Whose and What Social Media Complaints Have Happier Resolutions? Evidence from Twitter

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ABSTRACT: Many brands try to manage customer complaints on social media, helping their customers on a real-time basis. Inspired by this popular practice, in this study, we aim to understand whose and what complaints on social media are likely to have happier resolutions. We analyzed the complaint resolution experience of customers of a major U.S. airline, by exploiting a unique data set combining both customer–brand interactions on Twitter and how customers felt at the end of these interactions. We find that complaining customers who are more influential in online social networks are more likely to be satisfied. Customers who have previously complained to the brand on social media, and customers who complain about process-related rather than outcome-related issues are less likely to feel better in the end. To the best of our knowledge, this study is the first to identify the key factors that shape customer feelings toward their brand–customer interactions on
social media. Our results provide practical guidance for successfully resolving customers’ complaints through the use of social media—an area that expects exponential growth in the coming decade.

**KEY WORDS AND PHRASES**: airline industry, CLASS methodology, complaint management, customer service, Klout score, online complaints, social influence, social media, Twitter.

On March 13, 2014, Lauren Munhoven, a customer in Ketchikan, Alaska, turned to Twitter after wasting an hour on the phone with General Motors (GM), trying to get help with her 2006 Saturn Ion regarding a GM vehicle recall [16]. After she wrote a public tweet—“@GM your agents keep telling me to take my car to a GM dealer for the recall, after I’ve explained I live on an island in Alaska! Help!!!!”—a member of GM’s Twitter team helped. The company agreed to pay the $600 cost of a round-trip ferry to ship Ms. Munhoven’s car to the nearest dealer, about 300 miles away in Juneau, and to pay for a rental car for the time she would be without the Saturn. Ms. Munhoven credited the public nature of complaining on social media with getting GM’s attention, and she was so pleased that she posted a public thank-you to GM on Twitter.

Empowered by social media and mobile technologies, more and more customers are turning to social media platforms such as Twitter and Facebook to post their complaints to brands in real-time. In response, brands are striving to monitor and quickly respond to those complaints to prevent them from festering and damaging their reputation. Many consumer brands equip their social media teams with significant organizational customer relationship management (CRM) experience, as well as access to the associated CRM system, so that complaints can be effectively and efficiently managed online. For instance, airline social media teams today can do flight reservations and rebooking for customers in real-time. In the pre-social-media era, customers directly contacted the brand’s customer service call center to begin the organizational complaint management process, and the communication between the customer and the brand was always kept private and confidential. In contrast, social media has enabled customers to publicly express their dissatisfaction about a brand, and the brand’s dedicated social media team starts a conversation with the customer openly. Such conversations are typically open to third-party audiences such as the followers of the customer, or to anybody if the posts do not assume any privacy. The simplicity and timeliness of delivering customer service through social media might quickly turn an angry or unhappy customer into a calm, relieved, or even happy customer at the end of the interaction, thereby making it more likely that the brand will retain the customer.

Inspired by this growing phenomenon, in this study, we aim to understand whose and what complaints on social media are likely to have happier resolutions. On the customer side (i.e., whose complaint), we first examine whether a customer’s online social influence is related to whether the customer would feel better after
complaining to and interacting with a brand’s social media team. Second, we examine whether a customer’s past complaints are related to the customer’s complaint resolution experience on social media. A customer’s online influence and complaint history on social media are probably the two most salient and relevant customer characteristics in our context. Both are likely to affect a customer’s satisfaction with the complaint resolution, and both can be directly measured and easily used by a brand to customize its social media customer service. On the complaint side (i.e., what complaint), we investigate whether customers complaining about outcome-related issues (i.e., operations) and customers complaining about process-related issues (i.e., employees) have different degrees of satisfaction about their complaint resolution experience on social media. Prior literature [4, 34] has suggested different customer perceptions of outcome-related service failure and process-related service failure. Therefore, it is both intellectually interesting and practically important to understand whether the distinction between these two types of complaints has any implications for customer satisfaction regarding complaint resolution on social media.

To address our research questions, we first developed our Closed Loop Analytical Social Survey (CLASS) methodology, which is an innovative way of learning how happy a customer felt about an interaction in complaining to a brand’s social media customer service team. We directly queried 1,500 randomly selected customers with recent complaints to a major U.S. airline on Twitter. We then analyzed the profiles of the complaining customers, their complaints, and their responses to our survey questions to estimate an ordered logit model. The estimation results suggest that a customer’s satisfaction with the complaint resolution experience on social media is positively associated with the customer’s online social influence and is negatively associated with whether the customer has complained previously to the airline on social media. We also find that a customer’s satisfaction is positively associated with whether the complaint is outcome-related. To alleviate the concern about potential nonresponse bias, as complaining customers who are unhappier about their social media interaction may also be more likely to respond to surveys such as ours, we augmented our data with customers who did not respond to our survey and employed a Heckman-type procedure to estimate our model. The results are qualitatively the same as our benchmark model and indicate that nonresponse bias is not likely a major concern in this study.

Our study makes important contributions to the field of information systems (IS) and service management in the social media era. Previous studies mostly looked at the causes and the sources of consumer complaint behavior [11, 15, 32, 37], and the procedural determinants of the organizational complaint management process, with specific focus on repurchase intentions, potential word-of-mouth, and customer satisfaction with the outcomes [4, 7, 9, 34]. To the best of our knowledge, our study is the first to investigate factors that may potentially affect how complaining customers would actually feel after their interaction with customer service on social media. Given the growing importance of using social media to deliver customer service and the sparse literature studying this new phenomenon, our article offers
timely and much-needed empirical evidence to guide managers in practice. For example, our findings suggest that it is worthwhile to customize a brand’s response to a customer complaining on social media based on the customer’s complaint history, rather than treating each complaint as completely new. Although a brand may track complaints received via the traditional complaint management process, whether the same is true for the complaints received via social media is not evident. Thus, our findings on the importance of accounting for customers’ past complaints on social media in providing happier complaint resolutions contribute to the current literature on customer complaint management in the age of social media.

Another important contribution of our research is the CLASS methodology that we used to directly survey customers who received customer service through social media. Although many studies have used social media data to study various interesting questions, we leverage the power of social surveillance to establish the missing link between researchers and actual customers by using social media data in an active rather than passive manner. Such a methodology can be easily automated and leveraged to generate large amounts of customer satisfaction data, which could be extremely valuable to researchers, companies, and policymakers.

Literature Review

The study of complaint management is challenging because complaints and their handling are only triggered by a service failure, making systematic empirical research almost impossible to conduct in either a laboratory or a field environment [34]. As a result, it is difficult to find an ideal setup to do causal inference in a strict sense. Nevertheless, studies in traditional complaint management have used hypothetical service failure scenarios or incident recall techniques to capture customer perceptions about organizations’ complaint-handling processes. Thus, several complaint management frameworks have been developed over the years to model satisfaction, and other postcomplaint customer attitudes and behaviors [5, 9, 34, 41].

Tax et al. [41] examined the influence of a customer’s justice evaluations on complaint-handling satisfaction, trust, and commitment, differentiating between the distributive, procedural, and interactional justice aspects of service. Distributive justice in complaint handling refers to whether the complaint outcome was perceived to be deserved, met the customer’s needs, or was fair. Procedural justice refers to the perceived fairness of the complaint-handling process, including quality attributes such as accessibility, timing/speed, flexibility, process control (i.e., freedom to communicate views on a decision process), and decision control (i.e., the extent to which the customer is free to accept or reject an outcome). Interactional justice refers to the treatment the complainant receives in the direct interaction with the employees of the organization, which includes quality attributes such as explanation/causal account, empathy, politeness, honesty, and effort. This justice-evaluation approach provides a comprehensive list of complaint management quality attributes
and calls for a dimensional structure, if the different types of perceived justice are interpreted as quality dimensions of complaint management [36].

Another empirically tested approach to conceptualize customer satisfaction with service encounters involving failure and recovery was presented by Smith et al. [34]. Their model provided a framework for considering how the context of service failure (failure type, magnitude) and the attributes of service recovery (compensation, response speed, apology, initiation) influence customer evaluations through disconfirmation and perceived justice, thereby influencing satisfaction with the service encounter. Their findings suggest that satisfaction is related positively to perceptions of distributive, procedural and interactional justice. Also, a customer’s satisfaction level after a service failure is shown to depend on both the type and the magnitude of the failure. Moreover, all the service recovery attributes show positive effects on perceptions of justice, thereby positively influencing complaint satisfaction.

Davidow [9] presented a comprehensive framework of organizational complaint management, empirically differentiating between organizational response dimensions, customer satisfaction, and postcomplaint customer behaviors such as word-of-mouth activity and intention to repurchase. His model subsumed six organizational response dimensions (timeliness, facilitation, redress, apology, credibility, and attentiveness) that incorporated almost all the dimensions mentioned in prior studies of complaint management. His empirical study found only timeliness, credibility, redress, and attentiveness to have significant positive impacts on satisfaction.

Several other studies on traditional complaint management also showed mixed results regarding which aspects of organizational responses to complaints are most effective in shaping postcomplaint customer behavior [10]. Levesque and McDougall [25] investigated the connection between the type of problem and customer dissatisfaction with issues associated with service outcomes, service process, pricing, and location. Their findings suggest that customers are more likely to voice a complaint than to exit when they encounter problems and the importance of the problem is linked to the rate of taking action. Estelami [13] examined the impact of various procedural determinants of complaint handling such as compensation, employee behavior, and promptness, on the creation of outstanding complaint resolutions. The author found that consumer delight and disappointment with complaint outcomes are primarily influenced by the compensatory aspects of complaint resolutions. Strauss and Hill [39] explored company responses to genuine complaints via e-mails, and consumer reactions to those responses. They found 47 percent of the firms responded to the complaint e-mails, which in turn resulted in higher customer satisfaction and purchase likelihood. Additionally, response e-mails that were sent quickly, addressed the specific problem, and were signed with an employee’s name resulted in higher customer satisfaction.

Although delivering customer service on social media has become very popular today, there is little empirical research about the effectiveness of this practice. Our research thus fills this gap and contributes to the stream of research literature on customer complaint management in the digital age by investigating the key factors in postcomplaint customer satisfaction in the context of social media and offering
guidance on how customer service can be successfully delivered through social media platforms.

Development of Hypotheses

Building on the current research literature on complaint management, theories from social psychology, and anecdotal evidence on social customer service, in this section, we discuss the theoretical background of our hypotheses.

Social Influence

Online social influence is an important concept arising from the popularity of social media and companies’ growing desire to identify potential opinion leaders and influential word-of-mouth (WOM) on social media [31, 40]. One popular measure of a person’s online social influence is the person’s Klout score. According to Klout’s official website, klout.com, the Klout score algorithm uses more than 400 signals from several leading online social networks (e.g., Twitter, Facebook, Instagram, Foursquare, Blogger, Tumblr, Google+, and LinkedIn) and data from places such as Bing and Wikipedia to construct Klout scores. Since its launch in 2008, the Klout score has become a popular marketing tool, as several leading brands offer free and exclusive products and experiences (i.e., perks) to high Klout scorers, who are often happy to spread the brand message on social media, even though they are not required to do so. For example, for limited periods in recent years, American Airlines and Cathay Pacific Airways granted high Klout scorers access to their exclusive airport lounges, which would otherwise have been available only to their first-class or business-class passengers. Therefore, it is natural to examine the role of online social influence in shaping the satisfaction judgments of customers complaining to brands on social media.

There can be at least three potential mechanisms through which customers’ online social influence might be associated with their judgment about satisfaction regarding the resolution of a complaint received via social media: (1) the preferential customer service that may be offered to customers of high social influence, (2) certain personality characteristics of highly influential individuals, and (3) highly influential customers’ likely higher level of expectations of social media customer service. Next, we discuss each of these three mechanisms in detail.

Preferential Customer Service

First, a customer with greater online social influence might have a better relationship with a brand as a result of preferential treatment (e.g., access to airport lounges). A more positive relationship between a customer and a brand moderates the customer’s emotional reaction to, and results in higher satisfaction with a complaint resolution experience [44]. Preferential treatment is the practice of giving some customers
elevated recognition, and additional or enhanced products and services above and beyond standard firm value propositions and customer service practices [23]. For example, a company may offer preferential treatment to a customer by placing the customer higher on a priority list if there is a queue, and giving the customer more attention or faster service than other customers [35]. Practitioners and academic researchers have long been interested in identifying high-value customers [8]. The traditional view of preferential treatment assumes that the customers earned the special treatment through loyalty (i.e., their economic value) or effort. For example, frequent flyer programs offer priority boarding and first-class/business-class upgrades to airlines’ frequent travelers. However, in the age of social media, customers’ online social influence has become an important factor driving a brand’s prioritization decisions. As Allon and Zhang [1] argue, it is not only the value that customers bring in that matters to a company, but also the ability of those customers to influence others in the social network. Prioritization based on a customer’s online social influence has also become technically convenient in recent years. For example, Genesys, a global omnichannel customer experience and contact center solution provider for business clients, including major airlines, banks, and telecommunications companies, integrated the Klout score into its solutions. This enabled companies that used the Genesys platform to recognize their customers with high Klout scores and route them to specialized customer service agents, if they wished to do so. Although it is unclear how widely and to what extent preferential customer service that is based on online social influence has been adopted in practice, recent research [20] finds evidence that in the airline industry, customers with larger online social influence are more likely to receive a response, and also are more likely to receive a response faster when they complain through social media.

While preferential treatment might make a customer happier with the brand and thus happier with the complaint resolution experience, less-influential customers may feel unhappy about their overall complaining experience on social media not only because of the poorer treatment or a less-positive relationship due to poorer treatment, but also because they perceive influence-based preferential treatment as unfair [20]. Previous research indicates that perceived service unfairness induces negative emotional reactions, such as feelings of betrayal and anger, as well as behavioral responses, such as venting and revenge.

Customer Personality Traits

Certain personality characteristics might drive both a customer’s online social influence and satisfaction with complaint resolution. For instance, customers with greater online social influence may be happier people in general, so even in the absence of preferential treatment, the very personalities of these influential customers could lead to more-positive feelings about the complaint resolution experience. In fact, empirical studies in psychology show that happy people tend to be more likable and thus more popular than unhappy people [3, 14]. Although many
definitions of happiness have been used in the literature, in general, happy individu-
als are characterized as those who experience frequent positive emotions, such as
joy, interest, and pride, and infrequent (though not absent) negative emotions such as
sadness, anxiety, and anger [27]. Social influence is often associated with social
dominance [42]. Lucas et al. [26] found that across the world, positive feelings were
associated with tendencies for affiliation, dominance, excitement seeking, and social
interaction. Furthermore, influence has been shown to be associated with the Big
Five personality trait, emotional stability, which is a person’s ability to remain calm
when facing pressure or stress [26, 29]. Does this imply that the unobserved
personality features related to a person’s general level of happiness and emotional
stability cause people to be more influential in online social networks? Although the
literature in psychology seems to support this claim, we may never know for sure.
However, if this is the case, the positive emotions and emotional stability that make
a customer influential in online social networks might make the customer perceive
the experience with a brand as more pleasant.

Differential Customer Expectations

A customer who is highly influential online might have higher expectations for customer
service and be less likely to be satisfied with the complaint resolution experience. This
conjecture may be supported by theories from behavioral psychology, where influence
has long been studied as a prominent style of human behavior. For instance, the
celebrated psychologist, William Marston, who proposed the dominance, inducement,
submission, and compliance model of human behavior (DISC) [28], recognized influ-
ence as “inducement” behavior, characteristic of people who can persuade, attract,
convince, convert, and lead other people. Recently, the DISC model of human behavior
has been adapted and customized to customer service [22], where the inducement
behavior is characteristic of the “influential customers,” who are optimistic, persuasive,
inspiring, and trusting in their approach toward customer service organizations and
expect the same in return. Such influential customers have a need for social recognition,
and always want to be accepted. Therefore, we could expect influential customers to
have higher than normal expectations for social media customer service.

Hence, from a purely theoretical perspective, it is not clear which mechanism
would dominate in shaping a customer’s satisfaction regarding the resolution of a
complaint. However, considering the nature of individuals of higher online social
influence, it is more likely that the first two mechanisms would dominate the third
mechanism. Thus, if we use a customer’s Klout score to measure his or her online
social influence, we might observe a positive or negative correlation between the
Klout score and the customer’s satisfaction with the complaint resolution. To
investigate this, we propose the following hypothesis for empirical testing:

Hypothesis 1 (The Social Influence Hypothesis): The higher a complaining
customer’s Klout score is, the more likely the customer will feel better at the
end of a conversation with a brand on social media.
Prior Complaint Experience

The effect of past behavior on individuals’ attitudes, intentions, and behavior has long been recognized in studies of personality and social psychology. The idea that the extent of past complaining experiences becomes assimilated into an individual’s attitude toward complaining, is consistent with the behaviorist and situationist theories of psychology, which explain how past behaviors and exposure to situations shape and reinforce an individual’s behavioral dispositions in future situations [33]. From the perspective of customer–brand relationship, customers with prior complaint experience are likely to have a weaker relationship with the brand than customers without prior complaint experience do. Prior literatures suggest that there is a buffering effect of relationship strength. For example, Xia [44] finds that consumers with a stronger existing relationship with a brand will perceive a defensive reaction toward criticism by the brand as less inappropriate than those with a weaker existing relationship. Hence, the threshold for successful complaint resolution tends to be higher for customers who have had a negative experience with the brand in the past than for customers who have had no such experience. These differences in expectations may lead to differences in postcomplaint satisfaction. Based on these arguments, we propose the following hypothesis for empirical testing:

*Hypothesis 2 (The Prior Complaint Experience Hypothesis): A complaining customer is more likely to feel worse at the end of a conversation with a brand on social media if the customer has prior complaint experience with the brand.*

Complaint Type

When customers deal with service firms, the two main reasons for complaints are the failure to deliver the service and how the service was delivered [4]. The marketing literature recognizes these two types of service failures as *outcome and process failures* [4, 19, 25]. The outcome dimension involves what customers actually receive from the service, or the performance aspects of the service, and the ability of the organization to keep its promises and to solve problems when they arise [19]. Processes involve the functional or people aspects of the service and are a consequence of the behavior and customer-oriented service-mindedness of the employees [19]. Therefore, in an outcome failure, the organization does not fulfill the core service need, whereas in a process failure, the delivery of the core service is flawed or deficient in some way [34]. For example, in the airline industry, *outcome-related complaints* might include flight delays, flight cancellations, mishandled baggage, in-flight service-related issues (e.g., seats, wi-fi, meals), long queues at check-in counters, and boarding issues. *Process-related complaints* may include issues such as unprofessional employees, and issues related to the airline’s dedicated customer service (e.g., long on-hold times, pending refunds, mishandled complaints).
As per social exchange and equity theories [21, 43], a complaint encounter can be viewed as an exchange in which the customer experiences a loss due to the failure and the organization attempts to provide a gain, in the form of effective handling of the complaint, to make up for the customer’s loss. Service failures can result in the loss of economic resources (money, time) or psychological/social resources (status, empathy, esteem) for customers, and organizations often offer customers economic resources in the form of compensation, or psychological/social resources such as an apology [34]. An outcome failure involves a loss of economic resources, whereas a process failure involves a loss of psychological/social resources. Thus, we expect customers’ complaint satisfaction judgments to differ by the type of complaint, as outcome and process failures represent different categories of loss to the customer. The marketing literature provides very limited evidence on which type of failure has more influence on customers’ postcomplaint satisfaction. Smith et al. [34] found that customers who experienced process failures were more dissatisfied than those who experienced outcome failures. Bitner et al. [4] found that a large percentage of unsatisfactory service encounters were related to employees’ inability or unwillingness to respond effectively to service failure. Furthermore, prior studies indicate that operational failures themselves do not necessarily lead to customer dissatisfaction, since most customers accept that things may sometimes go wrong [12]. However, if it is the organization’s employees who failed to live up to customer expectations of service, it is less likely that the customers will be satisfied with their experience. Based on these arguments, we propose the following hypothesis for empirical test:

Hypothesis 3 (The Complaint Type Hypothesis): A complaining customer is more likely to feel better at the end of a conversation with a brand on social media if the complaint is outcome-related rather than process-related.

Data, Measures, and Methodology

Data Collection

We used the Twitter API (application program interface) to collect all the user tweets mentioning the official Twitter account of a major U.S. airline, which we have purposely kept anonymous, as well as all the tweets posted by that airline, from July 2014 to January 2015. We processed the tweets daily, when constructing our main data set of complaint-based conversations between the users (i.e., customers) and the airline on Twitter. We define a conversation as a dialogue between a customer and the airline on Twitter, containing all the tweets the customer sent to the airline regarding a particular complaint and the associated reply tweets from the airline. We obtained a variety of conversations users had with the airline, particularly on complaints, compliments, and on information sharing in general. Then we processed our data to identify all the complaint-based conversations, and randomly selected 40 percent of the conversations for further analysis. Taking the concise nature of
communication on Twitter into account, we picked only conversations with at least two replies from the airline, for our main data set. This process was repeated until we obtained 1,500 single-complaint-based conversations of different customers. On average, a conversation contained 6.4 total tweets (i.e., both user tweets and airline tweets), and 2.75 airline tweets. Customers interacted with the airline to complain mostly about flight delays, flight cancellations, mishandled baggage, in-flight service-related issues (e.g., seats, wi-fi, meals), long queues at check-in counters, boarding issues, rude flight attendants, and issues related to the airline’s dedicated customer service. To learn how these customers felt at the end of the conversation they had with the airline on Twitter, we developed the Closed Loop Analytical Social Survey (CLASS) approach to survey these customers using Twitter.

CLASS Methodology

We began by creating a dedicated Twitter account and started following each customer, as the instantaneous Twitter notification this creates is likely to capture the customer’s immediate attention. Next, we sent out a tweet to the customer asking her to follow us back, so we could communicate via direct messages (DM), keeping the conversation private and confidential. This tweet took the following form: “Hi Amy, we are studying how airlines treat customers on Twitter. Could you follow us so we can DM you 2 short questions? Thanks!” If the customer followed us back indicating a preference to interact, we sent a couple of direct messages asking two short questions: “Thx Amy. We are collecting voices on @airline to monitor their service. We want to learn your Twitter experience with them on December 7th and then (Q1) Did @airline solve your problem? (Q2) Did your conversation with @airline make you feel better, worse, or the same?” Upon receiving responses from the customer, we ended the conversation with a thank-you note. In Figure 1, we present a more general framework for this proposed new survey method. It can easily be adapted to any other social media user survey such as ours.

As expected, not all the customers followed us back. Some customers followed us, but did not respond to our DMs. Some customers who responded to our DMs did not stop at providing the answers, but explained their actual experience with the airline in detail. We offered the survey to 1,500 different customers and heard back from 503 of them, which is a response rate of 33.54 percent. Although our data collection methodology can be completely automated to increase the sample size, we are currently prevented from doing so due to Twitter API rules and rate limits. As a result, we did the survey manually and could only obtain a few data points each day.

Surprisingly, 53.2 percent of the customers reported that they felt worse at the end of the conversation with the airline on Twitter, while only 19.8 percent of the customers felt better and 27 percent felt the same. Among the various types of complaints present in the conversations, flight delays, cancellations, mishandled
baggage, in-flight service, and other operations-related issues contributed to about 65 percent of the total complaints. The rest of the complaints were process-related, including complaints related to unprofessional employees or the airline’s dedicated customer service. Furthermore, only 10.6 percent of the customers believed that the airline’s social media team resolved their problem. This was more evident among the customers who felt worse at the end, as 94.36 percent of them did not perceive their problem as resolved. Moreover, 39 percent of the customers reported handoffs, instead of having their complaint rectified by the social media team.

Variables

*Dependent variable:* Our dependent variable is *Emotional Outcome*, which equals 1 if the customer felt better, –1 if the customer felt worse, and 0 if the customer felt the same at the end of the conversation with the airline.

*Figure 1. The CLASS Methodology*
Independent variables: The primary independent variables of interest are the customer’s Klout score, whether the customer has prior experience complaining to the airline, and the complaint type (i.e., whether the complaint is outcome-related or process-related). Users’ Klout scores were obtained using the Klout API. To capture users’ prior experience for complaining to the airline, we used the Twitter API to collect the users’ historical tweets up to a maximum of 3,200, and examined whether they contained complaints sent to the airline at least 24 hours before the start of the conversation under consideration.

Control variables: We include a set of control variables to account for unobserved heterogeneity at the conversation level and the customer level. The first set of control variables includes the characteristics specific to the conversation between the customer and the airline such as whether:

- the airline apologized, provided an explanation, expressed gratitude, made a handoff during the conversation, or posted consecutive tweets during the conversation;
- the customer had their problem solved, ended the conversation, warned the airline about potential brand switching in future, or posted consecutive tweets during the conversation; and
- the airline or customer mentioned using direct messaging.

In addition, we controlled for the airline’s average response time, and the total number of tweets exchanged during the conversation.

The second set of control variables includes characteristics specific to the customer, such as gender, race, whether the customer had a verified Twitter account, the age of the Twitter account, whether the customer’s location/website/profile description was publicly available on Twitter, and the customer’s personality.

Controlling for the customer’s personality is important here, as personality traits are likely to influence a customer’s evaluation of the outcome. Therefore, for each customer, we derived the Big Five personality traits (openness, conscientiousness, extraversion, agreeableness, neuroticism) via a lexicon-based approach, using the customer’s past tweets as input to the *linguistic inquiry and word count* (LIWC) dictionary [17, 30]. Past tweets could be collected for only 453 customers, as some user timelines were private and some other profiles were no longer on Twitter. We augment our empirical model with the derived Big Five personality traits, accounting for the likely omitted variable bias due to differences in customer personality. The details on how we derived the personality traits are reported in Section A1 of the Online Appendix.

Table 1 explains the key variables in our empirical analysis. The summary statistics are presented in Table 2. The correlation matrix is presented in Section A2 of the Online Appendix.

Some of the service quality variables (e.g., handoff, apology) required manual coding. They are presented in Table 3, along with some sample tweets used to identify the respective constructs.
Table 1. Definitions of Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emotional Outcome</td>
<td>How the customer felt at the end of the conversation (obtained from Q1 of the survey) ((-1 = \text{worse}, 0 = \text{the same}, 1 = \text{better}))</td>
</tr>
<tr>
<td>Klout Score</td>
<td>Klout score of the customer as obtained via the Klout API (numeric value between 1 and 100)</td>
</tr>
<tr>
<td>Complaint Type</td>
<td>Binary variable indicating the complaint type ((1 = \text{outcome/operations, e.g., flight delay/cancellation, mishandled baggage, in-flight service, non-employee-related issues at airports, etc.}, 0 = \text{process/employees/dedicated customer service-related e.g., rude flight attendants, longer than usual holding times in contacting customer service, delays in responses from customer service, etc.}))</td>
</tr>
<tr>
<td>Prior Complaint Experience</td>
<td>Binary variable indicating whether the customer has prior complaining experience with the airline on Twitter ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Handoff</td>
<td>Binary variable indicating whether the social media team handed the customer off to some other department ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Problem Solved</td>
<td>Binary variable indicating whether the airline resolved the complaint on social media (obtained from Q2 of the survey) ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Apology</td>
<td>Binary variable indicating whether the airline apologized ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Explanation</td>
<td>Binary variable indicating whether the airline provided an explanation ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Gratitude</td>
<td>Binary variable indicating whether the airline expressed its gratitude to the customer ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Total Tweets Exchanged</td>
<td>Total number of tweets exchanged during the conversation</td>
</tr>
<tr>
<td>Average Airline Response Time</td>
<td>Average of response times between airline tweets and their respective parent user tweets, in seconds</td>
</tr>
<tr>
<td>Direct Messaging (DM)</td>
<td>Binary variable indicating whether the customer or the airline mentioned direct messaging ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Ended by Customer</td>
<td>Binary variable indicating whether it was the customer who ended the conversation ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Brand Switch Warning</td>
<td>Binary variable indicating whether the customer warned the airline about possible brand switching in the future ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Consecutive User Tweets</td>
<td>Binary variable indicating whether consecutive user tweets exist in the conversation ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Consecutive Airline Tweets</td>
<td>Binary variable indicating whether consecutive airline tweets exist in the conversation ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
<tr>
<td>Gender</td>
<td>Categorical variable indicating the customer’s gender, as obtained via Kairos (kairos.com) face detection API ((1 = \text{Female}, 2 = \text{Male}, 3 = \text{Unidentifiable}))</td>
</tr>
<tr>
<td>Race</td>
<td>Categorical variable indicating the customer’s race, as obtained via Kairos face detection API ((1 = \text{White}, 2 = \text{Black}, 3 = \text{Other}, 4 = \text{Unidentifiable}))</td>
</tr>
<tr>
<td>Verified Account</td>
<td>Binary variable indicating whether the customer’s account is verified on Twitter ((1 = \text{Yes}, 0 = \text{No}))</td>
</tr>
</tbody>
</table>

(continues)
Econometric Analysis

Benchmark Model

The latent perceived satisfaction from complaining to an airline on social media for customer $i$ in conversation $j$ is $Y_{ij}^s$, where

$$Y_{ij}^s = \beta_0 + D_j \beta_1 + C_{ij} \beta_2 + \varepsilon_{ij}.$$ 

Here, $D_j$ refers to the vector of observable characteristics of conversation $j$, and $C_{ij}$ refers to the vector of observable characteristics of customer $i$ in conversation $j$. $\varepsilon$ is an error term with cumulative distribution function $G$ such that $G(x) = 1 - G(-x)$.

Let $Y_{ij}$ be an ordered outcome of whether the customer felt worse, the same, or better at the end of the conversation with the brand, taking on the values $\{-1, 0, +1\}$ respectively. Let $\tau_1 < \tau_2$ be unknown thresholds such that:

$$Y_{ij} = -1 \quad \text{if} \quad Y_{ij}^s \leq \tau_1$$
$$Y_{ij} = 0 \quad \text{if} \quad \tau_1 < Y_{ij}^s \leq \tau_2$$
$$Y_{ij} = +1 \quad \text{if} \quad Y_{ij}^s > \tau_2$$

For simplicity, we denote by $X_{ij}$ all independent variables including the conversation and customer-related variables as well as the unit for the
constant term, and we denote by $\beta$ the vector of all coefficients including the
constant term $\beta_0$. The conditional distribution of $Y_{ij}$ given $X_{ij}$ can be defined as
follows:

$$
\Pr(Y_{ij} = -1 | X_{ij}) = \Pr(Y_{ij}^* \leq \tau_1 | X_{ij}) = G(\tau_1 - X_{ij}\beta),
$$

$$
\Pr(Y_{ij} = 0 | X_{ij}) = \Pr(\tau_1 < Y_{ij}^* \leq \tau_2 | X_{ij}) = G(\tau_2 - X_{ij}\beta) - G(\tau_1 - X_{ij}\beta),
$$

$$
\Pr(Y_{ij} = 1 | X_{ij}) = \Pr(Y_{ij}^* > \tau_2 | X_{ij}) = 1 - G(\tau_2 - X_{ij}\beta).
$$

The log likelihood function is given by:

$$
L_i(\tau, \beta) = \begin{cases} 
1 & [Y_{ij} = -1] \log \left[ G(\tau_1 - X_{ij}\beta) \right] \\
1 & [Y_{ij} = 0] \log \left[ G(\tau_2 - X_{ij}\beta) - G(\tau_1 - X_{ij}\beta) \right] \\
1 & [Y_{ij} = 1] \log \left[ 1 - G(\tau_2 - X_{ij}\beta) \right]. 
\end{cases}
$$
We further assume that the error term $\varepsilon$ follows a logistic distribution, and we estimate an ordered-logit model to test our hypotheses. Here we adopt the proportional odds assumption \cite{18} or the parallel regression assumption such that the relationship between each pair of outcome categories of the dependent variable is the same. To test this assumption, we performed a Brant test \cite{6}; it generated nonsignificant test statistics, providing evidence that the parallel regression assumption had not been violated. The regression results are reported in Columns (1) and (2) of Table 4.

<table>
<thead>
<tr>
<th>Table 3. Sample Tweets for Manually Coded Service Quality Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td>--------------</td>
</tr>
</tbody>
</table>
| Handoff | • @user Sonya; *have you reached out to our Customer Relations team?* They can help you with past date travel issues.  
  • @user *We’re sorry to hear this. Contact our Central Baggage Services for assistance with this.*  
  • @user *Our agents will help you with available options. Please see them as soon as you can*  |
| Apology | • @user *No one likes delays; especially on their birthday☺*. We apologize for the inconvenience.  
  • @user *We hear your frustration. Please accept our apology.*  
  • @user *We expect our team to always be cordial at all times; Ashley. Our apologies that you experienced otherwise.*  |
| Explanation | • @user *We show the equipment is out of service; Justin. Safety of our customers and crew is always our top priority.*  
  • @user *We’re sorry your flights delayed. There are major Air Traffic Control delays beyond our control.*  
  • @user *Weather can back up Air Traffic Control flows once things get moving again; Bianca. Our apologies for the inconvenience.*  |
| Gratitude | • @user *We’re glad we have you to Sacramento. Have a good rest of your Sunday and thanks for flying with us.*  
  • @user *We appreciate you feedback and thank you for the kind words for our staff.*  
  • @user *Our goal is to provide exceptional customer service. We’re sorry we missed the mark today. We appreciate your loyalty.*  |
| Direct Messaging (DM) | • @user *Please send us a DM with your bag tag number. We’ll take a look.*  
  • @user *We’re very sorry to hear this; Sharina. Did you file a report at <URL>? If so; DM your CR file number.*  
  • @user *Rachel; please DM your record locator or Baggage Report number. We’d like to check on that for you.*  |
| Brand Switch Warning | • @airline *Never Again!* 4 flight changes lost luggage. And my UNACCOMPANIED minor still not where she needs to be. *1st and last <airline> flight.*  
  • @airline *… Worst customer service. My mom has been through hell with you. Now both of us won’t fly with you. @airline2 wins again*  
  • Stuck on a plane for over an hour; gets told to wait at least another 20mins before further info? *Never EVER flying with @airline again* |
From Table 4, we see that Klout Score is positive and statistically significant (0.032, \( p < 0.01 \)). In terms of magnitude, for a one-unit increase in Klout Score, the odds of feeling better increase by a factor of 1.032 (3.2 percent) more than...
the odds of feeling the same or feeling worse.\textsuperscript{3} This finding suggests that as the Klout score increases, there is a corresponding increase in the probability of the customer feeling better at the end of a conversation with the airline on social media, thereby providing support for the Social Influence Hypothesis (H1).

To better evaluate how the probabilities of each emotional outcome changes as Complaint Type and Prior Complaint Experience vary, we generate their respective predicted probabilities while keeping the rest of the variables at their means. The results are reported in Table 5.

From Table 4, we also see that Prior Complaint Experience is negative and statistically significant (−0.528, \( p < 0.05 \)). In terms of magnitude, having prior complaint experience decreases the odds of feeling better by a factor of 0.59 (41 percent), than the odds of feeling the same or feeling worse. Moreover, the predicted probabilities (Table 5) indicate that there is 64.4 percent chance that the customer feels worse if the customer has had prior complaint experience, as opposed to a 51.7 percent probability of feeling worse if the customer has had no such experience. Thus, our findings suggest that a customer who previously complained is more likely to feel worse than to feel the same or better, thereby providing support for the Prior Complaint Experience Hypothesis (H2).

Finally, we see in Table 4 that Complaint Type is positive and statistically significant, (0.643, \( p < 0.01 \)). In terms of magnitude, customers with outcome-related complaints are more likely to feel better than those with process-related complaints by a factor of 1.903 (90.3 percent) more than the odds of feeling the same or feeling worse. As per the predicted probabilities (Table 5), there is a 65 percent chance that the customer feels worse at the end when the complaint is process-related, and just a 49.4 percent chance when the complaint is outcome-related. Accordingly, our findings suggest that process-related complaints are less likely to make a customer feel better at the end of a conversation with an airline on social media, thereby providing support for the Complaint Type Hypothesis (H3).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Emotional outcome</th>
<th>Probability at 0</th>
<th>Probability at 1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Complaint Type</strong></td>
<td>Worse</td>
<td>0.650*** (0.045)</td>
<td>0.494*** (0.031)</td>
</tr>
<tr>
<td></td>
<td>Same</td>
<td>0.242*** (0.030)</td>
<td>0.318*** (0.026)</td>
</tr>
<tr>
<td></td>
<td>Better</td>
<td>0.109*** (0.021)</td>
<td>0.188*** (0.022)</td>
</tr>
<tr>
<td><strong>Prior Complaint Experience</strong></td>
<td>Worse</td>
<td>0.517*** (0.029)</td>
<td>0.644*** (0.053)</td>
</tr>
<tr>
<td></td>
<td>Same</td>
<td>0.309*** (0.025)</td>
<td>0.245*** (0.034)</td>
</tr>
<tr>
<td></td>
<td>Better</td>
<td>0.175*** (0.020)</td>
<td>0.111*** (0.025)</td>
</tr>
</tbody>
</table>

*Notes:* Standard errors are in parentheses. Significance: ***\( p < 0.01 \)
We found that several other variables were statistically significant. For example, *Handoff* is negative and statistically significant (−0.465, p < 0.05). In terms of magnitude, handing the customer off to some other department, rather than the social media team taking care of the customer, decreases the odds of feeling better by a factor of 0.628 (37.2 percent), as compared with the odds of feeling the same or feeling worse. Thus, our findings suggest that a complaining customer is more likely to feel worse, if the airline’s social media team hands that customer off to some other department.

Furthermore, *Problem Solved* is positive and statistically significant (1.381, p < 0.01). In terms of magnitude, a customer’s perception of the problem as being fixed by the social media team increases the odds of feeling better by a factor of 3.981 (298.1 percent) as compared to the odds of feeling the same or feeling worse. Thus, *Problem Solved* has the largest positive effect on a customer’s emotional outcome at the end of the complaining encounter. This makes sense because one of the responses that a customer expects when a problem arises is a “fair fix” that at least returns the customer to the starting point before the service failure [9]. Our analysis reveals that this could mean a variety of possible resolutions including replacement, refund, repair, discounts, corrections, and appropriate remedial action. In the airline industry, these may include paying damaged baggage claims, rebooking, hotel and food vouchers in case of flight delays or cancellations, free miles, refunds, customer status upgrades, reporting unprofessional employees to management, and so on.

**Robustness Test: Nonresponse Bias**

Although we sent the survey to 1,500 Twitter users who had a complaint-based conversation with the airline on Twitter, we heard back from only about a third of them. Our main analysis was primarily based on the users who responded to the survey. If the unobservables that (1) determine customers’ satisfaction after the interaction with the brand on social media, and (2) increase the likelihood of not responding to the survey are correlated, then our model suffers from nonresponse bias. This would have been the case if users who did not respond to our survey were significantly different from those who responded to the survey. To correct for this, we randomly selected 200 users who did not respond to our survey and introduced these users into the main data set. Then we formulated an ordered probit model for customers’ emotional outcome, with selection on whether they responded to the survey. As the outcome covariates, we used the same set of variables used in the benchmark model. We particularly assume that how influential the customer is on social media (Klout score), gender, race, complaint type, customer account age, whether the customer had his or her location/website/profile description publicly available on Twitter, and whether the customer warned the airline about switching to another brand, affect the selection. Then we employ the Heckman procedure to estimate our
Table 6. Robustness Test: Heckman Selection

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1) Ordered Probit Model (Emotional Outcome)</th>
<th>(2) Selection Model (Responded to Survey)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Klout Score</td>
<td>0.016*** (0.005)</td>
<td>-0.001 (0.004)</td>
</tr>
<tr>
<td>Complaint Type</td>
<td>0.351*** (0.130)</td>
<td>0.061 (0.119)</td>
</tr>
<tr>
<td>Prior Complaint Experience</td>
<td>-0.287** (0.140)</td>
<td></td>
</tr>
<tr>
<td>Handoff</td>
<td>-0.266** (0.119)</td>
<td></td>
</tr>
<tr>
<td>Problem Solved</td>
<td>0.698*** (0.227)</td>
<td></td>
</tr>
<tr>
<td>Apology</td>
<td>0.151 (0.125)</td>
<td></td>
</tr>
<tr>
<td>Explanation</td>
<td>-0.094 (0.117)</td>
<td></td>
</tr>
<tr>
<td>Gratitude</td>
<td>0.317*** (0.133)</td>
<td></td>
</tr>
<tr>
<td>Total Tweets Exchanged</td>
<td>-0.072*** (0.027)</td>
<td></td>
</tr>
<tr>
<td>Log of Average Response Time</td>
<td>0.018 (0.061)</td>
<td></td>
</tr>
<tr>
<td>Direct Messaging (DM)</td>
<td>0.174 (0.152)</td>
<td></td>
</tr>
<tr>
<td>Ended by Customer</td>
<td>-0.221* (0.132)</td>
<td></td>
</tr>
<tr>
<td>Brand Switch Warning</td>
<td>-0.273 (0.169)</td>
<td>0.284** (0.137)</td>
</tr>
<tr>
<td>Consecutive User Tweets</td>
<td>0.147 (0.136)</td>
<td></td>
</tr>
<tr>
<td>Consecutive Airline Tweets</td>
<td>0.026 (0.576)</td>
<td></td>
</tr>
<tr>
<td>Gender—Male (base: Female)</td>
<td>-0.143 (0.129)</td>
<td>-0.243* (0.134)</td>
</tr>
<tr>
<td>Gender—Unidentifiable (base: Female)</td>
<td>-0.421 (0.494)</td>
<td>-1.555*** (0.565)</td>
</tr>
<tr>
<td>Race—Black (base: White)</td>
<td>0.016 (0.425)</td>
<td>0.625 (0.550)</td>
</tr>
<tr>
<td>Race—Other (base: White)</td>
<td>0.092 (0.315)</td>
<td>-0.420 (0.280)</td>
</tr>
<tr>
<td>Race—Unidentifiable (base: White)</td>
<td>-0.032 (0.172)</td>
<td>-0.126 (0.170)</td>
</tr>
<tr>
<td>Verified Account</td>
<td>-0.791 (0.558)</td>
<td></td>
</tr>
<tr>
<td>Customer Account Age</td>
<td>0.00002 (0.000)</td>
<td>0.000** (0.000)</td>
</tr>
<tr>
<td>Public Web Site/Location/Profile Bio</td>
<td>-0.218 (0.191)</td>
<td>0.033 (0.156)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>-0.063 (0.071)</td>
<td></td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>0.283* (0.161)</td>
<td></td>
</tr>
<tr>
<td>Extraversion</td>
<td>0.024 (0.105)</td>
<td></td>
</tr>
<tr>
<td>Neuroticism</td>
<td>-0.040 (0.175)</td>
<td></td>
</tr>
<tr>
<td>Openness</td>
<td>-0.082 (0.051)</td>
<td></td>
</tr>
<tr>
<td>Cut 1 Constant</td>
<td>0.289 (0.615)</td>
<td></td>
</tr>
<tr>
<td>Cut 2 Constant</td>
<td>1.063* (0.585)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td>0.549*** (0.210)</td>
</tr>
<tr>
<td>atanh ρ (ρ = error correlation)</td>
<td></td>
<td>0.971 (0.891)</td>
</tr>
<tr>
<td>Observations</td>
<td>653.00</td>
<td>653.00</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-773.21</td>
<td>-773.21</td>
</tr>
<tr>
<td>AIC</td>
<td>1,630.43</td>
<td>1,630.43</td>
</tr>
<tr>
<td>BIC</td>
<td>1,818.65</td>
<td>1,818.65</td>
</tr>
</tbody>
</table>

Notes: Standard errors are in parentheses. Significance: ***p < 0.01; **p < 0.05; *p < 0.1.

The results, which are presented in Table 6, are qualitatively the same as the benchmark model. Moreover, error correlation was not statistically significant at the $p < .05$ level, suggesting that nonresponse bias is not likely a major concern.
Extension

Given that 53.2 percent of the customers in our sample felt worse at the end of their conversations with the airline on Twitter, one naturally questions whether doing customer service on social media is worthwhile for a brand. As an extension to our study, we investigated this question by doing a short survey among customers who did not receive any response from the airline after complaining to the airline on Twitter. Again, we followed the CLASS approach; the survey questionnaire took the following form: “Our records show that @airline did not respond to your complaint on Twitter on January 14th. We want to learn your experience. (Q1) Rate your overall satisfaction regarding the way @airline handled your complaint on Twitter: Very Dissatisfied/Dissatisfied/Neither Satisfied Nor Dissatisfied/Satisfied/Very Satisfied (Q2) What is the likelihood that you would use Twitter again to complain to @airline in the future? Very Unlikely/Unlikely/Not Sure/Likely/Very Likely.”

We sent out 222 survey requests and heard back from 38 people. Of the respondents, 92.1 percent reported that they were either very dissatisfied or dissatisfied regarding the way the airline handled their complaint on Twitter (i.e., by choosing not to respond). Surprisingly, 81.58 percent of these respondents claimed that they are very likely or likely to use Twitter to complain to @airline in the future. One possible explanation of these results is that customers whose complaints are ignored by a brand are more motivated to punish the brand by publicly complaining on social media.

Considering the high percentage of people unhappy with the airline for not responding to their complaint, and their intention to keep complaining on social media, it seems that brands would still be much better off investing in social media customer service, even though it does not always effectively transform a disgruntled customer into a happy one. Moreover, recent research [38] has suggested that emotionally charted tweets tend to be retweeted more often and more quickly compared to neutral ones. Simply put, brands today have no option but to listen to and engage with their customers on a real-time basis in order to succeed. The democratization of media by social media platforms like Twitter has effectively raised the bar for customer service and will ultimately lead to more transparency and better service.

Managerial Implications

Our findings have important implications for the brands striving to harness the power of social media to deliver customer service.

First, our empirical test of the Social Influence Hypothesis (H1) indicates that complaining customers with a higher Klout score are more likely to feel better at the end of a conversation with a brand on social media. As we argued earlier, this may be because customers with greater social influence receive preferential customer service from the airline, or simply because socially influential customers are happier and emotionally more stable individuals in general. If it is social-influence-based
preferential customer service that is mainly at work, the result would suggest that a brand’s influence-based preferential treatment pays off during complaint resolution, at least for those customers who are treated better. However, given the controversial nature of this practice, and its implications on perceptions of fairness, brands should carefully examine the drivers of this practice within their social media teams and act accordingly.

On the other hand, if it is the happy and emotionally more stable nature of socially influential individuals that makes them more satisfied about the complaint resolution received, then this suggests that those customers with greater online social influence are simply easier to please. Hence, the brand can customize its marketing strategies accordingly, in targeting this particular customer segment. On the other hand, the result also reveals a challenge in achieving high satisfaction with less-influential customers. Nevertheless, the extension of our study shows that it is imperative for brands to monitor and engage with complaining customers on social media even though the customers may still be dissatisfied after their complaint resolution experience on social media.

Second, our empirical test of the Prior Complaint Experience Hypothesis (H2) indicates that customers with prior complaint experience with the airline are more likely to feel dissatisfied about their social media interactions with that brand. Hence, it may be worthwhile to customize the response to a customer complaining on social media, based on the customer’s social media-complaint history, instead of treating each complaint as completely new. Although a brand may keep track of all historical complaints received from each customer via the traditional complaint management process, whether the same is true for complaints received via social media is not evident. Thus, a direct implication for practice would be to keep track of all complaints from each customer and train the social media team to handle those customers accordingly.

Third, our empirical test of the Complaint Type Hypothesis (H3) shows that customers complaining about process-related issues (e.g., unprofessional employees or dedicated customer service) are more likely to feel worse at the end than those who complained about outcome or operations-related issues. Most customers understand that things may sometimes go wrong in airline operations, but when it comes to issues of employee attitude, they find it harder to forgive. Therefore, it is important to devise a separate response strategy to manage process-related complaints on social media. For example, in addition to reassuring the customer that action will be taken against the reported unprofessionalism, it may also be worthwhile to cheer the customer with some sort of compensation.

Another important implication for practice would be the pressing need to empower the social media team. We find that customers who were handed off to other departments are more likely to feel worse at the end. It appears that customers tend to perceive a service handoff as a way of “passing the buck,” rather than the social media team’s lack of ability to resolve the complaints. The reasons for the low problem resolution rate and the high handoff rate may be a lack of technology infrastructure, training opportunities, and budget available to social media teams.
Therefore, a careful social media investment strategy should be defined at the corporate level, enabling seamless integration between the social media team and the dedicated customer service of the brand. For instance, rather than letting the social media team ask the customer to contact the baggage claims department regarding lost baggage, the social media team should be able to access the relevant corporate databases to provide more complete and worthwhile social media customer service. Furthermore, social media teams should be given continuous and mandatory opportunities to learn to provide high-quality complaint resolutions faster.

Conclusion

As consumers become more empowered by social media, companies are under increasing pressures to improve not only the core value they deliver to their customers but also everything their customers experience [24]. To succeed in such a competitive environment, companies need to place customer experience into one holistic view for their present customers as well as for past and future customers. A key component of building a successful customer experience is establishing a systematic approach to ongoing listening to customers and to their perceptions of the way in which the company addresses their concerns. There are several common approaches to doing that, including focus groups, mystery shoppers, advisory panels, periodic surveys, and transactional surveys. Transactional surveys have the advantage of getting feedback while the service experience is still fresh, and they allow the company to act quickly if it detects a major service gap. This approach motivated the development of our Closed Loop Analytical Social Survey (CLASS) methodology, which leverages the popularity of social media as a novel and rapid way to conduct such transactional surveys. At a broad level, this research can be viewed as an example from service science, management, and engineering (SSME) which is an important multidisciplinary area [2].

Our study has some limitations. It assumes that a customer’s satisfaction regarding his or her interaction with the brand on social media genuinely reflects the customer’s true emotional status at the end of the conversation with the airline. This approach may not be perfect for at least two reasons. First, although we maintained the minimum possible interval between the end of the conversation on Twitter and the survey offer, this gap may psychologically cause customers to overestimate or underestimate how they actually felt at the end of the interaction. Second, some individuals, such as people with greater online social influence, may be particularly cautious in their social media interactions with brands, such that their conversations on social media may not reveal their actual preferences, while average customers may choose to express their concerns freely. Although we are unable to determine the extent to which these factors may affect our findings, their existence could undermine the importance of studies such as this one in determining the drivers of happier complaint resolutions on social media.
Acknowledgments: An early version of this study was previously circulated as “What Drives Successful Complaint Resolutions on Social Media? Evidence from the Airline Industry.” The authors thank the JMIS coeditors Rob Kauffman, Rajiv Dewan, Thomas Weber, Eric Clemons, the HICSS minitrack chairs, Jie Zhang, Yabin Jiang, and all the participants of the HICSS minitrack on “Integrating Business Operations, Information Technologies, and Consumer Behavior” in the Organizational Systems and Technology Track, for useful discussion and comments.

Supplemental File

Supplemental data for this article can be found on the publisher’s website at 10.1080/07421222.2017.1334465

Notes

1. The Big Five personality traits refer to openness, conscientiousness, extraversion, agreeableness, and neuroticism/degree of emotional stability; see [17] for details.
2. To automate the process, one needs to apply for special permission and be approved by Twitter.
3. See Greene and Hensher [18], for details on the interpretation of ordered logit coefficients.
4. The small sample size is due to both the low response rate and limiting rules imposed by Twitter.

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