews is summarized in Table 7 below. In the positive reviews, “security (20),” “safety (16)” and “authentication (12)” are the most common keywords. On the other hand, in the negative reviews, “authentication (147),” “ID (82),” “pattern (19)” and “fingerprint (17)” are the most common keywords. As shown in Table 6, in terms of keywords, the security/privacy dimension showed 269 negatives and 65 positives. This is partially attributed to the fact that “authentication” is too difficult at this points to use for a mobile bank, leading to many negative reviews. This is also attributed to the fact that the mobile bank app does not recognize the user “ID” at certain times, makes the users uncomfortable due to repeated requests for the “ID”

Table 3.
Confusion matrix

	Actual polarity	Positive	Negative
Predicted	Positive	24 (TP)	0 (FN)
Polarity	Negative	20 (FP)	103 (TN)

Note(s): TP: True Positive, FP: False Positive, FN: False Negative, TN: True Negative; Accuracy $= \frac{TP+TN}{TP+FN+TN+FP}$; Precision $= \frac{TP}{TP+FP}$; Recall $= \frac{TP}{TP+FN}$; $F-$Score $= \frac{2*Precision*Recall}{Precision+Recall}$

Table 4.
Topics and percent for customer complaints

Customer complaints	Key words	Percent (%)
Process	certification, id number, name, update	22
Interaction	inconvenience, people, transfer, card, telecommunication	25
Customer convenience	account, banking, error	23
Technology and function	use, id check, install, change, machine	29

In this way, the frequency of keywords for positive, neutral and negative reviews for the remaining 4 mobile bank service quality dimensions – Practicity, design/aesthetics, Sociality and enjoyment – are presented in Table 7.

As such, after frequency analysis for each polarity was completed for each service quality dimension keyword, the service quality score for each dimension could be calculated using the formula presented in Section 3.2.5. The quality score for each dimension, based on Table 8, is shown in Table 8.

For the results of measuring the mobile app service quality of Kakao Bank, presented in Table 8, the practicity of service quality was highest at 73.9%. Keywords related to Practicity that were extracted included “convenience,” “remittance,” “emergency payment,” “account management,” etc. We found that many customers left positive reviews for the mobile bank app since they experienced the convenience of bank transaction, remittance and account

Dimension	Keywords
Security/Privacy	Identification (ID), authentication, fingerprint, security, pattern, safety
Practicity	Convenience, remittance, emergency payment, account management
Design/Aesthetics	Interface, pattern, screen, video, one touch, reorganization, checkbook
Sociality	Counselor, counseling, connection, linkage, reservation, video conferencing
Enjoyment	Fun, joy, swiftness, mood, gratitude, satisfaction

Table 5. Definition and keywords of mobile bank service quality

Security/Privacy	Positive	Neutral	Negative
I.D.	3	3	82
authentication	12	27	147
fingerprint	8	4	17
security	20	4	1
pattern	6	17	19
Safety	16	4	3
Total	65	59	269

Table 6. Frequency of keywords for security/privacy dimension

Dimension	Positive	Neutral	Negative
Security/Privacy	65	59	269
Practicity	189	63	163
Design/Aesthetics	90	59	99
Sociality	51	55	82
Enjoyment	86	72	20

Table 7. Frequency of keywords for mobile bank service quality dimension

Dimension	Service quality score (Kakao bank)
Security/Privacy	61.1%
Practicity	73.9%
Design/Aesthetics	47.7%
Sociality	23.3%
Enjoyment	62.3%

Table 8. Quality score for each dimension

management. The second highest quality score for the mobile Kakao Bank was enjoyment. It can be seen that most users have left positive reviews with keywords such as fun, joy, gratitude and satisfaction.

The overall service quality score of Kakao Bank can be calculated using the formula presented in Table 4 from the sentiment analysis results. The overall quality score was computed as 64.1%, based on 78.2% positive and 17.1% negative reviews among all reviews. Currently, the Kakao Mobile Bank's service quality dimensional score is lower than its overall quality score, except for Practicity.

The analysis results of this study can be summarized as follows: First, in the sentiment analysis results, customers showed 78.2% positive and 17.1% negative sentiments for Kakao Bank. Second, the score by dimension of service quality was 61.07% for security/privacy, 73.76% for practicality, 47.69% for design/aesthetics, 23.31% for Sociality, and 62.26% for enjoyment. From the user's perspective, the top three most important mobile bank service quality dimensions are Practicity, enjoyment and security/privacy. Third, the overall service quality score of Kakao Bank is 64.1%. This means that customers using Kakao Bank have a high positive response to Kakao Bank, but do not perceive a high quality of service provided by Kakao Bank. Lastly, customer complaints were in the order of technology and function (29%), interaction (25%), customer convenience (23%) and process (22%).

With the help of these analysis results, we found out the following implications: First, from the customer's point of view, it was possible to see which factors are important among various dimensions of service quality, and which factors should be managed well. Second, by periodically finding customer complaints, service failures can be prevented in advance, and service quality and customer satisfaction can be improved.

5. Conclusions and limitations

5.1 Discussion

This study proposed a method to measure the service quality and to find customer complaints of mobile banks using sentiment analysis through text mining approach. For analysis, 3,900 reviews related to Kakao Bank were extracted from the Google Play store, and 3,340 reviews were ultimately analyzed after removing duplicate and advertising reviews. The results of the analysis are as follows: First, for the sentiment analysis results, customers showed 78.2% a positive sentiment and 17.1% a negative sentiment for Kakao Bank. In other words, most users showed a positive sentiment towards using Kakao Mobile Bank. Second, the frequency of each keyword for the sentiment polarity was computed by extracting keywords related to the mobile bank service quality dimension suggested in previous studies (Arcand *et al.*, 2017; Puriwat *et al.*, 2017). Based on this frequency, we calculated mobile bank service quality. The scores by dimension of service quality were 61.1% for security/privacy, 73.8% for practicity, 47.7% for design/aesthetics, 23.3% for sociality, and 62.3% for enjoyment. From the user's perspective, the top three most important mobile bank service quality dimensions were practicity, enjoyment and security/privacy. These results, in terms of importance, were found to be similar to those of Puriwat *et al.* (2017), who conducted a study examining the relationship between technology adoption of mobile banks and mobile bank service quality. Third, the overall service quality score of Kakao Bank was 64.1%. This means that customers using Kakao Bank have a high positive response to Kakao Bank, but they do not perceive a high quality of service provided by Kakao Bank. In other words, most customers use Kakao Mobile Bank for simple banking tasks such as simple transactions or accessing emergency funds, but do not use Kakao Mobile Bank for high-value and important tasks.

The factors that customers using Kakao Bank complain about were from the technology side (29), the interaction side (25%), customer convenience side (23%) and the process side (22%). The biggest complaining factor while using a mobile bank is related to the use of devices, identification and installation, etc. in terms of technology and function side.

5.2 Implication

The academic implication of this study first involved a method for measuring the service quality and finding out customer complaints of mobile banks using text mining and sentiment analysis. Most previous studies measured the service quality of mobile banks (Sagibe and Zapan, 2014; Jun and Palacios, 2016; Arcand *et al.*, 2017; Puriwat and Trijopsker, 2017) using survey-based structured data. We differentiated from quantitative research and attempted to measure service quality using qualitative research methods like text mining. This type of research does not rely on answers obtained by standardized questionnaires, but instead measures the actual service quality based on the intentional expression of the customer, which allows for the customer's sincere experience to be reflected in the service quality.

The practical implications are as follows. First, since many consumers interact with banking services using mobile apps, service quality management at the service encounter is most important. In the service quality measurement results, the practicity was highest with 73.9%. This means that users are most satisfied with convenience, money transfer, emergency money management, and account management in banking services using mobile apps. From a practical point of view, it is possible to maximize customer satisfaction by paying more attention to simple remittance and convenient account management. In addition, sociality was the lowest with 23.3%. This indicates that customers showed strong dissatisfaction with customer response and complaints when using mobile Kakao Bank. This means that there was a lack of smooth communication in non-face-to-face services. If Kakao Bank strives to improve the service quality of non-face-to-face services through offerings such as real-time video meetings, it is certain that the service quality of Kakao Mobile Banking will be improved.

Second, it is to detect and manage customer complaints early using topic modeling. In the research through the existing questionnaire, there is a difficulty in early detection of customer complaints, and there is a difficulty in periodically checking complaints. By periodically finding customer complaints, service failures can be prevented early, and service quality and customer satisfaction can be improved.

5.3 Limitations and future works

This study has some limitations despite these implications. By measuring service quality using unstructured data, service quality can be evaluated differently according to keyword extraction based on the subjective judgment of the researcher. This can be seen as a general limitation of unstructured data, but it can be partially resolved based on the results of various prior studies and the judgments of domain experts. Future research will be able to draw more meaningful results by classifying keywords in terms of service quality and combining text mining and quantitative research. In other words, it is possible to parameterize through validity and reliability verification of keywords in terms of service quality. It is expected that qualitative research can be developed with quantitative research to find richer implications. Second, it is considered to be a meaningful study to identify the possibility of failure according to the intensity of customer complaints and to derive a strategy for rapid recovery in case of failure. Lastly, by comparing customer complaint factors and customer behavior analysis through customer review analysis, it is expected that it can be extended to future customer behavior analysis research.

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Further reading

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