A new approach of social media analytics to predict service quality: evidence from the airline industry

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Abstract

Purpose – Research on how to use social media data to measure and evaluate service quality is still limited. To fill the research gap in the literature, the purpose of this paper is to open a new avenue for future work to measure the service quality in the service industry by developing a new analytical approach of using social media analytics to evaluate service quality.

Design/methodology/approach – This paper uses social media data to measure the service quality of the airline industry with the SERVQUAL metrics. A novel benchmark data set was created for each SERVQUAL metric. The data set was analyzed through text mining and sentiment analysis.

Findings – By comparing the results from social media with official service quality report from the Department of Transportation, the authors found that the proposed service quality metrics from social media are valid and can be used to estimate the service quality.

Practical implications – This paper presents service quality metrics and a methodology that can be easily adopted by other businesses to assess service quality. This study also provides guidance and suggestions to help businesses understand how to collect and analyze social media data for the purpose of evaluating service quality.

Originality/value – This paper offers a novel methodology that uses text mining and sentiment analysis to help the airline industry assess its service quality.

Keywords Text mining, Service quality, Sentiment analysis, Social media analytics, Emotional analysis

Paper type Research paper

1. Introduction

The use of social media platform (e.g. Facebook, LinkedIn, YouTube and Twitter) has grown significantly among consumers or companies to communicate and share experiences online. According to the research conducted by IBM Big Data, more than 2.5 quintillion bytes of social media data were generated daily in 2012 (Zikopoulos *et al.*, 2012). By 2020, 1.7 mb data will be created per second for every person on the Earth (DOMO Report, 2018). Twitter is one of the most popular social media platforms and has more than 326m monthly active users as reported in 2019 (Spisak, 2019). This trend has greatly motivated researchers

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and practitioners to adopt business analysis and big data mining approaches to extract insightful information from the collected large data (He *et al.*, 2015; Shahzad *et al.*, 2017; Hong *et al.*, 2017). Moreover, as it is becoming easier for consumers to connect and interact with companies through social media to voice their opinions (e.g. "like" or "comment" companies on Facebook, "follow" or "connect" companies via LinkedIn), scholars also have recommended managers to use social media to communicate with their customers in order to identify prospective business partners in the distribution channel (Shih, 2009) and support the creation of brand communities (Kaplan, 2012; Leek and Christodoulides, 2011).

To obtain a competitive advantage in the highly competitive business environment, companies are suggested to focus on improving service quality, rather than offering lower prices (Zeithaml *et al.*, 2000). Thus, it is essential for managers to continually measure and control the quality of the services/products they offer. Previous research relies heavily on survey-based self-report indicators (e.g. analytic hierarchy process (AHP), SERVQUAL and SERVPREF) to measure service quality and customer satisfaction (e.g. Parasuraman *et al.*, 1985; Tsaur *et al.*, 2002). However, the self-report measures are prone to many kinds of response bias, such as acquiescence bias, social desirability bias and conventional method variances (Schwarz, 1999). For example, Schwarz (1999) commented that "self-reports are a fallible source of data, and minor changes in question-wording, question format, or question context can result in major changes in the obtained results."

Mining social media provides a potential alternative to the traditional survey-based self-report measures. Social media analytics can be used to help researchers and practitioners study the data associated with a large customer base with a low cost and overcome some shortcomings of self-report measures. In the era of the internet, consumers increasingly use social media to share their experiences, opinions and feelings with a product/service. Mining the consumer-generated social media will generate rich, valuable information about product/service quality. More importantly, since social media occur naturally among consumers as a function of their experience with a product or service, text mining indicators are less subjective to conscious manipulation and response biases (Pennebaker and Francis, 1999). In addition, it is relatively easy to collect hundreds or thousands of reviews for a specific favorite product or service on the internet. To the contrary, it will be very costly and timely demanding to collect self-report measures from so many subjects by using traditional survey methods. Thus, taking advantage of the social media content to measure service quality is a promising and efficient approach to study product/service quality. Customer can use the reviews from either customer-driven review social media platform or business-driven review social media platform (Ha and Lee, 2018) to help them with the assessment of service quality. Shared experience and the number of likes available on social media are apparently related to the effectiveness of service evaluation (Ha and Lee, 2018). The public health care service quality can be reflected by social media as well (Lee *et al.*, 2018). Lee *et al.* (2018) used one of SERVQUAL metrics aligned with the Twitter data to track social media perception on the public health care. Another study recommended that marketers and managers should monitor the overall service quality of social media to increase client loyalty in the South African Banking Industry (Gavaza *et al.*, 2019). However, research on how to use social media data to measure and evaluate service quality in service industry is still scant (He *et al.*, 2018). To fill the research gap in the literature, this study aims to open a new avenue for future work to measure the service quality in the service industry by developing a novel analytical approach of using social media analytics to evaluate service quality.

In this study, we use the airline industry as our research context. This paper contributes to the literature in two important ways. First, this paper validates that social media analytics can predict the service quality for the airline industry by comparing social media data and Department of Transportation (DOT) data. Second, the innovative methodology that we used to provide the keywords for the six metrics of SERVQUAL can be effectively applied to measure service quality in other service industries.

DOT report is the official guideline of service quality measurement. Both individual consumers and the airline companies do not have access to the details of the complaints announced by the DOT report. Moreover, according to the time lags issue of DOT report, the airline companies may also miss the golden time when they are able to recover the service immediately after a failure happens. Due to these limitations of the DOT report, the data captured from social media platform could be an alternative way to capture significant market reactions in a real-time frame and access the number of complaints, concerns, opinions and compliments. One of the features of Twitter is "retweet," which is not the same as "reply." Users on Twitter who follow the other person who posted a message on Twitter can forward the same message with or without their own opinions and post it to Twitter again. Sometimes, retweeting requires even less than one minute. As a result of retweeting, a significant market event can be quickly spread on the internet to exert a significant impact on companies.

The majority of the US airline carriers have official accounts on Twitter. Their goal is to use social media as an important marketing tool to communicate with individual consumers and business partners. Twitter also offers a feature that enables managers to monitor these posts from other users (customers). If managers adopted this feature, there is a button showing "Responsive 24/7" on the left hand of the Business' Twitter home page. Among the 12 airline carriers, United Airlines and Alaska Airlines are the only 2 airline carriers that utilized this feature to improve the communication with their customers.

The remainder of the paper is organized as follows: Section 2 provides a brief review of the literature related to service quality and theoretical framework. Section 3 describes the procedure for using social media analytics to study the service quality and data collection. In Section 4, data analysis approaches and empirical results are presented. Finally, implications and limitations are the last section. Particularly, the implications on product/service preparation and the channel selection are discussed along with concluding remarks.

2. Literature review and theoretical framework

Service quality assessment is an important multi-disciplinary research topic for both researchers and practitioners. Service quality has been studied in many disciplines such as operational management, marketing and management information systems over several decades (e.g. Parasuraman *et al.*, 1985, 1988; Ramanathan and Karpuzcu, 2011). Researchers have developed different tools and instruments to evaluate service quality. Ladhari (2009) reviewed most of the instruments of service quality and found that SERVQUAL proposed by Parasuranman and his colleagues (1985, 1988) has been most widely used.

In order to measure service quality accurately, SERVQUAL is a multi-dimensional instrument, which is designed to capture consumers' expectations and perceptions of a service experience (Parasuraman *et al.*, 1985). Ten dimensions are covered in the original SERVQUAL instrument: access, communication, competence, courtesy, credibility, responsiveness, security, tangibility and understanding/knowing the customer (Parasuraman *et al.*, 1985). Three years later, Parasuraman *et al.* (1988) refined the ten dimensions into five major dimensions: reliability, responsiveness, assurance, empathy and tangibility. During the following 30 years, researchers have refined the SERVQUAL five dimensions across different service contexts. For example, Ramanathan and Karpuzcu (2011) expanded SERVQUAL to seven metrics including responsiveness, flexibility, availability, assurance, personnel contact quality, reliability and tangibles. Table I summarized the recent research and their dimensions for evaluating service quality in different context.

In this study, we focus on the airline industry. The airline business is one of the major service industries, relied upon by millions not only for transportation but also as a way of making a living. Previous studies have already adopted SERVQUAL instrument to evaluate

Table I.
A brief review of the service quality dimensions

Author(s)	Dimensions	Context
Yang and Fang (2004)	Responsiveness, reliability, credibility, competence, access, courtesy, communication, information, responsiveness and website design	E-service
Akbaba (2006)	Tangibles, adequacy in service supply, understanding and caring, assurance and convenience	Hotel industry
Polyorat and Sophonsiri (2010)	Tangibles and empathy, reliabilities, responsiveness and assurance	Chain restaurant
El Saghier and Nathan (2013)	Reliability, responsiveness, empathy and assurance	Banking services
Kitapci *et al.* (2013)	Empathy, tangibility, responsiveness and assurance	Supermarket
Thaichon *et al.* (2014)	Network quality, customer service and technical support, information quality and security and privacy	Internet service providers
Saeedpoor *et al.* (2015)	Tangibility, reliability, knowledge and skill of staff in maintaining mutual trust between customers and service providers, willingness to deliver services in a timely manner and to help customers, empathy	Life insurance firms
Ali and Raza (2017)	Compliance, assurance, reliability, tangibles, empathy and responsiveness	Service industry: Islamic bank

consumers' perception of airline service. Ostrowski *et al.* (1993) found that there is a positive relationship between service quality and customer loyalty (retained preference) in the commercial airline industry. Applying the fuzzy set theory to evaluate the service quality of the airline industry, Tsaur *et al.* (2002) used AHP approach and concluded that among the 15 service criteria, the most important attributes are "courtesy of attendants," "safety," "comfort and cleanness of seat" and "responsiveness of attendants." Mazzeo (2003) found that being on-time plays an important role in service quality in the airline industry. To maintain the market share, Mazzeo (2003) argued that when customers have more choices, companies have more incentive to improve service quality by offering lower prices and better service. Gupta (2018) found reliability, safety, tangibility and security are important attributes of airline service quality. Perçin (2018) conducted a study that evaluated the service quality of airline in Turkey by using the Fuzzy DEMATEL method. Their proposed method requires large amount of time and efforts to solicit feedback from multiple decision makers (Perçin, 2018). The recent research investigates the social media as the resource for sentiment analysis of Airport Service Quality and suggests Twitter content can beat the traditional research method by applying text mining and sentiment analysis (Martin-Domingo *et al.*, 2019). Based on the literature review, we identified six important dimensions of airline service quality. Table II presents the six dimensions along with the major attributes and keywords for each dimension. We will use the six-dimension service quality framework to guide our social media analytics. Among these six dimensions, security and safety is widely regarded as most important assets of the airline industry, especially after the 9/11 event.

3. A proposed approach to studying service quality by using social media analytics

One of the major objectives of this study is to establish an approach to studying service quality basing on social media analytics. As discussed in the introduction section, traditional SERVEQUAL research is largely based on self-report measures, which are subjective to different response bias, such as acquiescence bias, social desirability bias and common method variances. For example, the survey instrument for SERVQUAL constrains the information set based on the constructs available in the survey instrument. It is hard to compare service qualities across companies due to non-publicly available data (Rajaguru, 2016). Furthermore, a survey instrument is prone to sampling issues and response style biases (Suki, 2014).

Table II.
Six dimensions of airline service quality

Dimensions	Attributes and keywords
Responsiveness	Willingness to help passengers; providing prompt service; keeping passengers informed about delivery of service; keeping passengers updated if any modified schedule; quickly response customer's requirements
Assurance	Providing service actively; language skill or translation help of crew members; pilots' informative announcement in different contexts of culture; employee's skillfulness; courtesy towards customers
Tangibility	Comfortable seats and the cleanliness of the cabin; cleanliness of the aircraft interior and exterior; variety of food, food service and food quality; on-board entertainment: movie and music; the appearance of the crew; complimentary pillow or blankets
Reliability	Efficiency of the check-in process, flight punctuality, timeliness (arrival in promised time), handling of missing luggage complaints
Security and safety	Personal safety; luggage safety; animal safety
Communications	Communication between cabin crew and passengers; the ability to communicate with passengers in different languages; the communication between pilot and passengers; informative announcement during the flight

Sources: Ostrowski *et al.* (1993); Tsaur *et al.* (2002); Mazzeo (2003)

Another common type of measurement is post-service feedback. It has the limited information set based on single-question attributes and the sampling issues (Liou *et al.*, 2011). Since social media contain massive consumer-generated information, mining social media data may provide an effective and objective alternative approach to studying consumer behavior and service quality (Duan *et al.*, 2013). For example, Bates *et al.* (2014) leveraged big data analytics to identify and manage high-risk and high-cost patients. Xiang *et al.* (2015) used a text analytical approach to analyzing a large quantity of consumer reviews extracted from Expedia.com and understanding the relationship between hotel guests' experience and satisfaction. However, there is a lack of research to use social media analytics to measure the service quality in service industries.

To fill this gap, this study developed a procedure regarding how to collect and analyze social media data to evaluate service quality. The development of our approach is guided by the six-dimension SERVQUAL framework and is supported by the recent development in sentiment analysis.

As demonstrated in Figure 1, big data technology is used as a solution to capture and analyze social media data for targeted business and its competitors to visualize and compare among peers across different service quality measurement metrics. The first step retrieves data from a social media platform by provided API. Having the textual data and other quantitative data regarding one company, we save the data into CSV format. Next, text classification algorithms can be used to mine consumer-generated social media content based on the specified service quality measurement metrics. Then, the sentiment analysis, which is the computational detection and study of opinions, sentiments, emotions and subjectivities in the text, is used to identify consumers' service quality for each metric. This procedure can be extended to predict service quality in other industries as well by adopting the keywords of each metric of the SERVQUAL model.

The overall sentiment score of Dimension i is calculated by using the formula suggested by Duan *et al.* (2013):

$$S_i = \frac{N_{pi} - N_{ni}}{N_{pi} + N_{ni}},$$

where Npi denotes the number of positive sentences in Dimension i and Nni denotes the number of negative sentences in Dimension i. To make the process of conducting sentiment

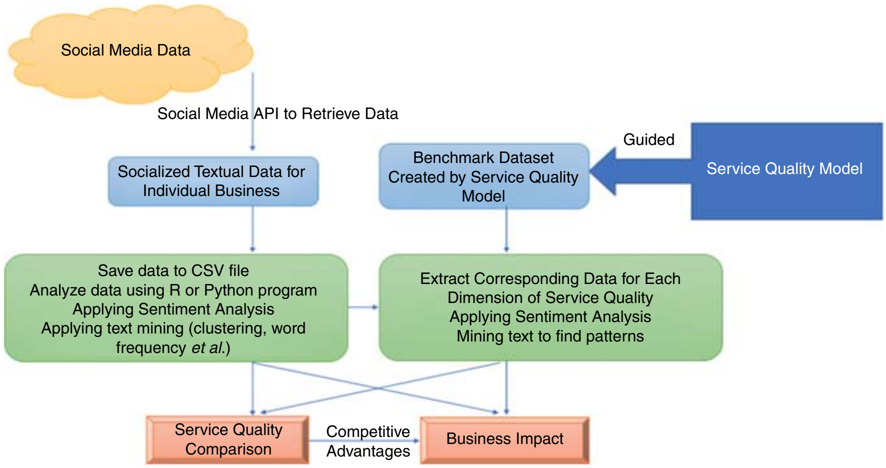

Figure 1.
A procedure for using social media analytics to study service quality

analysis easier, scholars can use existing sentiment analysis tools, such as Lexalytics, SentiWordNet, SentiStrength, Social Mention, Trackur, Sysomos and Viralheatto, to extract positive or negative sentiment scores (Pang and Lee, 2004). In this study, we adopted Lexicon-based sentiment analysis approach to capturing the sentiment score.

4. Methodology

This study concentrates on social media data and textual data analysis. We analyze the data retrieved from Twitter and then compare the official DOT data to find if social media analysis result can be used to predict the service quality efficiently. Sentiment analysis and regression model are applied to this paper and the details of the methodology are as follow.

4.1 Extracting data from social media: Twitter

We focus on Twitter in this study because it is a one of the most popular social media platforms that is widely used by consumers to post their opinions, complaints, concerns and compliments about a product/service. Twitter data on the 12 US airline carriers were collected for the time window of April 1, 2017 to June 30, 2017.

A Python program written by Twitter API was used to retrieve the tweets for the 12 airline carriers from April 1 to June 30, 2017. This program used the tweet.py to retrieve the old tweeter data. The data were saved in a JSON file with all useful information: username, posting date, geo-location, the number of retweets and the number of favorites, hashtags and permanent links.

4.1.1 Searching tweets. Python code has been developed to retrieve old tweets from Twitter, in which the username and keywords can be specified. It can set a maximum number of tweets, limit the location and set the time period. This program saves requested tweets in the CSV format after retrieval. For each airline carrier, we use "since" and "until" to limit the lower bound date and the upper bound date. The tweets were collected from any globe wise Twitter users who mentioned one of the specific airline carriers on Twitter during this specified period.

4.1.2 Preprocessing the retrieved Twitter data. After three months of Twitter data for all 12 airline companies were retrieved, the data were first saved in the CSV file. In each file, there are ten fields: username, date, retweets, favorites, text, geo, mentions, hashtags, id and permalink. The username, or "screen name" is unique on Twitter. In order to use the Twitter data to conduct analysis later, we preprocessed the Twitter data.

First, since this study focuses on the service quality of airline industry, we used the tweets posted by real customers, not by the airline staffs. Therefore, the tweets posted by airline's username were removed. In addition, because some tweets do not reveal any useful information that can be used to measure service quality, those tweets were removed from the data set. For example, if a tweet did not contain any words, or the tweet only contained one word, such as "Ok," "hi" or "yes," it was removed.

Second, we removed the keywords that were used to retrieve the Twitter data. For example, the original tweet "@VirginAmerica some of the best customer service I have ever had. companies could learn a lot from their operations," were processed as "some of the best customer service I have ever had. companies could learn a lot from their operations." There are some typos in the tweets, but they are normal and frequently occur in textual data on social media platforms.

Third, to match the words listed in the Lexicons database (all lower case), all the tweets (in text field of the Excel file) were converted to lower case. We use Lexicons to conduct sentiment analysis. This is an essential step before we conduct the sentiment analysis. In computer languages, lower case and upper case are different values. In order to compare words, they must in the same case, lower case or upper case. For example, if the word "Great" will not be identified by Lexicons since the Lexicons database only contains the word "great."

Fourth, we needed to remove all of the meaningless information in the tweets. For example, we removed "http" and "https," which is always shown in tweets as the beginning of the URL. After that, we trimmed the blank spaces in tweets. Table V shows the Twitter data for 12 airline carriers from April 1 until June 30, 2017. Finally, to meet the requirements of word corpus creation for sentiment analysis, all punctuation and blank spaces in tweets were removed. We reported all of the word clouds of Tweets for each airline carrier in the Table AI.

Table III provides a brief description of the processed tweet data. According to the table, United Airlines was mentioned by the largest number of unique users (135,569 unique users). American Airlines received the highest number of average tweets per user (2.09). It seems that American Airlines customers are more likely to communicate with the airline company on Twitter than other airlines' customers. The largest number of tweets was received by Delta Airlines, which was mentioned over 227,000 times during this period (April–June 2017).

Airline carriers	Number of tweets from April 1 to June 30, 2017	Number of unique users	Average tweets per user
United Airlines	224,789	135,569	1.66
Alaska Airlines	26,616	13,969	1.91
Southwest Airlines	68,522	42,561	1.61
Frontier Airlines	7,301	4,574	1.60
American Airlines	150,454	72,071	2.09
Delta Airlines	227,121	116,165	1.96
ExpressJet	58	45	1.54
Hawaiian Airlines	3,401	2,025	1.68
SkyWest Airlines	231	141	1.64
Spirit	23,045	13,095	1.76
JetBlue Airlines	49,503	24,693	2.00
Virgin America	11,817	7,270	1.63

Table III. The descriptive of processed twitter data

4.2 Reported data from the Department of Transportation (DOT)

To capture different airline companies service quality and market performance, we collected the data from the 2017 Air Consumer Report from US DOT for the time period of from the 2nd quarter (April, May and June) to the 3rd quarter (July, August and September). We used this data source because the DOT Air Consumer Report contains important objective indicators of service quality, including flight delays, mishandled baggage, oversold, consumer complaints, airline animal incident reports and the customer service report to the Department of Homeland Security. The Air Consumer Report included the information of 12 major US carriers including Spirit, ExpressJet, JetBlue, SkyWest, Frontier, American, United, Virgin America, Alaska, Southwest, Delta and Hawaiian. This report is divided into the following six sections:

(1) flight delays;

(2) mishandled baggage;

(3) oversold;

(4) consumer complaints (flight problems, baggage, reservation/ticketing/boarding, customer service, fares, refunds, oversold, disability, discrimination, advertising, animals, other);

(5) customer service reports to the transportation security administration (TSA); and

(6) airline reports of the loss, injury or DEATH of animals during air transportation.

These sections that deal with flight delays, mishandled baggage and oversold are based on the data collected by the Department's Bureau of Transportation Statistics. The section that focuses on consumer complaints is based on the data compiled by the OAEP's Aviation Consumer Protection Division (ACPD). The section that deals with customer service reports to the Department of Homeland Security's TSA is based on the data provided by TSA. The section that covers animal incidents during air transport is based on reports required to be submitted by the airlines to the ACPD. The specific items that we used in this study include on-time rate, involuntary denied boarding (per 10,000 passengers), mishandled baggage (per 1,000 passengers) and customer complaints (per 100,000 passengers). Table III provides a description of these key variables for 12 airline carriers in this study.

As demonstrated in Table IV, Hawaiian has the highest on-time rate in the three consecutive months, while Virgin America has the lowest on-time rate in the first two months and the second lowest in the following month. The overall on-time rate for all airline carriers shows that April has the better on-time rate than the other two months (averaging approximately 76 percent). Regarding mishandled baggage, ExpressJet performed the worst in all of three months; most airline carriers reported about 2.6 incidents of mishandled baggage per 1,000 passengers, with American Airlines and Southwest Airlines having the poorest performance in baggage handling. Spirit Airlines had the most complaints across all of three months, followed by Virgin America, United and Frontier.

Following Bowen and Headley (2017), we adopted the Air Quality Rating (AQR) to measure the service quality of US airline carriers in this study. In order to calculate the AQR score, on-time rate (OT), denied boarding (DB), mishandled baggage (MB) and customer complaints (CC) reported by DOT data were input to the following formula:

$$\mathrm{AQR} = \frac{(+8.63 \times \mathrm{OT}) + (-8.03 \times \mathrm{DB}) + (-7.92 \times \mathrm{MB}) + (-7.17 \times \mathrm{CC})}{(8.63 + 8.03 + 7.92 + 7.17)}.$$

The AQR of these 12 airline carriers was reported in Table V.

Airline carriers	Month	On-time (%)	Involuntary denied boarding	Mishandled baggage	Customer complaints
Alaska	April	81.6	0.42	1.41	1.00
	May	82.6	0.42	1.60	0.44
	June	82.9	0.42	1.85	0.47
Frontier	April	79.5	0.49	2.31	2.42
	May	76.6	0.49	2.57	3.01
	June	73.1	0.49	2.39	1.86
Southwest	April	79.5	0.64	2.43	0.50
	May	77.3	0.64	2.90	0.59
	June	73.3	0.64	3.35	0.50
United	April	81.9	0.44	2.12	3.04
	May	82.3	0.44	2.12	2.02
	June	79.4	0.44	2.47	2.09
Hawaiian	April	*88.8*	0.08	2.52	1.58
	May	*89.7*	0.08	3.00	1.05
	June	*90.4*	0.08	2.47	0.60
SkyWest	April	80.0	0.26	3.03	0.81
	May	82.4	0.26	2.61	0.70
	June	81.0	0.26	3.08	0.47
American	April	78.7	0.56	2.81	2.68
	May	80.1	0.56	2.56	2.15
	June	73.2	0.56	3.20	2.09
Spirit	April	77.0	*1.25*	1.46	*7.20*
	May	69.0	*1.25*	1.65	*11.39*
	June	68.3	*1.25*	1.82	*7.38*
ExpressJet	April	75.7	0.63	*4.67*	1.79
	May	76.8	0.63	*3.45*	1.18
	June	75.1	0.63	*4.00*	0.83
Virgin America	April	64.6	0.53	1.42	2.94
	May	58.7	0.53	1.57	3.12
	June	67.2	0.53	1.73	2.70
Delta	April	76.9	0.09	3.04	2.52
	May	82.8	0.09	1.67	1.21
	June	82.8	0.09	2.08	0.80
JetBlue	April	72.4	0.04	1.50	1.19
	May	67.2	0.04	1.66	1.44
	June	60.6	0.04	1.65	1.27

Table IV. DOT airline consumer report (April–June 2017)

Airline carriers	AQR score April	May	June
Alaska	*−0.46*	*−0.38*	*−0.45*
Frontier	−1.01	−1.24	−0.94
Southwest	−0.61	−0.81	−0.91
United	−1.10	−0.87	−0.98
Hawaiian	−0.85	−0.76	−0.53
SkyWest	−0.83	−0.65	−0.72
American	−1.20	−1.05	−1.21
Spirit	*−1.89*	*−3.11*	*−2.25*
ExpressJet	−1.47	−1.08	−1.14
Virgin America	−0.95	−1.07	−0.99
Delta	−1.22	−0.49	−0.50
JetBlue	−0.55	−0.57	−0.54

Table V. AQR score for 12 airline carriers (April–June 2017)

4.3 Text mining and supervised classification guided by SERVQUAL framework

Text mining, defined as the most use of large online text collections to discover new facts and trends about the world itself (Hearst, 1999), has been widely used in different disciplines, such as linguistics, computer science, computational statistics and information technology. Standard techniques in text mining are text classification, text clustering, word frequency and co-occurrence words, document summarization and latent corpus analysis (Meyer *et al.*, 2008). In this study, we used the supervised classification technology to evaluate the six dimension of service quality. The supervised classification technology uses the Naïve Bayes theorem to classify the text into different categories. Before sentiment analysis, three graduate students reviewed the Twitter data independently and identified the keywords that can represent each of the service quality dimensions. All three graduate students were trained with knowledge about airline service quality before they started to identify the keywords from Twitter data set. When they had disagreement on one key word, they discussed together until reaching a consensus. A list of the finalized keywords is presented in Table VI. We also reported some tweet examples that are related to each dimension of service quality in Table AII.

4.4 Sentiment analysis and data visualization

Sentiment analysis is the process of determining the emotional tone behind a series of words, which can be used to gain an understanding of the attitudes, opinions and emotions expressed within an online text (He *et al.*, 2015, 2016; Munezero *et al.*, 2014). We parsed the tweets we extracted out into individual words. In the next step, we counted and compared the difference between the number of positive words and the number of negative words. We use the open source R program package (https://github.com/exploratory-io/exploratory_func) to calculate the sentiment score of the sentence. This package can map the predefined sentiment type (positive or negative) or the value (how positive or how negative). It also has the indictor for the intensity of the sentiment. Measuring only the positivity or negativity of the sentiment is not enough to evaluate the mood or emotion of the customers. For example, here are two tweets in the data set: "I'm feeling so good!" and "I'm feeling much better!"

Dimensions of service quality	Keywords
Responsiveness	Nice, kind, call, phone, cell, reschedule, schedule, information, info, notify, handle, rude, counter agent, minor, unaccompanied, help, refund, track, prefer, hotel, helpful, wonderful, agent, gate, callback, support, website, site, love, great, app, club, status, mile, 1k, frequent, lounge, mvp, best, attentive
Assurance	Translate, English, service, rude, customer service, manager, favorite, win, treat, landing, awesome, perfect, issue, solve, elevate points, care, remove, poor, behavior, thrown, dumped, drag, cost, change, culture, skill, courtesy, upgraded, upgrade, professionalism, complaint, refund, hotel, reimbursed, reimbursement
Tangibility	Food, beverage, drink, wine, clean, dirty, meal, choice, music, movie, comfortable, uncomfortable, pillow, blanket, repair, game, sit, water, amenity, cabin, crew, bathroom, seat, air conditioner, wifi, breakfast, dinner, window, aisle, staff, neck, body, wi-fi
Reliability	Check in, delay, on time, luggage, miss, baggage, handle, depart, arrival, lost, mechanical, failure, bags, bag, checked, late, wait, hour, board, cancel, inconvenience, cancelled, delayed, departed, departure, arrivals, arrive, carry on
Security and safety	Safe, safety, safely, animal, cat, dog, cage, security, secure
Communications	Open, foreigners, communicate, communication, talk, announcement, announce, attendants, attendant, pilot, contact, answer, response

Source: Built and integrated from this research

Table VI. Keywords of each dimension of service quality

Although both of above two sentences are positive, these two sentences express the intensity that influences the different results in emotion, because "so" and "much" are the intensifiers in these sentences and score differently. "I'm feeling so good" scores higher arousal than "I'm feeling much better."

Sentiment scores are calculated by the sum of positive minus negative, then they are divided by the number of words in the tweet. The sentiment score ranges from −1 to +1. "−1" means that the tweet is completely negative in sentiment, while "+1" means that this tweet is completely positive in sentiment. In this study, we used dictionary-based methods (Lexicon) to calculate the sentiment score. Technologically, the sentiment score was calculated all center around the determination of text *T*'s average sentiment with sentiment dictionary *D* through the following equation:

$$h_D^T = \frac{\sum_{w \epsilon D} h_D(w) \cdot f^T(w)}{\sum_{w \epsilon D} f^T(w)} = \sum_{w \in D} h_D(w) \cdot p^T(w),$$

where i denotes each of the words in a given sentiment dictionary D as w, word sentiment scores as $h_D(w)$, word frequency as $f^T(w)$ and normalized frequency of w in T as $P^T(w) = f^T(w)/\sum_{w \in D} f^T(w)$. Adopting this way, we can measure the sentiment of a text in a manner analogous to take the temperature of a room. Analyzing the contribution of each individual word is important to sentiment analysis and this equation allows for a meaningful interpretation.

In order to double-check the accuracy of sentiment analysis, several major Lexicons dictionaries were used to calculate the sentiment for each tweet. Affective Norms of English Words (ANEW) dictionary has classified the words and has assigned them two elements to measure the emotions: valence and arousal (Russell, 1980). Valence is the direction of the emotion, and arousal is the level/amount of the physical response. For example, the positive words "happy" and "relax" have different arousal levels. "Happy" has a higher arousal level than "relax." To apply the ANEW dictionary, each tweet was given a score for valence and arousal. Both valence and arousal are positive scores. The higher the valence score, the more the positive direction of this tweet. The higher the arousal score, the more intensive the emotion expressed by the tweet. For example, for a message "funny that you tweeted this after a cancellation of a flight from dca > sfo because of lack of crew," its sentiment score equals to 0.01147079, valence score equals to 6.25 and arousal score equals to 7.92.

4.5 Data analysis and results

In order to test the relationship between social media Twitter data and DOT reported data, we used multiple regression model to find the relationships between sentiment score and AQR score. The AQR score is the dependent variable. It was calculated based on the data collected from the DOT report. The independent variables come from social media data: the volume of tweets, the sentiment score, the valence score and the arousal score (using the ANEW dictionary, the scores range from 1 to 10). We also added some control variables to rule out other potential alternative explanations that are not the focus of the study including the volume of Tweets, the number of passengers, the number of scheduled flights, the number of months on Twitter, the number of followers on Twitter and an indicator regarding whether an airline had an online response on Twitter. The following equation shows the initial regression model used in this study:

$$\mathrm{AQR} = \alpha + X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + \ldots + X_k\beta_k + \varepsilon.$$

Because there are 36 observations for three months of data for 12 airline carriers, the sentiment score was calculated by average of the sentiment score for a month. To calculate the value of arousal and valence of one tweet, we summed up the value of arousal and valence of each word in one tweet. Table VII presents the descriptive statistics of all of the variables.

Before running the regression model, the volume of tweets, the number of passengers and the number of scheduled flights were converted to natural logarithm values. Figure 2 presents the correlation matrix of all variables in data visualization mode. We used multiple regression analysis to answer the research question and reported the results in Table VIII.

In the first model, we included all control variables in the model. However, in this model, we found two high variance inflation factors (VIF). According to the suggested multicollinearity threshold of 10 (Gefen *et al.*, 2000), the number of passengers (VIF: 25.234) and the number of scheduled flights (VIF: 25.214) were not tolerant in this model. Hence, we

Table VII. Descriptive statistical of all variables

Variables	Min.	Max.	Mean	SD
AQR	−3.11	−0.380	−0.9853	0.55148
Volume of tweets	7	144,939	21,785.33	31,912.341
Average sentiment score	−0.026	0.148	0.046	0.043
Anger	1	43,493	4,907.61	8,425.617
Anticipation	4	47,999	7,483.42	10,870.964
Disgust	1	33,243	3,794.56	6,487.302
Fear	4	53,495	5,964.06	10,261.335
Joy	3	29,815	5,112.58	7,022.114
Sadness	4	43,351	5,686.86	9,020.981
Surprise	1	24,555	3,551.28	5,271.454
Trust	6	67,179	9,193.25	14,078.762
Sum of valence	15	118,636.98	21,074.838	29,113.552
Sum of arousal	17.5	127,637.64	21,858.771	30,472.918
Control variables				
Passengers	653,156	14,090,883	4,694,609.58	4,460,462.60
Scheduled flights	198	3,965	1,374.75	1,173.339
Months on Twitter	63	121	99.62	18.652
Twitter followers (×1000)	2.5	2,019.00	764.181	754.284
Online response on Twitter (dummy variable)	0	1	0.17	0.378

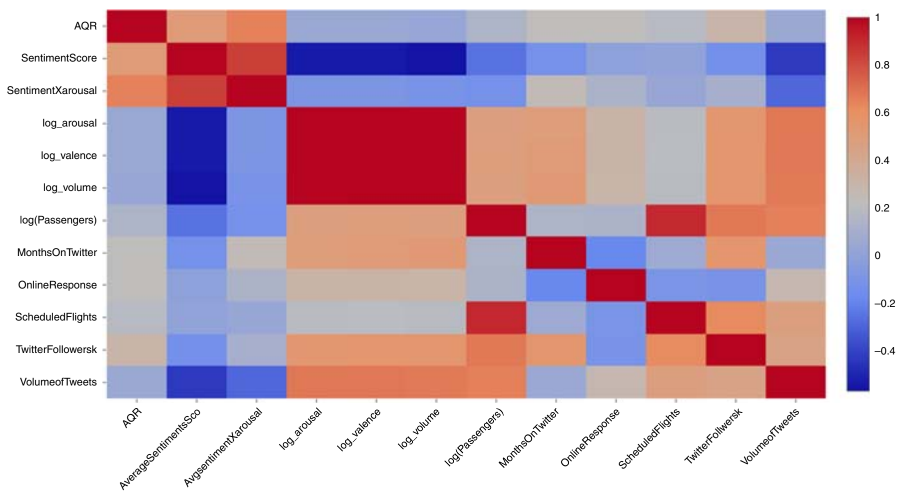

Figure 2. Correlations matrix of all variables

Dependent variable	AQR (Model 1)	AQR (Model 2)	AQR (Model 3)
(Constant)	−2.18	−1.41	−2.207
Log (volume of tweets)	−1.39 (0.139)	−0.274* (−0.107)	
Average sentiment score			7.237** (1.66)
Log (the number of passengers)	−1.475 (9.112)	0.000 (2.85)	0.020 (2.43)
Log (the number of scheduled flights)	0.0005 (0.000)		
Months on Twitter	0.013* (0.009)	−0.010 (0.006)	0.005 (0.005)
Twitter followers	0.0002 (0.000)	0.0003* (0.0004)	0.0003 (0.0002)
Twitter online response	0.806** (0.253)	0.765** (0.258)	0.442* (0.191)
R^2	0.389	0.335	0.502
Adjust R^2	0.262	0.224	0.419

Notes: Bracketed values are the standard error term of the coefficient. $^{*}p < 0.10$; $^{**}p < 0.05$

Table VIII. Regression model results

decided to eliminate the number of scheduled flights and keep the number of passengers in the second model (Model 2). The results of Model 2 are presented in Table VIII. In the next step, the mean of the sentiment score that represents the monthly sentiment for each airline carrier was included into the Model 3 to check whether social media data can be used to measure service quality dimensions measured in DOT consumer reports.

The result of Model 3 in Table VIII represents that the R^2 value was 0.500 of this model, with p-value 0.001 (significant at level of 5 percent). The coefficient of the average sentiment score was 7.349 ($p < 0.01$), which means that the sentiment score was positively related to AQR. Therefore, the sentiment score of tweets can be used to aligned with the DOT Air Travel Consumer Report.

5. Discussion

This paper introduces a research framework for assessing service quality through social media analytics and also validates service quality results from social media using official service quality reports in the airline industry. Having applied the SERVQUAL model to propose six dimensions of service quality in the airline industry, we have gathered and analyzed the social media data from Twitter by using sentiment analysis to confirm that the sentiment scores of tweets are aligned with the DOT Air Travel Consumer Report. By comparing the results from social media with official service quality report from the DOT, this study found that the proposed service quality metrics from social media are valid and can be used to estimate the service quality.

Since the sentiment score is aligned with AQR score that is generated from the DOT consumer report, researchers and marketers in the airline industry can get an alert about service quality in a short time. They do not have to wait to see the DOT consumer report two months later. Another interesting finding is that the number of scheduled flights and the number of passengers also affect the AQR score, which means that more consumers use social media tools to complain about the experiences they have met aboard airline carriers.

The sentiment scores and the online Twitter response function are the two factors to evaluate service quality. Customers want their opinions to be heard by the service providers. With social media tools, the airline carriers could receive valuable opinions from their customers promptly, and the customers could be happy with the improved services and responded complaints.

6. Conclusion and implications

Customer complaints in business context have not been the focus of much research (Homburg and Rudolph, 2001; Rossomme, 2003). Business services tend to be technically more complex than consumer services (Dawes *et al.*, 1993; Gordon *et al.*, 1993) and include maintenance, repair and operation services (Jackson *et al.*, 1995; Mathe and Shapiro, 1993). The lack of research focus is particularly intriguing given the high growth in business services currently (Brown, 2002; Fitzsimmons *et al.*, 1998). This novel methodology can help service industry improve service quality by responding to the social media posts and interacting with their customers more quickly. As more and more organizations use social media to disseminate information and interact with their customers, our proposed methodology contributes to the society's efforts to harness the potential power of big social media. Our findings validate the value of social media-based service quality metrics and offer a foundation to make the social media ecosystem more efficient toward digital transformation and sustainable societies. Customers can post any complaints, compliments and suggestions on a business on social media at any time by using their mobile devices. This information posted on social media can be used as the real-time feedback from customers rather than soliciting customer feedback through self-reported surveys. Customer can get the rapid response from the business on social media and hopefully get the issues resolved in a timely manner. There are lots of challenges in service industry nowadays. Since word-of-mouth is important to businesses in today's competitive marketplace, online social media-based word-of-mouth is considered critical to brand reputation and is an important way to attract and retain customers.

We will further discuss the practical role of social media use as a positive influencer in a business context, especially on the product/service preparation and the channel selection.

6.1 Theoretical implications

This study contributes to the literature in several notable ways. First, this study extended the traditional research on SERVQUAL by developing an alternative approach to evaluate service quality basing on social media analytics. Past research on SERVQUAL model and service quality relies heavily on self-report measures. Guided by the SERVEQUAL framework, this study established an approach to evaluating different service quality dimensions by collecting and analyzing the social media data posted by consumers. Moreover, we found that the sentiment scores generated by the sentiment analysis are significantly related to the service quality indicators reported in the DOT Air Travel Consumer Report, which provides initial evidence of the validity and utility of our approach. Our findings also support Seggie *et al.*'s (2007) proposition that the internet and social media will diminish the importance of subjective marketing measures and increase the possibilities and importance of objective measures.

This study is an early attempt to adopt information technology in measuring service quality, and ultimately improving firm performance. Our empirical findings show that the sentiment scores of tweets are aligned with the objective measured provide by DOT Air Travel Consumer Report. Specifically, our findings emphasize the importance of the following technologies in measuring and improving service quality: designing a technological procedure using social media analytics to study service quality, extracting and collecting consumers' feedback and information from social media platforms and develop the keyword sets for service quality matrices that suitable for social media analytics. Above all, our research responds to calls for scholars to adopt social media analytics and other information technologies to improve firm performance.

6.2 Managerial implications

Managerially, this study provided a guideline regarding how to collect and analyze tweets to evaluate service quality. Following this guideline, managers will be able to better learn from social media. They may incorporate the knowledge they learned from social media posts to improve their service design and delivery for their organizations. By adopting or adapting our methodology, organizations are able to leverage social media information and involve customer into their service delivery process and fulfill their role of value co-creators, which will lead to better customer service and positive impact upon society. In the business context, social media analytics may be able to provide an effective and efficient approach to evaluating and selecting suppliers and partners for companies. Instead of directly collecting information from consumers, companies typically use third-party institutions to evaluate the reputation and service quality of their partners and suppliers (Meents *et al.*, 2003). Studies indicate that customer complaints and feedbacks have not been focus of business research (Homburg and Rudolph, 2001; Rossomme, 2003). The findings of our study call for more companies' attention to social media. The sentiment contained in social media can be used as an indicator of a supplier or partners' reputation and service quality. For example, an airline company is involved in a large extended business network. An airline company's success largely depends on the quality of the support provided by its suppliers, such as catering service providers, airline fuels and lubricants provider, and aircraft storage and maintenance provider *et al.* Moreover, the airline industry is characterized with large strategic alliances. Many airlines developed strategic partnership with other airlines (e.g. Oneworld, Star Alliance and Skyteam). The prevalence of social media and digital information may provide companies with low-cost and rich information to evaluate and select their potential suppliers' and partners' qualifications. Moreover, sentiment analysis can also help companies to monitor and evaluate the impact of its suppliers and partners' bad publicity and crisis. The company can take quick response to prevent loss. For example, the incident of United Airline in April 2017 was posted on social media and the airline company responded using their social media account. The partners of United Airline also can apply social media analytics and the methods we developed in this manuscript to find which dimension of SERVQUAL needs to be addressed. The competitors can take advantage of social media analysis to promote their service as well.

7. Limitations and further research

Some limitations of this study could be addressed in future research. First, this study used only one social media platform – Twitter. Some other popular social media websites such as Facebook and Instagram are not included in our analysis. Future research may employ multiple social media platforms to cross-validate the findings of this study. Second, the sentiment analysis used in this study was mainly based on two significant Lexicons (two dictionaries) to calculate the sentiment for each tweet. Sentiment analysis has applied the Lexicons and words may be evaluated out of context. Another advanced technology could be adapted to include the images posted by customers. Third, we analyzed the tweets in English. There are many other languages that have been used in Twitter. It might be helpful to include other languages such as Korean, Russian, Japanese and Mandarin into social media analysis.

References

Akbaba, A. (2006), "Measuring service quality in the hotel industry: a study in a business hotel in Turkey", *International Journal of Hospitality Management*, Vol. 25 No. 2, pp. 170-192.

Ali, M. and Raza, S.A. (2017), "Service quality perception and customer satisfaction in Islamic banks of Pakistan: the modified SERVQUAL model", *Total Quality Management & Business Excellence*, Vol. 28 Nos 5-6, pp. 559-577.

Bates, D.W., Saria, S., Ohno-Machado, L., Shah, A. and Escobar, G. (2014), "Big data in health care: using analytics to identify and manage high-risk and high-cost patients", *Health Affairs*, Vol. 33 No. 7, pp. 1123-1131.

Bowen, B.D. and Headley, D.E. (2017), "The airline quality rating (AQR) report", Embry-Riddle Aeronautical University in Prescott, AZ, available at: https://airlinequalityrating.com/ (accessed May 2, 2018).

Brown, S.W. (2002), "Opportunities for business-to-business services scholarship: a commentary", *Australasian Marketing Journal*, Vol. 10 No. 1, pp. 10-12.

Dawes, P.L., Dowling, G.R. and Patterson, P.G. (1993), "Determinants of pre-purchase information search effort for management consulting services", *Journal of Business-to-Business Marketing*, Vol. 1 No. 1, pp. 31-61.

DOMO Report (2018), "Data never sleeps", DOMO, Marietta, GA, available at: www.domo.com/solution/data-never-sleeps-6 (accessed February 2, 2019).

Duan, W., Cao, Q., Yu, Y. and Levy, S. (2013), "Mining online user-generated content: using sentiment analysis technique to study hotel service quality", *System Sciences (HICSS), 2013 46th Hawaii International Conference on, IEEE*, pp. 3119-3128.

El Saghier, N. and Nathan, D. (2013), "Service quality dimensions and customers' satisfactions of banks in Egypt", *Proceedings of 20th International Business Research Conference*, pp. 4-5.

Fitzsimmons, J.A., Noh, J. and Theis, E. (1998), "Purchasing business services", *Journal of Business and Industrial Marketing*, Vol. 13 Nos 4/5, pp. 370-380.

Gavaza, B.K., Viljoen, K.L. and Cilliers, L. (2019), "The influence of social media service quality on client loyalty in the South African banking industry", *Acta Commercii*, Vol. 19 No. 1, pp. 1-10.

Gefen, D., Straub, D. and Boudreau, M.-C. (2000), "Structural equation modeling and regression: guidelines for research practice", *Communications of the Association for Information Systems*, Vol. 4 No. 1, p. 7.

Gordon, G.L., Calantone, R.J. and di Benedetto, C.A. (1993), "Business-to-business service marketing", *Journal of Business and Industrial Marketing*, Vol. 8 No. 1, pp. 45-57.

Gupta, H. (2018), "Evaluating service quality of airline industry using hybrid best worst method and VIKOR", *Journal of Air Transport Management*, Vol. 68, May, pp. 35-47.

Ha, E.Y. and Lee, H. (2018), "Projecting service quality: the effects of social media reviews on service perception", *International Journal of Hospitality Management*, Vol. 69, January, pp. 132-141.

He, W., Tian, X., Chen, Y. and Chong, D. (2016), "Actionable social media competitive analytics for understanding customer experiences", *Journal of Computer Information Systems*, Vol. 56 No. 2, pp. 145-155.

He, W., Tian, X., Hung, A., Akula, V. and Zhang, W. (2018), "Measuring and comparing service quality metrics through social media analytics: a case study", *Information Systems and e-Business Management*, Vol. 16 No. 3, pp. 579-600.

He, W., Shen, J., Tian, X., Li, Y., Akula, V., Yan, G. and Tao, R. (2015), "Gaining competitive intelligence from social media data: evidence from two largest retail chains in the world", *Industrial Management & Data Systems*, Vol. 115 No. 9, pp. 1622-1636.

Hearst, M. (1999), "Untangling text data mining", *Proceedings of the 37th Annual Meeting of the Association for Computational Linguistics on Computational Linguistics, Association for Computational Linguistics*, *Morristown, NJ*, pp. 3-10.

Homburg, C. and Rudolph, B. (2001), "Customer satisfaction in industrial markets: dimensional and multiple role issues", *Journal of Business Research*, Vol. 52 No. 1, pp. 15-33.

Hong, H., Xu, D., Xu, D., Wang, G.A. and Fan, W. (2017), "An empirical study on the impact of online word-of-mouth sources on retail sales", *Information Discovery and Delivery*, Vol. 45 No. 1, pp. 30-35.

Jackson, R.W., Neidell, L.A. and Lunsford, D.A. (1995), "An empirical investigation of the differences in goods and services as perceived by organisational buyers", *Industrial Marketing Management*, Vol. 24 No. 2, pp. 99-108.

Kaplan, A.M. (2012), "If you love something, let it go mobile: mobile marketing and mobile social media 4x4", *Business Horizons*, Vol. 55 No. 2, pp. 129-139.

Kitapci, O., Taylan Dortyol, I., Yaman, Z. and Gulmez, M. (2013), "The paths from service quality dimensions to customer loyalty: an application on supermarket customers", *Management Research Review*, Vol. 36 No. 3, pp. 239-255.

Ladhari, R. (2009), "A review of twenty years of SERVQUAL research", *International Journal of Quality and Service Sciences*, Vol. 1 No. 2, pp. 172-198.

Lee, H.J., Lee, M. and Lee, H. (2018), "Understanding public healthcare service quality from social media", *International Conference on Electronic Government, Springer, Cham*, pp. 40-47.

Leek, S. and Christodoulides, G. (2011), "Brands: just for consumers? Introduction to the special issue on B2B branding", *Industrial Marketing Management*, Vol. 40 No. 7, pp. 1060-1062.

Liou, J.J., Hsu, C.-C., Yeh, W.-C. and Lin, R.-H. (2011), "Using a modified grey relation method for improving airline service quality", *Tourism Management*, Vol. 32 No. 6, pp. 1381-1388.

Martin-Domingo, L., Martín, J.C. and Mandsberg, G. (2019), "Social media as a resource for sentiment analysis of airport service quality (ASQ)", *Journal of Air Transport Management*, Vol. 78, July, pp. 106-115.

Mathe, H. and Shapiro, R.D. (1993), *Integrating Service Strategy in the Manufacturing Company*, Chapman & Hall, London.

Mazzeo, M.J. (2003), "Competition and service quality in the US airline industry", *Review of Industrial Organization*, Vol. 22 No. 4, pp. 275-296.

Meents, S., Tan, Y.H. and Verhagen, T. (2003), "Distinguishing different types of trust in online B2B marketplaces", *A Research Agenda for Emerging Electronic Markets*, Vol. 53.

Meyer, D., Hornik, K. and Feinerer, I. (2008), "Text mining infrastructure in R", *Journal of statistical software*, Vol. 25 No. 5, pp. 1-54.

Munezero, M.D., Montero, C.S., Sutinen, E. and Pajunen, J. (2014), "Are they different? Affect, feeling, emotion, sentiment, and opinion detection in text", *IEEE Transactions on Affective Computing*, Vol. 5 No. 2, pp. 101-111.

Ostrowski, P.L., O'Brien, T.V. and Gordon, G.L. (1993), "Service quality and customer loyalty in the commercial airline industry", *Journal of Travel Research*, Vol. 32 No. 2, pp. 16-24.

Pang, B. and Lee, L. (2004), "A sentimental education: sentiment analysis using subjectivity summarization based on minimum cuts", *Proceedings of the 42nd Annual Meeting on Association for Computational Linguistics*, Association for Computational Linguistics, July, p. 271.

Parasuraman, A., Zeithaml, V.A. and Berry, L.L. (1985), "A conceptual model of service quality and its implications for future research", *The Journal of Marketing*, Vol. 49 No. 4, pp. 41-50.

Parasuraman, A., Zeithaml, V.A. and Berry, L.L. (1988), "Servqual: a multiple-item scale for measuring consumer perceptions of service quality", *Journal of Retailing*, Vol. 64 No. 1, pp. 12-40.

Pennebaker, J. and Francis, M. (1999), "Linguistic inquiry and word count: LIWC".

Perçin, S. (2018), "Evaluating airline service quality using a combined fuzzy decision-making approach", *Journal of Air Transport Management*, Vol. 68, May, pp. 48-60.

Polyorat, K. and Sophonsiri, S. (2010), "The influence of service quality dimensions on customer satisfaction and customer loyalty in the chain restaurant context: a Thai case", *Journal of Global Business and Technology*, Vol. 6 No. 2, p. 64.

Rajaguru, R. (2016), "Role of value for money and service quality on behavioural intention: a study of full service and low cost airlines", *Journal of Air Transport Management*, Vol. 53, June, pp. 114-122.

Ramanathan, R. and Karpuzcu, H. (2011), "Comparing perceived and expected service using an AHP model: an application to measure service quality of a company engaged in pharmaceutical distribution", *Opsearch: Indian Journal of Operational Research*, Vol. 48 No. 2, pp. 136-152.

Rossomme, J. (2003), "Customer satisfaction measurement in a B2B context: a conceptual framework", *Journal of Business & Industrial Marketing*, Vol. 18 No. 2, pp. 179-195.

Russell, J.A. (1980), "A circumplex model of affect", *Journal of Personality and Social Psychology*, Vol. 39 No. 6, pp. 1161-1178.

Saeedpoor, M., Vafadarnikjoo, A., Mobin, M. and Rastegari, A. (2015), "A SERVQUAL model approach integrated with fuzzy AHP and fuzzy TOPSIS methodologies to rank life insurance firms", *Proceedings of the International Annual Conference of the American Society for Engineering Management, American Society for Engineering Management (ASEM)*, p. 1.

Schwarz, N. (1999), "Self-reports: how the questions shape the answers", *American Psychologist*, Vol. 54 No. 2, p. 93.

Seggie, S., Cavusgil, E. and Phelan, S. (2007), "Measurement of return on marketing investment: a conceptual framework and the future of marketing metrics", *Industrial Marketing Management*, Vol. 36 No. 6, pp. 834-841.

Shahzad, B., Lali, I., Nawaz, M.S., Aslam, W., Mustafa, R. and Mashkoor, A. (2017), "Discovery and classification of user interests on social media", *Information Discovery and Delivery*, Vol. 45 No. 3, pp. 130-138.

Shih, C. (2009), *The Facebook Era: Tapping Online Social Networks to Build Better Products, Reach New Audiences, and Sell More Stuff*, Prentice Hall, Upper Saddle River, NJ.

Spisak, K. (2019), "2019 social media trends and statistics", available at: www.business2community.com/social-media/2019-social-media-trends-statistics-02156179 (accessed February 20, 2019).

Suki, N.M. (2014), "Passenger satisfaction with airline service quality in Malaysia: a structural equation modeling approach", *Research in Transportation Business & Management*, Vol. 10, April, pp. 26-32.

Thaichon, P., Lobo, A., Prentice, C. and Quach, T.N. (2014), "The development of service quality dimensions for internet service providers: retaining customers of different usage patterns", *Journal of Retailing and Consumer Services*, Vol. 21 No. 6, pp. 1047-1058.

Tsaur, S.H., Chang, T.Y. and Yen, C.H. (2002), "The evaluation of airline service quality by fuzzy MCDM", *Tourism Management*, Vol. 23 No. 2, pp. 107-115.

Xiang, Z., Schwartz, Z., Gerdes, J.H. Jr and Uysal, M. (2015), "What can big data and text analytics tell us about hotel guest experience and satisfaction?", *International Journal of Hospitality Management*, Vol. 44, January, pp. 120-130.

Yang, Z. and Fang, X. (2004), "Online service quality dimensions and their relationships with satisfaction: a content analysis of customer reviews of securities brokerage services", *International Journal of Service Industry Management*, Vol. 15 No. 3, pp. 302-326.

Zeithaml, V.A., Parasuraman, A. and Malhotra, A. (2000), "A conceptual framework for understanding e-service quality: implications for future research and managerial practice", Working Paper, Report Summary No. 00-115, Marketing Science Institute, Cambridge, MA.

Zikopoulos, P., Parasuraman, K., Deutsch, T., Giles, J. and Corrigan, D. (2012), *Harness the Power of Big Data the IBM Big Data Platform*, McGraw Hill Professional, New York, NY.

Further reading

Chevalier, J.A. and Mayzlin, D. (2006), "The effect of word of mouth on sales: online book reviews", *Journal of Marketing Research*, Vol. 43 No. 3, pp. 345-354.

Hu, M. and Liu, B. (2004), "Mining and summarizing customer reviews", *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD-2004), Seattle, WA, August 22–25*.

Korfiatis, N., Stamolampros, P., Kourouthanassis, P. and Sagiadinos, V. (2019), "Measuring service quality from unstructured data: a topic modeling application on airline passengers' online reviews", *Expert Systems with Applications*, Vol. 116, February, pp. 472-486.

Pang, B. and Lee, L. (2008), "Opinion mining and sentiment analysis", *Foundations and Trends® in Information Retrieval*, Vol. 2 Nos 1-2, pp. 1-135.

Pennebaker, J.W., Mehl, M.R. and Niederhoffer, K.G. (2003), "Psychological aspects of natural language use: our words, our selves", *Annual Review of Psychology*, Vol. 54 No. 1, pp. 547-577.

Appendix 1

Table AI.
Word clouds of Tweets for each airline carrier

 Alaska Airline	 American Airline
 Delta Airlines	 ExpressJet
 Frontier Airlines	 Hawaiian Airlines
 JetBlue	 SkyWest Airlines
 Southwest Airlines	 Spirit
 United Airlines	 Virgin America

Appendix 2

Dimensions of service quality	Tweets examples
Responsiveness	I love alaskaair left my wallet on the plane at O'Hare last night and their staff went above and beyond to find it. you guys rock
	many thanks to your pdx crew coming from lax. they had to deal with some awful folks & they handled it like champs. #iflyalaska
	had a great flight as always and just wanted to say thanks you providing a way to see family at an affordable price
	gonna make me miss my flight home? you pay for hotel
	you can move your united status to alaska – do it!
	on flight 380 from nashville to las vegas. dave was the best flight attendant i've ever had! so attentive
Assurance	trying to convert elevate points. get world's most generic error message with no actual contact info!!
	looks like this flight to sd is paaacked! hopefully i don't get thrown off.
	we just got married and taking to our honeymoon! we got the special treatment!! thanks you so much dawn and linda from alaska 31
	I just experienced the perfect landing in by the captain of flight 2,221. awesome job!!!
	@delta $150 bucks each way for unaccompanied minor fee? whew! I guess we'll be flying alaska @$25 each way. thx #smarttravel
Tangibility	cabin crew on flight 934 today was awesome
	inflight entertainment is awesome
Reliability	baggage handle destroyed
	we're all ready to go now. it was more funny than an inconvenience and was handled well by the staff!
	almost an hour and still no luggage. have a little pity on the weary travelers :-(
	app says flight 975 arrived at 10:08. funny we're still taxiing for a gate. guess i'll get my baggage guarantee at 10:28
Security and safety	nice to visit family but even better to get home. safe travels
	thank god great & safe flight to #seattle. special thanks to for making it a smooth one!
	was there any explanation for why that happened? safe travels to you and the dog.
	alaska airlines you just lost a customer. if you won't accommodate a service dog when the seat is paid for is ridiculous. cassius you rock
Communications	thanks for the update – patiently waiting
	gate agent at koa boarded me and walked up to the plane & pilot said no boarding. communicate people!
	please figure out how to communicate better with your customers. need better planes and some kind of hotel options if no flights
	flight attendant made an announcement that we were clear to fly and continued boarding at 930ish. but pilots couldn't be found

Table AII. Tweets sample of service quality dimension

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