Understanding User-Generated Content and Customer Engagement on Facebook Business Pages

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Abstract

With the growth and prevalence of social media platforms, many companies have been using them to engage with customers and encourage user-generated content about their products and services. However, there has not been much research on the characteristics of user-generated content on these platforms and, correspondingly, their impact on customer engagement. In this paper, we analyze user-generated posts from Facebook business pages of multiple companies to understand what users post on Facebook business pages and how post valence and content characteristics affect engagement, measured as the number of likes and comments received by a post. We control for a variety of factors, including post linguistic features, poster characteristics, and post context heterogeneity. Our analysis demonstrates that, for user-generated posts on Facebook business pages, negative posts are significantly more prevalent than positive posts, which contrasts with the "J-shaped" valence distribution of online consumer reviews. We also show that engagement depends not only on the valence of a post but also on the specific ways in which a post is positive or negative. We observe three types of customer complaints respectively related to product and service quality, money issues, and social and environmental issues. Our analyses show that social complaints receive more likes, but fewer comments, than quality or money complaints. Such nuances can only be uncovered by analyzing the actual post content, going beyond the valence of the posts. Furthermore, we theoretically discuss and empirically demonstrate that liking and commenting are engagement behaviors with different antecedents. For example, positive posts tend to attract more likes yet fewer comments than neutral posts. Overall, our research shows that user-generated posts on Facebook business pages represent a distinctive form of user-generated content, which is conceptually different from online consumer reviews. Our work advances the knowledge on user-generated content and has practical implications for firms' social media marketing strategy.

Keywords: social media, user-generated content, word-of-mouth, customer engagement, Facebook

1. Introduction

The increasingly pervasive use of social networking tools has greatly transformed the way in which companies organize their online marketing activities (Aral et al. 2013). In addition to delivering their messages through traditional, marketer-controlled communication channels, many businesses host brand communities on social networking platforms such as Facebook and Twitter, to engage their customers and encourage user-generated content (Goh et al. 2013; Dholakia and Durham 2010; Kiron et al. 2013). In particular, Facebook business page is a feature launched in 2007 to help businesses connect and interact with their customers. As of 2017, there have been more than 60 million business pages hosted on Facebook.[1] In some cases, customers become advocates who spread awareness and speak positively about the company's products and services (e.g., Swarovski's campaign on Facebook and Instagram encouraged customers to share photos of their products[2]). At the same time, challenges coexist with opportunities in managing user-generated content (UGC) on social networking platforms. Companies usually have very little control over what customers post, and negative UGC can severely damage the brands (Goh et al. 2013).

Despite the enthusiasm and millions of dollars in investments from businesses, there have been limited theoretical understanding and empirical investigation of UGC in brand communities on social media (e.g., on Facebook business pages). Prior research has focused primarily on consumer reviews on online shopping websites and discussion forums around books, movies, TV shows, hotels, and restaurants (Chevalier and Mayzlin 2006; Forman et al. 2008; Godes and Mayzlin 2004, 2009; Archak et al. 2011; Ghose and Ipeirotis 2011). The few studies of UGC in brand communities on social media (e.g., Goh et al. 2013; Ma et al. 2015) have conceptualized and examined the content as electronic word-of-mouth, similarly to the work on online consumer reviews. However, we believe that UGC in brand communities hosted on social media is conceptually different from online consumer reviews in several important ways. Online reviews tend to be structured feedback on specific products, in the format of ratings and textual descriptions, provided by customers, who typically have purchased the products, to inform other consumers' purchasing

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[1] https://sproutsocial.com/insights/facebook-stats-for-marketers/. Last access 01/02/2018.
[2] https://www.facebook.com/business/success/swarovski. Last access 01/02/2018.

decisions. In contrast, UGC in brand communities on social media are typically open-ended expressions, provided by any users who have an interest in interacting with the businesses or other customers, and consumed by recipients with a wider variety of goals that are not necessarily purchase-oriented. These differences suggest that both what users post on social media platforms like Facebook business pages and the resulting impact of the UGC are likely to be different from online consumer reviews. To advance our understanding of this new form of UGC, we combine qualitative and quantitative analyses of archival data and insights from an exploratory online survey to answer two research questions. *(1) What kinds of posts, in terms of valence and content, do users generate on Facebook business pages? (2) How do posts' valence and content factors influence other users' engagement with the posts?*

We focus on user-generated posts ("user posts" in short) instead of marketer-generated posts because, compared to marketer-generated posts: (1) user posts are much larger in volume, and therefore can have a cumulatively greater impact; (2) user posts tend to be perceived as more credible, because peer customers are often perceived as more trustworthy than the company (Chen and Xie 2008); and (3) user posts have been shown to play a more influential role in driving purchases (Goh et al. 2013). Meanwhile, other researchers have studied the impact of marketer-generated posts on Facebook business pages (e.g., Goh et al. 2013; Lee et al. 2017), whereas few studies have examined user-generated posts.

In this paper, we focus on two post attributes: valence and content. Valence captures the degree to which a post is positive, negative, or neutral. Content captures the substance of a post, and can reflect the *specific* ways in which a post is positive, negative, or neutral (e.g., whether it is a complaint about product quality or a complaint about corporate social responsibility issues, both being negative). Valence is a key characteristic that has been studied extensively in the online reviews literature (e.g., Godes and Mayzlin 2004). We decided to examine content, in addition to valence, because prior research has shown that the textual content of a message contains additional information that is often not captured by valence (e.g., Archak et al. 2011).

In terms of the impact of UGC, we study engagement behavior as the outcome for two reasons. First, increased engagement has been linked to increases in brand loyalty, purchase expenditures, and profitability (Dessart et al. 2015, Goh et al. 2013, Kim et al. 2013). Second, both theoretical and empirical understanding of engagement antecedents, especially in the context of social media, is still limited and, thus, represents a high-priority research direction (Maslowska et al. 2016, p. 470). In this paper, we examine two types of engagement behaviors: *liking* a post and *commenting* on a post, both of which are canonical ways in which users can engage with posts on Facebook, and both have been used to measure the overall engagement level in previous research of similar contexts (e.g., Lee et al. 2017; Gummerus et al. 2012). Differently from prior research that often treats liking and commenting as interchangeable measures of engagement, we explicitly study liking and commenting as distinct forms of engagement behaviors.

Combining content analysis and econometric modeling, we analyzed 12,000 posts from the business pages of 41 Fortune 500 companies in 6 industries for the year 2012. In contrast to the widely observed positivity of online consumer reviews, users on Facebook business pages posted substantially more negative posts than positive ones. Average ratio of negative to positive posts was 1.93 to 1. Econometric analyses showed that both positive and negative posts received more likes than neutral posts, and negative posts received more likes and more comments than positive posts. Analysis of post content revealed 7 categories as *positive testimonial and appreciation, complaint about product and service quality, complaint about money issue, complaint about social and environmental issues, customer question, customer suggestion,* and *irrelevant messages*. Our analyses also showed that the three types of complaints, while all being negative, received different numbers of likes and comments. Compared to *complaints about product and service quality* and *complaints about money issues, complaints about social and environmental issues* received more likes but fewer comments. Our results also confirmed that liking and commenting are two distinctive forms of engagement, in that they have different sets of antecedents. Finally, we conducted an exploratory online survey to complement our quantitative analysis. The survey provided valuable insights to help explain some of the key findings and advance our understanding of user motivations for visiting a business page, contributing content, and engaging with other users' posts.

Our work makes three novel contributions to the Information Systems literature. First, we are among the first to conceptually and empirically differentiate UGC in brand communities on social media from online consumer reviews, and to show how valence and content characteristics of UGC drive engagement in the new context. Our work shows the prevalence of negative valence and develops a category framework to characterize the content. Second, our research highlights the importance of examining specific content categories beyond valence. UGC with the same valence yet different content categories receive different types and levels of engagement. These insights help advance conceptual understanding of UGC and inform empirical strategies (statistical, machine-learning-based, etc.) to analyze it. Finally, our work highlights the theoretical distinctions between liking and commenting as two forms of engagement and also shows how the same valence or content factors can have differential effects on the two. This finding has both theoretical and practical implications for quantifying and promoting user engagement in social media marketing.

2. Literature Review and Theoretical Development

Several bodies of literature in IS and Marketing shed light on our conceptualization and theorizing of user posts on Facebook business pages, including the literature on electronic word-of-mouth, online consumer reviews, and member engagement in online brand communities. In Sections 2.1 and 2.2, we draw insights from the electronic word-of-mouth and online review literature to theorize the likely valence and content characteristics of user posts. In Sections 2.3 and 2.4, we draw insights from engagement in online brand communities to theorize the impact of valence and content on engagement behavior. Due to the relatively novel nature of our research context and lack of direct empirical evidence, we describe our speculations of the potential patterns, without explicitly formulating hypotheses.

2.1. Electronic Word-of-Mouth and Facebook Business Pages as the New Context

As a type of online UGC, user posts on Facebook business pages are closely related to electronic word-of-mouth. Word-of-mouth (WOM in short) refers to the informal communication by consumers to other consumers about their evaluations of goods and services (Anderson 1998) or about the ownership, usage, or characteristics of particular goods and services (Berger 2014). Existing literature on electronic WOM focuses primarily on online consumer reviews. Online consumer reviews have emerged to become an influential force of consumer behavior, because the source (other customers) are perceived as more credible than the brand, and the channel (online, instead of offline) allows greater reach to the audience (Berger 2014). Several attributes of online consumer reviews, including volume, valence, and variance of review ratings have been linked to sales of a variety of products, such as books (Chevalier and Mayzlin 2006), movies (Liu 2006; Dellarocas et al. 2007; Duan et al. 2008), restaurants (Lu et al. 2013), and video games (Zhu and Zhang 2010).

In this paper, we argue that user posts on Facebook business pages are conceptually different from online consumer reviews in several ways, such as *source*, *intended audience*, and potential *effects* on consumer behaviors, all of which are key dimensions of UGC (Berger 2014).

First of all, the two types of content are generated by different *sources*. While online consumer reviews, such as product reviews on Amazon, are typically generated by consumers with purchasing experiences, user posts on Facebook business pages can be generated by both consumers who had purchased products or services and Facebook users without purchasing experiences. In addition, the sources of online reviews and user posts may differ in their identifiability. While reviewer identity information is not always available for online reviews, user identity information is much more transparent and visible on social media platforms like Facebook. Source identifiability can affect both what sources share and how recipients process the information (Berger 2014). Second, the two types of content have different *intended audiences*. For online consumer reviews, the intended audience is typically other consumers who are interested in purchasing the products. For user posts on Facebook business pages, the intended audience include both the companies and other Facebook users.[3] The difference in audience composition may influence what people choose to say (Berger 2014) and the degree to which the audience engages with the content. For example, compared to online reviews, posts on Facebook business pages may be more open-ended, in the sense that users can post not only information about a firms' products (Goh et al. 2013) but also complaints when customers perceive Facebook business pages as firms' "new" customer service centers (Kiron et al. 2013). Third, the *effects* of user posts on consumer behaviors are likely to be different

[3] Characteristics of the source and intended audience of user posts on Facebook business pages are also confirmed by our exploratory online survey. We discuss the details of the survey in Appendix A15.

from the effects of online reviews. While the readers of online consumer reviews often use the reviews to decide whether to buy a product, users on Facebook business pages may encounter a post at any stage of the marketing funnel (Anderson et al. 2011), such as awareness, consideration, or conversion. As a result, posts on Facebook business pages may not have as direct and pronounced an effect on purchase as online product reviews. Therefore, in this work, we focus on customer engagement as the outcome of interest, which, when properly cultivated, can act as a powerful driver of sales growth and profitability (Cvijikj and Michahelles 2013; Hoffman and Fodor 2010).

2.2. Valence and Content Characteristics of User Posts

Due to the differences discussed in the previous section, insights from online consumer reviews may not generalize to user posts on Facebook business pages. In this section, we review the literature on online reviews and speculate how the patterns may be similar or different for UGC on Facebook business pages.

A key observation about online consumer reviews is that their valence follows a "J-shaped" distribution, with large numbers of positive reviews, some negative reviews, and few moderate ones (Hu et al. 2009). This positive prevalence can be attributed to at least two reasons. First, most online reviews are written by people who have purchased the product, i.e., who tend to have higher product valuations. Hu et al. (2009) refer to such behavior as "*purchasing bias*". Second, some of the positive reviews can also be driven by consumers' *self-enhancement* motive, i.e., to look good to themselves and to others (Berger, 2014). Talking about positive experiences projects a more positive image of oneself (e.g., the person makes good choices or decisions) or serves as evidence of one's expertise (Wojnicki and Godes 2011).

However, for user posts on Facebook business pages, the purchasing bias and the self-enhancement tendency may not be as strong or prevalent. The purchasing bias is weaker because the source of user posts includes Facebook users who have not purchased products or services and whose evaluations of the business are not necessarily high.[4] The self-enhancement motivation may become less important because users face a broader audience, including both other users and the focal businesses. The audience mixture makes the

[4] Our survey (Appendix A15) shows that, among the users who had posted on Facebook business pages, about 10% reported they had never purchased products or services from the businesses.

pages a viable channel to voice negative opinions in order to punish companies for bad products or services (Richins 1983; Sundaram et al. 1998), seek redress (Ma et al. 2015), or warn other consumers and help them avoid bad experiences (van Doorn et al. 2010; Zhang et al. 2014). As a result, the valence distribution of user posts is not clear a priori, and we hope to characterize the pattern through our empirical analyses.

In terms of content, online consumer reviews primarily focus on information and evaluations of products and services (Anderson 1998; Berger 2014). In general, for UGC in both offline and online settings, researchers have developed various taxonomies, which we summarize in Table 1.

Table 1. UGC Content Types in Different Contexts

Reference	Context	Content Types
Mangold et al. (1999)	Service marketplace	Quality, price, and value of service.
Richins and Root-Shaffer (1988)	Automobile purchase	Personal experience, advice-giving, product news, and negative WOM.
Schindler and Bickart (2012)	Online reviews for books and automobiles	Positive evaluative statements, negative evaluative statements, product-descriptive statements, and reviewer-descriptive statements.
Smith et al. (2012)	WOM on Twitter, Facebook, and YouTube	Promotional self-representation, brand-centric information, marketer-directed communication, response to online marketer action, factual brand information, and brand sentiment.
Cho et al. (2002)	Complaints in online feedback systems	Customer service, product quality, price, delivery problems, misleading information, trust issues, tracking, and promotion.

As shown in Table 1, the specific categories of UGC are highly context-specific and may not be readily applicable for classifying user posts on Facebook business pages. In this research, we aim to develop a new content framework for user posts on Facebook business pages.

2.3. Customer Engagement in Online Brand Communities

In this section, we briefly review the literature on customer engagement in online brand communities. Engagement has been defined as "the intensity of an individual's participation and connection with the organization's offerings and activities initiated by either the customer or the organization" (Vivek et al. 2012). Customer engagement plays a central role in online brand communities (McAlexander et al. 2002; Muniz and O'Guinn 2001), and Brodie et al. (2013) define consumer engagement in an online brand community as "specific interactive experiences between consumers and the brand, and/or other members of the community" (p. 107). They further indicate that customer engagement is highly context-dependent, and its manifestations and levels of intensity can change over time and across contexts. Engagement behaviors can include both UGC creation (e.g., posting content) and UGC consumption (e.g., liking and commenting on others' content) (Gummerus et al. 2012). Engagement targets can be either the marketer-generated content (MGC) from the brand or UGC from other customers (Van Doorn et al. 2010).

In this paper, we examine two types of engagement behaviors towards user posts: liking a post and commenting on a post. According to Maslowska et al. (2016), liking and commenting are significant yet underexplored brand dialogue behaviors through which customers can engage with the brand and other consumers. They add metavoicing or metaknowledge to user-generated content so that other users can gauge the content's popularity or value (Majchrzak et al. 2013). Prior studies (e.g., Cvijikj and Michahelles 2013, Lee et al. 2017) have treated likes and comments as alternative engagement measures and did not *conceptually* differentiate the two. As mentioned earlier, we explicitly consider liking and commenting as two conceptually distinct forms of engagement, and below we discuss the theoretical reasoning behind this.

Over the years, researchers have identified three key dimensions to characterize engagement behavior (Brodie et al. 2011), including the level of *cognitive* effort required (Shevlin 2007; Oestreicher-Singer and Zalmanson 2013), the *emotional* states expressed, and the *behavioral* manifestation (Brodie et al. 2011). Drawing insights from the literature, liking and commenting differ in at least two regards: the level of effort or involvement and emotional complexity. Compared with commenting, liking is less cognitively demanding and represents a lower level of involvement with the content. More specifically, liking is a "lightweight, one-click feedback action" (Scissors et al. 2016), whereas commenting is a deliberate form of "composed communication" that takes time and cognitive capacity to compose (Burke and Kraut 2014; Swani et al. 2013). In terms of emotional complexity, liking is mainly used to express positive, affirmative emotions such as agreement, empathy, acceptance, or awareness (Scissors et al. 2016), whereas commenting can convey more complicated emotions such as appreciation, denial or disagreement, anger, or a combination of multiple emotions. Appendix A1 summarizes our review of the engagement literature and provides a comprehensive, systematic comparison of liking and commenting.

2.4. Impact of Post Valence and Post Content on Engagement

In this section, we briefly review related research on how valence and content characteristics of UGC affect engagement in the contexts of online reviews, online communities, and social media platforms. Two key patterns emerge. First, compared to neutral messages, both positive and negative messages tend to have a greater impact. For example, online reviews with either a positive or negative valence had a greater impact on readers' perceptions of helpfulness and purchasing decisions than neutral reviews (Yin et al. 2014; Chevalier and Mayzlin 2006). Positive posts on Facebook boosted sales of televisions, negative posts reduced sales, and neutral posts had no impact (Corstjens and Umblijs 2012). In online communities, the use of either positive or negative words in a message increased one's chance of getting a reply (Arguello et al. 2006). Second, negative messages tend to have a stronger influence than positive messages because negative information and emotions receive more processing and produce "larger, more consistent, more multifaceted, or more lasting effects" (Baumeister et al. 2001, p. 325). This is known as the "negativity bias", which has been confirmed in many contexts including online reviews and online communities (e.g., Chevalier and Mayzlin 2006, Arguello et al. 2006).

Compared to the impact of valence, studies on the impact of content are relatively sparse, although several studies have highlighted the importance of studying the textual content of UGC (e.g., Archak et al. 2011; Ghose and Ipeirotis 2011; Ghose et al. 2012). For example, Archak et al. (2011) showed that product features derived from textual reviews of cameras on Amazon, such as ease of use, product size, and picture quality, had a significant predictive power of product sales, over and above the volume and valence of the reviews. Also, there is evidence in the marketing literature that information with the same valence but different types of content can have different effects on purchase intensions or other behaviors. Mohr and Webb (2005) found that, when subjects were presented with both corporate social responsibility (CSR, i.e., the firms' relationships with the environment or social welfare) and pricing news about a brand, negative CSR news decreased their purchase intent to a greater extent than negative pricing news.

Due to the differences between user posts on Facebook business pages and the other contexts, whether and how existing findings generalize to user posts remain unclear. Therefore, we rely on empirical analysis to uncover the relationships between post valence and content and engagement. We further speculate that the same valence/content factor may have different effects on likes vs. comments, because of the aforementioned theoretical distinctions between these two engagement forms. Empirically examining the antecedents of likes and comments separately will allow us uncover these nuanced differences.

3. Methods

3.1. Research Setting and Data

We chose Facebook business pages as our research setting for several reasons. Facebook is the largest social media platform, both in terms of number of active users and the scale of marketing activities.[5] Its large user base and active interactions between businesses and users make it a suitable context to study our research questions. Figure 1 shows screenshots of Walmart's business page on Facebook and an example of user-generated posts. We built a software tool in Python to connect with Facebook Graph API to download data.

Figure 1: Screenshots of the Facebook Business Page of Walmart and User-Generated Posts

(a) (b)

Note. Panel (a) shows Walmart's Facebook business page. Panel (b) shows the user posts, located in the "Posts to Page" section next to the main timeline.

In this paper, we focus on Fortune 500 companies because they play an important role in the economy and typically are early adopters of Facebook business pages. We chose six industries that are consumer-facing: Airlines, Commercial Banks, Consumer Products, Food and Drug Stores, General Merchandisers, and Specialty Retailers. We started with the Fortune 500 list from 2012 and found 41 companies in total that belonged to these six industries. We downloaded all posts on their Facebook pages in 2012, which were about 530 thousand in total. In addition to post messages, our data included post creation time, media type (status, link, photo, or video), and number of likes and comments each post

[5] https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/; https://www.huffingtonpost.com/young-entrepreneur-council/the-10-best-social-media_b_11654820.html. Last access 01/02/2018.

received. We then drew a stratified sample of 2,000 posts by company in each industry (i.e., the sampling strata are companies within a specific industry), and obtained a sample of 12,000 posts. Appendix A2 shows the list of all industries and corresponding companies.

3.2. Post Valence Analysis

Our first analysis was to classify post valence. We recruited Amazon Mechanical Turk (MTurk) workers to perform this task. MTurk is an online marketplace for work where requesters can submit tasks, called Human Intelligent Tasks or HITs, to be completed at relatively low costs. Workers, also called Turkers, can accept a task, work on it, and get paid once their output is approved by requesters. Appendix A3 shows an example of our valence classification task.

We instructed workers to carefully read the post and decide whether the post had an overall positive, negative, or neutral valence. To assure quality, we restricted the task to workers in the U.S. who had a 95% or higher task acceptance rate. Each post was labeled by five workers, and we used the majority rule to determine the valence of a post. If three or more workers selected the same valence, then the post was labeled as having that valence. Using the majority rule, we were able to label 98.7% of the posts without ambiguity. For the remaining 1.3% where workers did not reach an agreement (e.g., 1 positive, 2 negative, 2 neutral votes), we tried two labeling strategies: (1) labeling them as neutral, or (2) labeling them as the relatively more dominant non-neutral valence (negative in the example). Our main results were qualitatively the same no matter which labeling strategy we used.[6] Throughout the paper, we present results based on the first labeling strategy.

3.3. Post Content Analysis

Our second analysis was to classify post content. Due to the lack of established content framework for user posts on Facebook business pages, we took the Grounded Theory approach (Glaser and Strauss 1967), which is a qualitative approach to identify common themes and develop theory using empirical data. The

[6] We ran additional analyses by (1) dropping the 1.3% of posts that lacked agreement in valence coding, (2) dropping the 3,899 posts that lacked unanimity in valence coding (i.e., not all 5 workers agreed on a single valence coding). Our main results remained qualitatively the same, confirming the robustness of our results.

approach includes two stages: *open coding* and *structured coding*.

During the *open coding* stage, two research assistants blind to the literature and to our research questions independently analyzed a random set of 3,159 posts (not part of our 12,000 sample) to identify common themes. We worked with the two assistants through several iterations to make sure that the common themes had saturated and then started consolidating and organizing them into high-level categories. Our analysis suggested 7 categories: *positive testimonial and appreciation* (*positive testimonial* in short), *complaint about product and service quality* (*quality complaint* in short), *complaint about money issues* (*money complaint* in short), *complaint about social and environmental issues* (*social complaint* in short), *customer question, customer suggestion,* and *irrelevant message*. Table 2 shows the definition and example of each content category.

During the *structured coding* stage, we first had the two research assistants code the sample of 3,159 posts into the 7 categories. We then posted this sample to MTurk with detailed instructions and illustrative examples to show how to classify the posts into the 7 categories. Appendix A4 shows an example of our content classification task. To assure quality, we restricted the work to workers in the U.S. who had "classification master" qualifications, meaning that they had consistently demonstrated high performance in classification tasks. Each post was labeled by five workers, and we used the majority rule to determine whether a post fell into a specific category. Across the 7 categories, Cohen's kappa ranged from 0.61 to 0.87 between the research assistants and MTurk coding. This established the reliability of using MTurk for classification. Next, we posted the sample of 12,000 posts on MTurk, of which 80.3% were classified into one category, 9.75% into two categories, 0.53% into three or more categories, and 9.42% into no category. A post may fall into no category because its content was unusual, meaningless, or ambiguous.[7]

To assure the validity and generalizability of the content category framework, we triangulated it with two other sources. First, we compared our framework with the content categories in Table 1. Some of our categories, such as *positive testimonial* and *quality/money complaint*, also appeared in previous

[7] Examples are "*I took southwest to Seattle*" [Southwest Airlines], "*Hi target*" [Target], and "*Special dark*" [Hershey's].

frameworks (Mangold et al. 1999; Richins and Root-Shaffer 1988; Cho et al. 2002). Other categories, such as *social complaint* and *customer question/suggestion*, were unique types of UGC in our context. Second, we surveyed practitioner articles on user posts on Facebook business pages and how page owners should respond to user posts. The advice included: providing customer support by answering customer questions, thanking and promoting positive testimonials, and acknowledging customer suggestions or complaints.[8] These insights provide additional support and validation of our content category framework.

Table 2: Definitions and Examples of the Content Category Framework

Categories	**Definitions**	**Example Post**
Positive Testimonial and Appreciation	Positive testimonials or appreciations for the company (e.g., saying how wonderful the company is or how much the user loves it, thanking the company).	*Thanks for the amazing gift box! I cannot wait to try the cinnamon pops!!* [Kellogg's]
Complaint about Product and Service Quality	Complaints about product and service quality (e.g., poor quality products or bad services).	*Not to be mean but Kelloge krave is one the worst tasting cereals I have eaten. I swear I wish I had my receipt or something.* [Kellogg's]
Complaint about Money Issues	Complaints about money issues (e.g., hefty fees or high prices).	*Why do charge so much money for air fares in a city thats small in revenue? #corporatecrooks.*[Delta]
Complaint about Social and Environmental issues	Complaints about the company's standing on social or environmental issues such as labor, human rights, social equality, or pollution.	*Chocolate is good, child labor is bad! Time to separate the two!!!!* [Hershey's]
Customer Question	Questions directed at the company and/or other users (e.g., inquiry about products and services).	*My daughter just got diagnosed with a tree nut allergy- do you have a list of your products that are nut free? Thanks!* [Kellogg's]
Customer Suggestion	Customer suggestions to the company (e.g., recommendation of new products and service to offer).	*It would be really nice if the bags in the cereal boxes were resealable like zip-lock to keep the contents fresh.... just a suggestion.* [Kellogg's]
Irrelevant message	Not related to the company. It may be user self-promotion, promotional links, adult content, etc.	*GOOD MORNING ERIKA CAN YOU BELIEVE SUMMER IS FADING AWAY FAST?* [Family Dollar]

Note. Company names are indicated in square brackets.

3.4. Variables

Our two *dependent variables* are the number of likes and the number of comments that a post received. A greater number of likes or comments indicates greater engagement. Our key independent variables are *post valence* and *post content categories*. For post valence, we created two dummy variables representing

[8] Sources: http://www.socialmediaexaminer.com/social-media-research-shows-what-people-expect-from-brands; http://www.syncapse.com/why-consumers-become-facebook-brand-fans; http://www.verticalresponse.com/blog/5-facebook-no-nos-that-turn-off-your-customers. Last access 08/08/2016.

positive and negative valence, with neutral valence as the base. For content categories, we created seven dummy variables corresponding to the seven categories, with posts that did not belong to any category as the base. We also included several control variables as discussed below.

Post Linguistic Characteristics. We controlled for message length and readability. Longer messages tend to be more informative and include product specifics; as a result, readers often find longer messages more helpful or diagnostic than shorter messages (Mudambi and Schuff 2010). Similarly, readability has been shown to affect engagement in both online product reviews (Ghose and Ipeirotis 2011) and online communities (Arguello et al. 2006, Johnson et al. 2015). Messages that are easier to read and comprehend can be understood by more people and therefore attract greater engagement. We measured post length by the number of words in a post. We measured readability by Automated Readability Index[9] (ARI), which takes into account the average length of words and the average length of sentences (Smith and Senter 1967). Higher ARI score means the text has longer words or longer sentences and is written in a more sophisticated manner (Ghose and Ipeirotis 2011).

Poster Characteristics. Source characteristics, such as source credibility, network position, or participation patterns may affect engagement (Berger 2014). A key attribute of the source is activeness, which has been linked to high status and larger impact on other members (Preece and Shneiderman 2009). We proxied poster activeness by the total number of posts a user posted in 2012 on the business page.

Post Context. The degree to which a message attracts attention and engagement also depends on contextual factors, such as when and where it is publicized. Reading and replying to messages take time and effort. The abundance of user-generated content on social media platforms implies that content published on the same platform will have to compete with other content for attention (Wang et al. 2013). In our study, we controlled for competition with three measures. First, at the page level, we controlled for *page popularity*, which was the total number of posts posted on the business page in 2012, including both user-generated posts and marketer-generated posts. Second, at the individual post level, we controlled for

[9] ARI score = 4.71*(#characters/#words) + 0.5*(#words/#sentences) – 21.43

post-level user-generated content and *post-level marketer-generated content*, which were the number of user- and marketer-generated posts that were posted from 24 hours before to 24 hours after a focal post was created on the page. Third, external factors could also affect *general interest* in a company and activities on its page. For example, there was a spike of activities on Volkswagen's Facebook page after the revelation of its emission scandal.[10] Using data from the LexisNexis database, we counted the number of media reports about the company within 1 day prior to the creation of the focal post (denoted as *LexisNexis_1*).

Other Control Variables. We included several dummy variables to control for the industry of a company and the media type of a post (e.g., status, link, photo, and video). We also controlled for the size of the company by including company assets in 2012. Finally, we log-transformed 5 of our variables to reduce skewness including *word count*, *page popularity*, *post-level UGC/MGC*, and *asset*.

3.5. Data and Sample

From our initial sample of 12,000 posts, we excluded 4 sets of posts. First, we removed 174 posts that had fewer than 2 words or fewer than 6 characters because these posts did not contain enough meaningful information. Second, we removed 1,121 posts that were posted by third parties, such as non-profit organizations and local businesses, instead of individual users. Third party posts were identified based on the poster information. As shown in Appendix A5, third-party posts were mostly *positive testimonial* and self-promotional messages (e.g., thanking the company for charity events) and differed substantially from individual user posts. Third, two companies, Land O'Lakes, Inc. and American Express, only had 3 user posts in total in our sample, which was insufficient for meaningful analysis. We removed these 3 posts. Finally, we identified and removed 21 posts with abnormal content, such as URLs or meaningless characters, because their valence and content could not be measured. Our final sample included 10,681 user-generated posts from 39 companies.

3.6. Empirical Strategy

We ran negative binomial regression because our dependent variable was count data with significant

[10] http://www.mediapost.com/publications/article/266265/reeling-vw-dials-social-activity-way-back.html. Last access 01/01/2018.

overdispersion (supported by likelihood-ratio test for all regressions, $p < 0.001$). To account for company-level heterogeneity, we ran both conditional fixed effects and random effects negative binomial models because they generate consistent estimations (Greene 2008; Hausman et al. 1984). We estimated the models using the *xtnbreg* procedure in Stata. The two specifications generated qualitatively similar results. Below we present results from the random effects negative binomial models, and include results from the conditional fixed effects models in Appendix A8.

We conducted several diagnostic analyses to check model assumptions. For multicollinearity, we ran regression models with OLS and checked variance inflation factors (VIF). All VIF values were below 4, suggesting multicollinearity was not a concern. We also checked for potential outliers. Residual plots showed 1 outlier post that received more than 1,000 likes. We removed it from our analysis (its inclusion did not change our results). We did not find any signs of heteroskedasticity issues. We report descriptive statistics for key variables and their correlations in Table 3. We include a complete table of descriptive statistics for all variables in Appendix A6, and correlation coefficients among variables in Appendix A7.

Table 3. Descriptive Statistics and Correlations for Key Variables (N = 10,640)

	Variables	**Mean**	**SD**	**Correlations**										
				1	2	3	4	5	6	7	8	9	10	11
1	*Likes*	1.44	3.97	1.00										
2	*Comments*	1.67	3.56	0.28	1.00									
3	*Positive Valence*	0.26	0.44	0.02	-0.12	1.00								
4	*Negative Valence*	0.50	0.50	0.12	0.14	-0.59	1.00							
5	*Positive Testimonial*	0.23	0.42	0.01	-0.10	0.84	-0.52	1.00						
6	*Quality Complaint*	0.25	0.44	0.01	0.18	-0.34	0.56	-0.30	1.00					
7	*Money Complaint*	0.06	0.24	0.01	0.08	-0.15	0.25	-0.14	0.16	1.00				
8	*Social Complaint*	0.18	0.39	0.21	-0.03	-0.27	0.44	-0.25	-0.21	-0.11	1.00			
9	*Customer Question*	0.19	0.39	0.12	0.04	-0.23	-0.21	-0.23	-0.15	-0.07	-0.18	1.00		
10	*Customer Suggestion*	0.07	0.26	0.06	-0.02	-0.05	-0.02	-0.09	-0.10	-0.06	0.02	-0.06	1.00	
11	*Irrelevant Message*	0.08	0.27	0.03	-0.07	0.03	-0.25	-0.16	-0.17	-0.08	-0.14	-0.14	-0.08	1.00

Note. Indices 1-11 in the columns for correlation results represent the 11 variables we report here. For a complete table of descriptive statistics and correlations of all variables, see Appendix A6 and Appendix A7.

One potential threat to the validity of our model is unobserved heterogeneity in post views. Users need to first view a post before liking it or commenting on it. Facebook uses an algorithm called "EdgeRank" to determine what posts appear in a user's *personal newsfeed* and in what order. The algorithm considers affinity between the poster and the reader, the content of the post, and time decay since the creation of the content.[11] If the display of user posts on Facebook business page were subject to the influence of EdgeRank, then our regressions may suffer from omitted variable bias, because the unobserved heterogeneity in post views may be correlated with our independent variables and also affect our dependent variables. Such endogeneity would be very challenging to remove completely because the algorithm configuration is proprietary and unknown to the public. However, the influence of EdgeRank is less of a concern for posts on Facebook business pages. During our data collection, user posts on a business page can be generated in one of two ways. Users can visit the page and write posts inside the "Post" textbox (as shown in Figure 1). Alternatively, users can publish posts on their own timelines and tag the business with the "@" sign (e.g., @WalMart). The posts that are directly created on a business page can only be seen by visitors to that page, and are not propagated to the posters' or other fans' friend networks. The visibility of these posts is not affected by the EdgeRank algorithm. In contrast, the posts with tags of the business will appear both on the business page and on the poster's own timelines; their visibility is subject to the workings of EdgeRank.[12] Another situation under which posts from a business page can be propagated to personal newsfeed is when the post gets *shared* by a user. Our sample included 32 posts with tags and 8 posts that have received at least 1 share.[13] For the rest of the sample, we are confident that our *post context* variables (i.e., *page popularity*, *post-level UGC/MGC*, and *LexisNexis_1*) can sufficiently control for the heterogeneity of post views. After removing the 40 posts, our final sample included 10,640 posts. Notably, our results remained qualitatively the same even when these 40 posts were included (see Appendix A9).

4. Model Estimation and Results

In this section, we present the main empirical results. We discuss possible explanations and implications of our findings in Section 5.

4.1. Distributions of Post Valence and Content

Comparison of our coding of post valence and post content categories showed both overlaps and

[11] http://sproutsocial.com/insights/facebook-news-feed-algorithm-guide/. Last access 01/01/2018.
[12] Facebook does not reveal details about business page design. Authors acquired this information by opening a real business page on Facebook and experimenting with different ways of generating user posts.
[13] These posts can be identified by examining the returned JSON objects from Facebook Graph API. Details can be found at https://developers.facebook.com/docs/graph-api/reference/v2.2/post.

discrepancies between the two. The majority of the posts that were labeled as having a positive valence were also classified into the positive content category (*positive testimonial*). The majority of the posts that were labeled as having a negative valence were also classified into the negative content categories (*quality complaint*, *money complaint*, or *social complaint*). Cohen's Kappa was 0.83 for positive and 0.89 for negative, indicating a high level of overlaps between valence and content. On the other hand, some content categories such as *customer question* and *customer suggestion* did not have a clear valence tendency. About 67% of *customer question* posts were labeled as neutral and 46% of *customer suggestion* posts were labeled as negative. Appendix A10 shows some examples of the two categories.

Of the 10,640 posts in our final sample, 5,308 were negative and 2,751 were positive, with the remaining 2,581 being neutral. The ratio of negative to positive posts was 1.93 to 1. A chi-square test confirmed that negative posts were more prevalent than positive ones ($p < 0.001$). Furthermore, at the company level, 28 out of 39 companies had more negative posts than positive posts.[14] One-sided t-tests showed that, at both industry level and company level, there were significantly more negative posts than positive ones ($p < 0.01$ at industry level, $p < 0.001$ at company level). Figure 2a shows the percentage of positive and negative posts in the six industries. Negative posts were more prevalent than positive posts in *every* industry, with some variations across industries. For example, commercial banks had the highest percentage of negative posts, followed by consumer products, airline, general merchandisers, food and drug stores, and specialty retailers. There were also differences across content categories. Figure 2b shows the percentages of the three types of complaints across industries. Airlines and commercial banks had higher levels of *quality complaint*, whereas consumer products companies had higher levels of *social complaint*. In general, *money complaint* was less common than *quality complaint* or *social complaint*.

4.2. Impact of Post Valence and Content on the Number of Likes

Table 4 shows the effects of post valence, content, and other variables on the number of likes. Some basic control variables, including industry dummies, post type dummies, and firm assets are omitted from the

[14] Companies that had more positive than negative posts are: Campbell's Condensed Soup, Discover, Dollar Tree, Hershey's, Kraft Foods, Nordstrom, PepsiCo, PetSmart, Rite Aid, Sears Outlet Stores, and Southwest Airlines.

regression table for brevity. We include the complete regression table with all variables in Appendix A11. Aside from these basic controls, Models 1, 2, and 3 incrementally added post linguistic features, post context, and poster characteristic. Model 4a added post valence and Model 4b added post content. Valence and content variables were not included in the same regression because they were highly correlated. We assessed model fit using Deviance, AIC, and BIC,[15] and the latter two adjusted for large samples and large numbers of covariates (Raftery 1995). Models 4a and 4b had the lowest BIC values and the best fit with our data. Therefore, we discuss the results of these two models.

Figure 2a: Percentages of Positive and Negative Posts across Industries

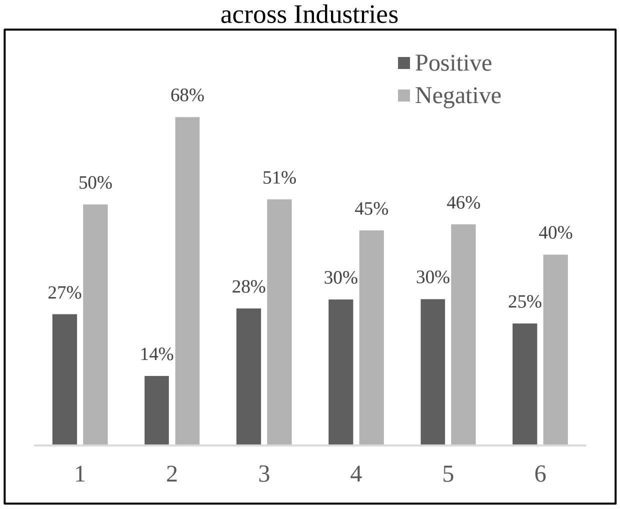
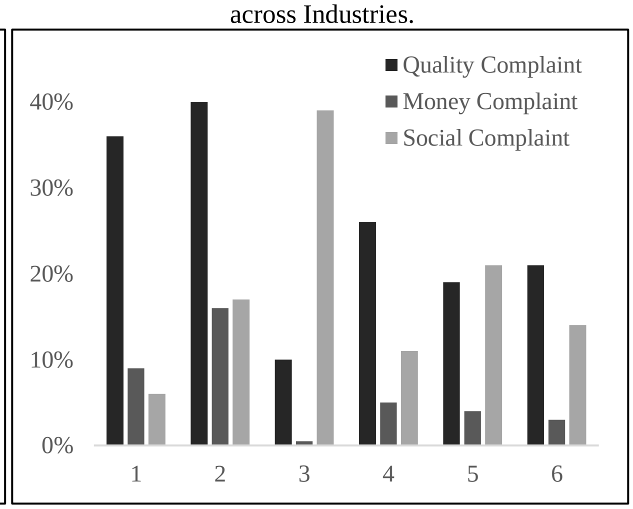


Figure 2b: Percentages of Different Types of Complaints across Industries.



Note. Industry 1 – Airline; 2 – Commercial Banks; 3 – Consumer Products; 4 – Food and Drug Stores; 5 – General Merchandisers; 6 – Specialty Retailers.

As shown in Model 4a, compared to a neutral post, a positive post received 72% more likes ($b = 0.54$, $p < 0.001$, $exp(0.54) = 1.72$) and a negative post received 118% more likes ($b = 0.78$, $p < 0.001$, $exp(0.78) = 2.18$). The coefficient of negative valence was significantly higher than the coefficient of positive valence ($p < 0.001$), suggesting that negative posts received more likes than positive posts. Furthermore, posts with the same valence but different content categories received different levels of likes. As shown in Model 4b, *social complaint* received more likes than *quality complaint* or *money complaint* ($b = 0.93$ versus 0.10 or 0.13, $p < 0.001$). All else being equal, *social complaint* received 129% more likes than *quality complaint*

[15] Denote the log-likelihood, degree of freedom, and sample size of estimated model as *LL*, *k*, and *N*, respectively. Then $Deviance = -2LL, AIC = 2k - 2LL, BIC = k\ln(N) - 2LL.$

(*exp*(0.93–0.10) = 2.29), and 123% more likes than *money complaint* (*exp*(0.93–0.13) = 2.23). Compared to the base, i.e., posts not in any category, *customer suggestion* received more likes, *customer question* received fewer likes, and posts that were irrelevant to the company's business were not statistically different.

Table 4: Random Effects Negative Binomial Regression – Impact on the Number of Likes (N = 10,640)

	Model 1	Model 2	Model 3	Model 4a	Model 4b
Log(Word Count)	0.16***	0.17***	0.17***	0.10***	0.15***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
ARI Score	0.01***	0.01***	0.01***	0.01***	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(Page Popularity)		−0.41***	−0.40***	−0.36***	−0.34***
		(0.05)	(0.05)	(0.05)	(0.05)
Log(Post-Level UGC)		0.26***	0.26***	0.22***	0.14***
		(0.01)	(0.01)	(0.01)	(0.01)
Log(Post-Level MGC)		−0.14***	−0.14***	−0.12***	−0.09***
		(0.02)	(0.02)	(0.02)	(0.02)
LexisNexis_1		0.01***	0.01***	0.01***	0.01***
		(0.00)	(0.00)	(0.00)	(0.00)
User Activeness			0.004***	0.004***	0.003**
			(0.00)	(0.00)	(0.00)
Positive Valence				0.54***	
				(0.05)	
Negative Valence				0.78***	
				(0.05)	
Positive Testimonial					0.25***
					(0.05)
Quality Complaint					0.10*
					(0.05)
Money Complaint					0.13
					(0.07)
Social Complaint					0.93***
					(0.05)
Customer Question					−0.54***
					(0.06)
Customer Suggestion					0.29***
					(0.05)
Irrelevant Message					−0.02
					(0.07)
Deviance	30049.36	29540.22	29527.9	29225.58	28836.58
ΔDeviance	200.86***	509.14***	12.32***	302.32***	691.32***
AIC	30077.37	29576.22	29565.91	29267.58	28888.58
BIC	30179.18	29707.12	29704.08	29420.30	29077.66

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Post linguistic features, post context, and poster characteristic also had significant effects on the number of likes. Both post length and readability were positively associated with the number of likes, suggesting that longer posts and more sophisticatedly written posts received more likes. We also explored the quadratic terms of word count and ARI score; neither was significant at the 0.05 level. Post context exhibited different effects on likes depending on which measure was used. At page level, posts on a popular page with higher traffic received fewer likes. At individual post level, posts surrounded by more marketer-generated posts received fewer likes, whereas posts surrounded by more user-generated posts received more likes. Higher general interest toward a focal company (*LexisNexis_1*) was associated with more likes. Finally, user activeness was positively associated with number of likes, suggesting that posts created by active users received more likes than those created by less active users. We also found significant differences across industries and post media types. Posts on the pages of specialty retailers received more likes than posts on the pages of other industries. Compared to status updates, posts with links received fewer likes whereas posts with photos received more likes (see Appendix 11 for results on these control variables).

4.3. Impact of Post Valence and Content on the Number of Comments

Table 5 shows the effects of post valence, content, and other variables on the number of comments. We include the complete regression table in Appendix A12. Similarly, Models 4a and 4b had the lowest BIC values and the best fit with our data. We discuss the results of these two models. As shown in Model 4a, positive posts received 70% as many comments as neutral posts (b = -0.35, p < 0.001, exp(-0.35) = 0.70), and negative posts were not significantly different from neutral posts in the number of comments (b = 0.05, p = 0.14). However, compared with positive posts, negative posts received more comments (p < 0.001). Again, we found that posts with the same valence but different content categories received different levels of comments. As shown in Model 4b, *social complaint* received fewer comments than *quality complaint* or *money complaint* (b = −0.21 versus 0.27 or 0.13, p < 0.001). All else being equal, *social complaint* received 38% fewer comments than *quality complaint* (exp(-0.21−0.27) = 0.62), and 29% fewer comments than *money complaint* (exp(-0.21−0.13) = 0.71). In addition, our results suggested that, compared to posts not belonging to any categories, *customer question* received more comments, *customer suggestion* was not significantly different, and *irrelevant message* received fewer comments (b = −0.82, p < 0.001).

Post linguistic features, post context, and poster characteristic also had significant effects on the number of comments. According to Model 4b, longer posts received more comments, but ARI score was not significantly associated with the number of comments. The quadratic term of word count was significant (b = −0.04, p < 0.001) and the quadratic term of ARI score was not significant. Increasing post length from

Table 5: Random Effects Negative Binomial Regression – Impact on the Number of Comments (N = 10,640)

	Model 1	Model 2	Model 3	Model 4a	Model 4b
Log(Word Count)	0.31***	0.29***	0.30***	0.26***	0.22***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ARI Score	−0.01**	−0.01*	−0.01*	−0.01**	−0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(Page Popularity)		−0.16**	−0.15*	−0.13*	−0.10
		(0.06)	(0.06)	(0.06)	(0.06)
Log(Post-Level UGC)		−0.22***	−0.22***	−0.24***	−0.19***
		(0.01)	(0.01)	(0.01)	(0.02)
Log(Post-Level MGC)		0.08***	0.08***	0.08***	0.07***
		(0.02)	(0.02)	(0.02)	(0.02)
LexisNexis_1		0.0002	0.0001	−0.0002	0.002
		(0.00)	(0.00)	(0.00)	(0.00)
User Activeness			0.002*	0.002*	0.003**
			(0.00)	(0.00)	(0.00)
Positive Valence				−0.35***	
				(0.04)	
Negative Valence				0.05	
				(0.03)	
Positive Testimonial					−0.21***
					(0.04)
Quality Complaint					0.27***
					(0.04)
Money Complaint					0.13**
					(0.05)
Social Complaint					−0.21***
					(0.05)
Customer Question					0.36***
					(0.04)
Customer Suggestion					−0.05
					(0.05)
Irrelevant Message					−0.82***
					(0.08)
Deviance	33996.5	33655.74	33651.78	33503.26	33121.1
ΔDeviance	658.26***	340.76***	3.96*	148.52***	530.68***
AIC	34024.50	33691.75	33689.78	33545.25	33173.11
BIC	34126.31	33822.65	33827.95	33679.97	33362.19

Note. * $p<0.05$; ** $p<0.01$; *** $p<0.001$. Bootstrap standard errors in parentheses.

a few words to 150-400 words increased the number of comments, beyond which the effect began to decrease. Post context had different effects on comments depending on the measures. At individual post level, posts surrounded by more marketer-generated posts received more comments, and posts surrounded by more user-generated posts received fewer comments. Neither page popularity nor general interest toward a focal company was significant. Finally, user activeness was positively associated with the number of comments, suggesting that posts made by active users received more comments than those posted by less active users. Our analyses also showed significant differences across industries and post media types. Compared to specialty retailers, posts on the pages of commercial banks and consumer products companies received fewer comments and posts on the pages of general merchandisers received more comments. Posts with links received fewer comments than status updates, and posts with photos received more comments than status updates.

4.4. Additional Analyses and Robustness Checks

We conducted several additional analyses and robustness checks to validate our findings. First, our main results are based on content categories developed from qualitative data analysis using the grounded theory approach. While the content categories represent what naturally emerged from an iterative coding process, they contained a mixture of several dimensions. For instance, the *quality complaint* category mixes the valence (negative) with the substance (statement about quality of products and services). Therefore, we repeated our main analyses under an alternative coding scheme by treating valence and content as *orthogonal*. Our main results remained consistent. Details of the alternative coding and results are included in Appendix A13. Second, we conducted a series of robustness checks with alternative variable operationalizations (e.g., changing time windows of measuring user activeness and post context) and alternative model specifications (e.g., logistic regressions for whether a post received any likes or comments). Our results remained qualitatively the same. Due to space limitations, descriptions of these robustness checks and results are included in Appendix A14.

Third, we conducted an exploratory online survey to gain insights about why users visit Facebook business pages and their motivations to post and engage with others. We gathered 123 valid responses from participants on Amazon Mechanical Turk who are in the U.S., have Facebook accounts, and have visited at least one business page. In the survey, we asked about (1) demographic information of users who have visited Facebook business pages including age, gender, and relationships with the businesses, and (2) motivations to visit business pages, read user posts, write posts, or like and comment on posts from other users using a five-point Likert scale. A complete list of the survey questions is included in Appendix A15. Some descriptive information of survey participants is shown in Table 6. A brief summary of the top motivations for engaging in different activities is included in Appendix A15.

Table 6. Descriptive Information of Survey Participants

Gender	Female: 58%; Male: 42%
Age	≤ 25: 17%; 25-34: 47%; 35-44: 27%; 45-54: 5%; ≥ 55: 4%
Relationship with the focal businesses	- 70% have purchased products or services from the businesses; - 46% are considering purchasing from the businesses; - 10% have never purchased from the businesses before; - 4% are employees of the businesses.
Frequency of user activities	- > 50% **visit** business pages at least once a week; - 70% **read** user posts at least monthly; - 73% have **posted** themselves at least once; - 84% have **liked** user posts at least once; - 76% have **commented** on user posts at least once.

Several things are worth noting from our survey responses. First, while most visitors are customers, around 10% of visitors never had purchasing experiences with the businesses. Second, users *visit* the page and *read* user posts not only to get information about the business and to learn about other users' experiences, but also to be part of the user communities (59% of participants agreed with the latter). Third, primary motivations to *post* include not only sharing experiences with other users, but also requesting *customer service* from the business (55% of participants agreed with the latter). Fourth, there are indeed differences in motivations for liking and commenting. Users *like* posts mainly because they agree with the posts or they share similar experiences; users *comment* on posts also to join the discussions by sharing their own experiences and to answer other users' questions. Overall, our survey indicates that user posts are created by a combination of customers and users with no purchasing experiences. Their intended audience include both other users and the focal businesses. The motivations of creating and consuming user posts are not merely purchase-oriented and include a broad set such as requesting customer service and being part of the user community.

5. Discussion

In this paper, we set out to answer two questions. What do users post on Facebook business pages? How do the valence and content of user posts affect engagement with the posts? We have three key findings. First, we theorize and empirically demonstrate that user posts on Facebook business pages represent a relatively new phenomenon that is different from online consumer reviews. The prevalence of negative user posts is in sharp contrast with the "J-shaped" distribution of online reviews on Amazon or other sites, where positive ratings and reviews are the majority. We believe this contrast is partly driven by differences in users' motivations to post. The primary motivation to write online reviews is to share one's opinions about the products and services and help other consumers' make better purchase decisions. In comparison, users post on Facebook business pages to communicate with *both other users and the focal businesses*. The high volume of complaint messages and additional customer questions and suggestions implies that some Facebook users regard business pages as a new channel to communicate directly with businesses and to receive *customer service*. The prevalence of negative messages on the business pages represents a significant challenge to many businesses. Future research should aim to uncover the complete nature of Facebook business pages as a new channel of interacting with customers and explore effective response strategies to manage customer complaints and other service requests on social media.

Our second finding is that the two major forms of engagement – liking and commenting – have distinct antecedents. Factors that increase the number of likes may not increase the number of comments. Most notably, positive posts received more likes but fewer comments than neutral posts, social complaints received more likes but fewer comments than quality/money complaints, and customer questions received more comments but fewer likes than customer suggestions. Insights from our exploratory online survey provide plausible explanations for some of these patterns. For example, consider the finding that *social complaint* receives more likes but fewer comments than *quality complaint* and *money complaint*. *Quality complaints* and *money complaints* generally pertain to personal experiences and, therefore, are likely to invite discussions and comments from other users. In fact, many survey respondents rated "I want to add to the discussion by sharing my experience" as an important motivation of commenting. *Social complaints*, in contrast, typically have broad social appeal, and liking such posts expresses agreement and empathy with the posters, which is highly consistent with the fact that our survey respondents rated "I agree with the content of the posts" as the most important reason for liking.

Our third finding is the interplay between post valence and post content, and how going beyond valence to study the impact of post content reveals interesting heterogeneity among different kinds of posts. Notably, while the three types of customer complaints are all negative in valence, we found they have different effects on engagement. Compared to positive posts, *quality complaint* and *money complaint* received fewer likes and more comments whereas *social complaint* received more likes and fewer comments. These nuanced but important effects would be overlooked if only valence information were to be examined, without differentiating the content. These findings demonstrate the benefit of combining sentiment analysis and content analysis to obtain deeper insights from textual data. In future work, researchers should also consider alternative data-driven methods such as topic modeling (Blei 2012) and use it to complement human coding, to discover common themes and content categories in textual data.

Our research has important implications for social media marketing practice. First, companies have little control over how users behave and what users post on their business pages. This is of particular concern to companies whose users are more likely to use the page as an outlet to complain and vent their negative feelings. Companies should be aware of this challenge and not simply regard Facebook business page as a marketing channel. Instead, companies should carefully consider and evaluate whether Facebook business pages is an appropriate venue to interact with their customers and have a strategy to respond to negative posts, because they tend to attract more attention than positive and neutral ones. Furthermore, negative voices often reflect potential or pervasive issues of the companies' products, services, and corporate social responsibility practices, and can be used as valuable feedback. Second, companies need to be aware that likes and comments are two distinct forms of engagement that should be measured separately. In social media campaigns, companies should set specific goals for likes and comments and be cognizant of the trade-offs among different outcomes. Instead of simply counting likes or comments, companies should analyze the specific content that attracts the likes and comments (e.g., likes of customer complaints are not a positive sign of customer engagement). Third, despite the popularity of sentiment analysis in social media analytics, our results suggest that there is great need and value to go beyond simple valence and to analyze the content of social media posts. Combining sentiment analysis with content analysis has the potential to reveal subtle patterns of customer behaviors to advance theory and improve practice.

Our research suggests several directions for future work. First, our empirical strategy took advantage of the fact that most user posts in our sample are not subject to the influence of EdgeRank. If comprehensive knowledge about the EdgeRank algorithm were available, we could explore alternative methods to address the endogeneity issue. Second, we only analyzed the textual content of a post, even though some posts contained multimedia content such as photos or videos. Incorporating multimedia information in the coding process is another interesting avenue for future research. Third, future research can also extend our analyses to study small- and medium-sized businesses, nonprofit organizations, or business-to-business contexts, to consider the moderating roles of product and service attributes, or to examine the entire online customer journey across multiple platforms. Finally, we believe our findings generalize to other social media platforms, which often follow Facebook's design. For instance, the Like button was introduced by Facebook and later became a standard feature on numerous other platforms, such as Twitter, YouTube, and Instagram. Nonetheless, future studies can replicate our findings in other contexts.

To conclude, this is only a first step toward understanding this new form of UGC on Facebook business pages. Many companies marched into the new territory of social media marketing with limited understanding of user behavior in this context. Our study sheds light on the challenges that companies need to be aware of and prepared for. By demonstrating the distinctive nature of this new form of UGC, we hope to call for more research to understand a suite of interesting questions around it, such as the economic impact of positive and negative posts and the appropriate response or intervention strategies that companies can utilize to manage UGC on Facebook, especially the negative one. We believe the answers to these questions will further deepen our understanding of social media marketing and inform business practice.

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ONLINE SUPPLEMENT

Appendix A1. Conceptual Differences between Liking and Commenting as Engagement Behaviors

Reference	Applicable Dimensions	Liking a post	Commenting on a post
Van Doorn et al. (2010)	Valence	Mainly positive toward the post.	Could be positive or negative.
	Form/Modality	Requires low resource level.	Requires high resource level.
	Customer Goals	Express agreement, empathy, enjoyment, etc.	Express opinion and engage in discussion.
Brodie et al. (2011)	Cognitive	Requires low cognitive resources.	Requires high cognitive resources.
	Emotional	Mainly positive emotions.	Could be either positive or negative.
	Behavioral	Liking and commenting are different engagement behaviors.	
Patterson et al. (2006)	Absorption	Low level of concentration on the post.	High level of concentration on the post.
	Dedication	Relatively weak involvement with the post.	Relatively strong sense of belonging to the post.
	Vigor	Low level of energy.	High level of energy.
	Interaction	Mainly one-way feedback.	Mainly two-way discussion.
Shevlin (2007)		Low level engagement.	High level engagement.
Oestreicher-Singer and Zalmanson (2013)		Mainly low level behaviors such as *Content Consumption/Organization*.	Mainly high level behavior such as *Community Involvement*.

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Appendix A2. Data Collection: List of Industries and Companies

Table A2. Data Collection: 6 Industries and Corresponding Companies

Industries	Companies
Airlines	Southwest Airlines, United, American Airlines, Delta, US Airways
Commercial Banks	Bank of America, Discover, Wells Fargo, U.S. Bank, Ally Bank, American Express, Sun Trust
Consumer Products	Dole, Kellogg's, Hershey's, Kraft Foods, Campbell's Soup, ConAgra Foods, PepsiCo, Land O'Lakes
Food and Drug Stores	Walgreens, CVS, Safeway, Rite Aid, Kroger
General Merchandisers	Target, Walmart, Macy's, Kohl's, Dollar General, Nordstrom, Dillard's, Sears, Family Dollar
Specialty Retailers	PetSmart, Best Buy, GameStop, Dick's Sporting Goods, AutoZone, Dollar Tree, Office Max

Appendix A3. A sample task on MTurk to label post valence

Facebook Posts Sentiment

In this HIT, you will read a post made by a user on a company's Facebook page. Please carefully read the post and then choose its overall sentiment as positive, negative, or neutral. If a post has both positive and negative contents, you should choose the sentiment that is most applicable to the post as a whole. Please make your decision solely based on the text listed below.

Here is a post from the Facebook page of **Southwest Airlines**:

" Thanks for singing happy birthday to me on my flight from Ontario to Las Vegas! "

What is the overall sentiment of this post? Please select one of the following options.

- Positive
- Negative
- Neutral

Submit

Appendix A4. A sample task on MTurk to label post content and the corresponding instruction

Instructions of How to Perform the HIT

Below we describe the categories. Please read the descriptions carefully.

- Positive Testimonial and Appreciation: the post includes a positive testimonial or a form of appreciation for the company (e.g., saying how wonderful the company is or how much the user loves it, thanking the company)
- Complaint about Product and Service Quality: the post includes a complaint about product and service quality of the company (e.g., poor quality products or bad services)
- Complaint about Money Issues: the post includes a complaint about money issues with the company (e.g., hefty fees or high prices)
- Other Complaint about the Company: the post includes a complaint about the company but it's NOT about product/service quality or money issues. Instead, for example, it may be a complaint about the company's standing on social or environmental issues such as labor, human rights, social equality, or pollution
- Customer Question: the post includes a question directed at the company (e.g., inquiry about its products)
- Customer Suggestion: the post includes a customer suggestion to the company (e.g., recommendation of new products and service to offer)
- Irrelevant Message: the post has nothing to do with the company on whose page this post appears. It may be user self promotion, promotional links, adult content, etc.
- None of the above: the post doesn't belong to any of the above categories

Facebook Posts Categorization

Below you will see a post from **US Airways's** fan page.

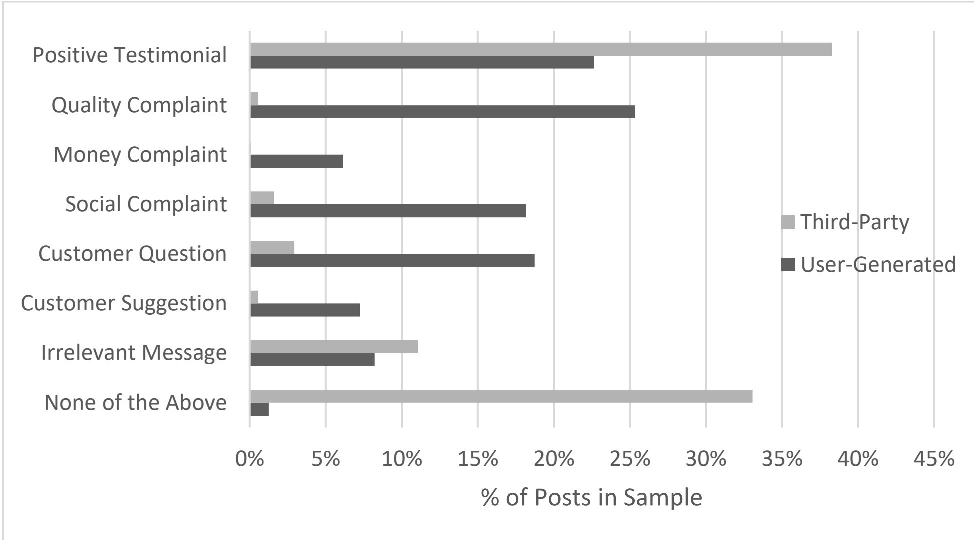
Can I ask a question here?? How many bottles of liquor I can bring into the US from Mexico??

Please read the post carefully and check all categories that apply. If no categories apply, check "none of the above" and enter a new category to describe the post.

- Positive Testimonial and Appreciation
- Complaint about Product and Service Quality
- Complaint about Money Issues
- Other Complaint about the Company
- Customer Question
- Customer Suggestion
- Irrelevant Message that has nothing to do with the Comany
- None of the above (Type your own category here)

Submit

Appendix A5. Content category comparison between user-generated posts and third-party posts



Note. We systematically identified 1,121 third-party posts based on their poster information.

Appendix A6. Variable Definitions and Descriptive Statistics (N = 10,640)

Category		Variables	Mean	Median	SD	Min	Max
Dependent Variables		*Likes*	1.44	0	3.97	0	154
		Comments	1.67	1	3.56	0	81
Independent Variables	**Valence (dummy variables)**	*Positive Valence*	0.26	0	0.44	0	1
		Negative Valence	0.50	0	0.50	0	1
	Content Categories (dummy variables)	*Positive Testimonial*	0.23	0	0.42	0	1
		Quality Complaint	0.25	0	0.44	0	1
		Money Complaint	0.06	0	0.24	0	1
		Social Complaint	0.18	0	0.39	0	1
		Customer Question	0.19	0	0.39	0	1
		Customer Suggestion	0.07	0	0.26	0	1
		Irrelevant Message	0.08	0	0.27	0	1
Control Variables	**Post Linguistic Characteristics**	*Word Count*	44.46	25	66.90	2	1781
		ARI Score	5.03	4.63	4.94	−14.62	47.08
	Poster Characteristic	*User Activeness*	2.79	1	10.12	1	247
	Post Context	*Page Popularity* (in thousands)	19.78	12.48	24.55	1.16	125.86
		Post-Level UGC (in thousands)	0.39	0.079	1.26	0	10.27
		Post-Level MGC	7.98	4	25.18	0	534
		LexisNexis_1	5.58	2	8.71	0	81
	Industry (dummy variables)	*Airline*	0.18	0	0.38	0	1
		Commercial Bank	0.17	0	0.37	0	1
		Consumer Product	0.17	0	0.37	0	1
		Food and Drug Store	0.15	0	0.35	0	1
		General Merchandiser	0.17	0	0.38	0	1
		Specialty Retailer	0.17	0	0.38	0	1
	Media Type (dummy variables)	*Status*	0.94	1	0.24	0	1
		Link	0.02	0	0.15	0	1
		Photo	0.03	0	0.18	0	1
		Video	0.003	0	0.06	0	1
	Assets (in billions)		270	22.10	648	2.33	2129

Appendix A7. Correlations among key variables (N = 10,640)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1.00																		
2	0.28	1.00																	
3	0.02	-0.12	1.00																
4	0.12	0.14	-0.59	1.00															
5	0.01	-0.10	0.84	-0.52	1.00														
6	0.01	0.18	-0.34	0.56	-0.30	1.00													
7	0.01	0.08	-0.15	0.25	-0.14	0.16	1.00												
8	0.21	-0.03	-0.27	0.44	-0.25	-0.21	-0.11	1.00											
9	0.12	0.04	-0.23	-0.21	-0.23	-0.15	-0.07	-0.18	1.00										
10	0.06	-0.02	-0.05	-0.02	-0.09	-0.10	-0.06	0.02	-0.06	1.00									
11	0.03	-0.07	0.03	-0.25	-0.16	-0.17	-0.08	-0.14	-0.14	-0.08	1.00								
12	0.09	0.20	-0.26	0.43	-0.23	0.42	0.24	0.06	-0.05	0.00	-0.21	1.00							
13	0.05	0.05	-0.15	0.20	-0.14	0.14	0.05	0.11	-0.08	0.03	-0.06	0.33	1.00						
14	0.04	0.06	0.02	-0.04	0.01	-0.03	-0.03	-0.02	-0.02	-0.01	0.06	-0.03	0.02	1.00					
15	0.02	0.03	0.02	-0.05	0.00	-0.02	-0.04	-0.04	-0.02	0.03	0.07	-0.09	-0.06	0.00	1.00				
16	0.12	-0.05	-0.08	0.14	-0.08	-0.12	-0.07	0.35	-0.11	0.07	0.00	-0.05	0.02	-0.03	0.60	1.00			
17	0.07	-0.02	0.03	-0.08	0.02	-0.05	-0.02	-0.07	0.04	0.01	0.06	-0.08	-0.04	-0.04	0.28	0.15	1.00		
18	0.00	-0.02	-0.10	0.15	-0.09	0.11	0.13	0.03	-0.05	-0.02	-0.04	0.06	0.03	0.00	0.12	0.05	0.02	1.00	
19	0.10	-0.03	-0.13	0.19	-0.10	0.20	0.18	-0.05	-0.03	-0.02	-0.11	0.10	0.02	-0.02	-0.01	-0.16	0.01	0.62	1.00

Note. 1. Number of Likes; 2. Number of Comments; 3. Positive Valence; 4. Negative Valence; 5. Positive Testimonial; 6. Quality Complaint; 7. Money Complaint; 8. Social Complaint; 9. Customer Question; 10. Customer Suggestion; 11. Irrelevant Message; 12. Log(Word Count); 13. ARI Score; 14. User Activeness; 15. Log(Page Popularity); 16. Log(Post-Level UGC); 17. Log(Post-Level MGC); 18. LexisNexis_1; 19. Log(Assets).

Appendix A8. Regression results using conditional fixed effects negative binomial models

	Likes	Likes	Comments	Comments
Constant	1.6010***	1.6232***	1.6344***	1.6690***
	(0.4361)	(0.4439)	(0.4830)	(0.4838)
Industry = Airlines	-0.4375***	-0.3022**	-0.1237	-0.1642
	(0.1066)	(0.1094)	(0.0953)	(0.0956)
Industry = Commercial Banks	-0.7859**	-1.0306***	-1.0693***	-0.7806**
	(0.2675)	(0.2768)	(0.2454)	(0.2456)
Industry = Consumer Products	-0.2515*	-0.4240***	-1.0309***	-0.9134***
	(0.1232)	(0.1266)	(0.1243)	(0.1247)
Industry = Food and Drug Stores	-0.8078***	-0.8729***	-0.1081	-0.0592
	(0.1209)	(0.1232)	(0.1119)	(0.1119)
Industry = General Merchandisers	-0.3563***	-0.4178***	0.3291***	0.3270***
	(0.1049)	(0.1063)	(0.0963)	(0.0962)
Type = link	-0.3466**	-0.4629***	-1.0357***	-0.6745***
	(0.1170)	(0.1171)	(0.1318)	(0.1319)
Type = photo	0.9659***	0.9736***	0.0419	0.3232***
	(0.0673)	(0.0694)	(0.0782)	(0.0792)
Type = video	0.2291	0.1388	-1.0616**	-0.6475
	(0.2377)	(0.2349)	(0.3528)	(0.3544)
Log(Asset)	-0.0395	0.0097	0.0695	0.0150
	(0.0399)	(0.0414)	(0.0364)	(0.0364)
Log(Word Count)	0.0982***	0.1448***	0.2602***	0.2235***
	(0.0152)	(0.0153)	(0.0129)	(0.0137)
ARI Score	0.0107***	0.0083**	-0.0080**	-0.0047
	(0.0030)	(0.0030)	(0.0029)	(0.0029)
Log(Page Popularity)	-0.3761***	-0.3631***	-0.2441***	-0.2178***
	(0.0572)	(0.0589)	(0.0639)	(0.0636)
Log(Post-Level UGC)	0.2195***	0.1366***	-0.2408***	-0.1905***
	(0.0127)	(0.0133)	(0.0147)	(0.0155)
Log(Post-Level MGC)	-0.1134***	-0.0865***	0.0811***	0.0687***
	(0.0228)	(0.0225)	(0.0168)	(0.0169)
LexisNexis_1	0.0132***	0.0112***	0.0005	0.0022
	(0.0023)	(0.0023)	(0.0023)	(0.0022)
User Activeness	0.0042***	0.0027**	0.0023*	0.0030**
	(0.0010)	(0.0010)	(0.0011)	(0.0010)
Positive Valence	0.5385***		-0.3539***	
	(0.0490)		(0.0378)	
Negative Valence	0.7733***		0.0490	
	(0.0473)		(0.0337)	
Positive Testimonial		0.2452***		-0.2098***
		(0.0509)		(0.0429)
Quality Complaint		0.0984*		0.2715***
		(0.0469)		(0.0365)
Money Complaint		0.1264		0.1300**
		(0.0667)		(0.0467)
Social Complaint		0.9280***		-0.2088***
		(0.0500)		(0.0518)
Customer Question		-0.5437***		0.3614***
		(0.0572)		(0.0358)
Customer Suggestion		0.2895***		-0.0543
		(0.0538)		(0.0538)
Irrelevant Message		-0.0208		-0.8209***
		(0.0747)		(0.0794)
Number of Observations	10640	10640	10640	10640

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A9. Regression results incorporating 32 user posts with tags of the businesses and 8 user posts that have been shared

	Likes	Likes	Comments	Comments
Constant	1.1170**	1.1074**	0.6274	0.6633
	(0.3984)	(0.4039)	(0.4639)	(0.4607)
Industry = Airlines	-0.2803**	-0.1320	-0.0492	-0.0911
	(0.0980)	(0.1000)	(0.0922)	(0.0922)
Industry = Commercial Banks	-0.5706*	-0.7524**	-0.7461**	-0.4693*
	(0.2384)	(0.2439)	(0.2321)	(0.2302)
Industry = Consumer Products	-0.1164	-0.2783*	-0.8473***	-0.7273***
	(0.1102)	(0.1125)	(0.1186)	(0.1181)
Industry = Food and Drug Stores	-0.6197***	-0.6621***	-0.0028	0.0421
	(0.1105)	(0.1118)	(0.1067)	(0.1060)
Industry = General Merchandisers	-0.2230*	-0.2711**	0.2584**	0.2547**
	(0.0967)	(0.0978)	(0.0922)	(0.0918)
Type = link	-0.3447**	-0.4569***	-1.0270***	-0.6588***
	(0.1131)	(0.1135)	(0.1276)	(0.1278)
Type = photo	1.0021***	1.0070***	0.0692	0.3457***
	(0.0658)	(0.0679)	(0.0762)	(0.0771)
Type = video	0.3836	0.2812	-1.1752***	-0.7475*
	(0.2171)	(0.2152)	(0.3531)	(0.3546)
Log(Asset)	-0.0515	-0.0110	0.0410	-0.0116
	(0.0365)	(0.0373)	(0.0346)	(0.0345)
Log(Word Count)	0.1004***	0.1462***	0.2609***	0.2241***
	(0.0152)	(0.0153)	(0.0129)	(0.0137)
ARI Score	0.0101***	0.0078**	-0.0080**	-0.0049
	(0.0030)	(0.0030)	(0.0029)	(0.0029)
Log(Page Popularity)	-0.3262***	-0.3040***	-0.1157	-0.0915
	(0.0513)	(0.0525)	(0.0609)	(0.0599)
Log(Post-Level UGC)	0.2115***	0.1285***	-0.2444***	-0.1931***
	(0.0127)	(0.0132)	(0.0147)	(0.0155)
Log(Post-Level MGC)	-0.1073***	-0.0799***	0.0825***	0.0703***
	(0.0227)	(0.0223)	(0.0167)	(0.0168)
LexisNexis_1	0.0134***	0.0116***	-0.0003	0.0015
	(0.0023)	(0.0023)	(0.0023)	(0.0022)
User Activeness	0.0042***	0.0027**	0.0023*	0.0031**
	(0.0010)	(0.0010)	(0.0011)	(0.0010)
Positive Valence	0.5322***		-0.3483***	
	(0.0488)		(0.0378)	
Negative Valence	0.7687***		0.0540	
	(0.0473)		(0.0337)	
Positive Testimonial		0.2499***		-0.2065***
		(0.0509)		(0.0429)
Quality Complaint		0.1132*		0.2751***
		(0.0470)		(0.0365)
Money Complaint		0.1318*		0.1310**
		(0.0667)		(0.0468)
Social Complaint		0.9262***		-0.2105***
		(0.0502)		(0.0518)
Customer Question		-0.5309***		0.3647***
		(0.0571)		(0.0357)
Customer Suggestion		0.2953***		-0.0519
		(0.0540)		(0.0538)
Irrelevant Message		0.0046		-0.8176***
		(0.0740)		(0.0787)
Number of Observations	10680	10680	10680	10680

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A10. Example Customer Question and Customer Suggestion Posts with Different Valence

Content Categories	**Valence**	**Example Posts**
Customer Question	Positive	*I just saw that Campbells has a mobile truck in St.Louis! I wonder what they serve?? Soup only? I bet that truck would do great here in Vegas.* [Campbell's Soup]
	Negative	*I didn't receive my coupon :(what happened?* [Target]
	Neutral	*What are the movies this time? Anyone know yet?* [Best Buy]
Customer Suggestion	Positive	*I think u should add one more layer to the kit kat but make that peanut butter! I eat kit kats with P.B. OMG they are the best so how about adding one pb layer?* [Hershey's]
	Negative	*Remove Unsafe GMOs from your products!* [Kellogg's]
	Neutral	*Please create a Windows Phone app.* [Ally Bank]

Appendix A11: Complete Main Regression Results on Likes

	Model 1	Model 2	Model 3	Model 4	Model 5a	Model 5b
Constant	0.13	-0.41	1.80***	1.75***	1.40***	1.43***
	(0.25)	(0.26)	(0.40)	(0.40)	(0.40)	(0.41)
Industry = Airlines	-0.23*	-0.27**	-0.34***	-0.35***	-0.39***	-0.25*
	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
Industry = Commercial Banks	-0.07	-0.12	-0.74**	-0.70**	-0.75**	-0.96***
	(0.18)	(0.18)	(0.24)	(0.24)	(0.25)	(0.25)
Industry = Consumer Products	0.06	0.05	-0.21	-0.20	-0.23*	-0.40***
	(0.09)	(0.09)	(0.11)	(0.11)	(0.11)	(0.12)
Industry = Food and Drug Stores	-0.67**	-0.69***	-0.72***	-0.72***	-0.74***	-0.80***
	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)	(0.12)
Industry = General Merchandisers	-0.31**	-0.26**	-0.26**	-0.26**	-0.32**	-0.37***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Type = link	-0.55**	-0.54***	-0.48***	-0.49***	-0.34**	-0.46***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Type = photo	0.75***	0.84***	0.88***	0.86***	0.97***	0.98***
	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Type = video	-0.12	0.01	0.13	0.10	0.24	0.15
	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
Log(Asset)	-0.09**	-0.09**	-0.02	-0.02	-0.04	0.005
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Log(Word Count)		0.16***	0.17***	0.17***	0.10***	0.15***
		(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
ARI Score		0.01***	0.01***	0.01***	0.01***	0.01**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(Page Popularity)			-0.41***	-0.40***	-0.36***	-0.34***
			(0.05)	(0.05)	(0.05)	(0.05)
Log(Post-Level UGC)			0.26***	0.26***	0.22***	0.14***
			(0.01)	(0.01)	(0.01)	(0.01)
Log(Post-Level MGC)			-0.14***	-0.14***	-0.12***	-0.09***
			(0.02)	(0.02)	(0.02)	(0.02)
LexisNexis_1			0.01***	0.01***	0.01***	0.01***
			(0.00)	(0.00)	(0.00)	(0.00)
User Activeness				0.004***	0.004***	0.003**
				(0.00)	(0.00)	(0.00)
Positive Valence					0.54***	
					(0.05)	
Negative Valence					0.78***	
					(0.05)	
Positive Testimonial						0.25***
						(0.05)
Quality Complaint						0.10*
						(0.05)
Money Complaint						0.13
						(0.07)
Social Complaint						0.93***
						(0.05)
Customer Question						-0.54***
						(0.06)
Customer Suggestion						0.29***
						(0.05)
Irrelevant Message						-0.02
						(0.07)
Deviance	30250.22	30049.36	29540.22	29527.9	29225.58	28836.58
ΔDeviance		200.86***	509.14***	12.32***	302.32***	691.32***
AIC	30274.22	30077.37	29576.22	29565.91	29267.58	28888.58
BIC	30361.49	30179.18	29707.12	29704.08	29420.30	29077.66

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A12: Complete Main Regression Results on Likes

	Model 1	Model 2	Model 3	Model 4	Model 5a	Model 5b
Constant	-0.04	-0.77**	0.54	0.50	0.72	0.75
	(0.23)	(0.23)	(0.46)	(0.46)	(0.47)	(0.46)
Industry = Airlines	0.15	0.10	-0.12	-0.12	-0.06	-0.10
	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
Industry = Commercial Banks	0.29*	0.32*	-0.88***	-0.86***	-0.77**	-0.50*
	(0.14)	(0.14)	(0.23)	(0.23)	(0.23)	(0.23)
Industry = Consumer Products	-0.49***	-0.45***	-0.92***	-0.91***	-0.86***	-0.74***
	(0.08)	(0.08)	(0.12)	(0.12)	(0.12)	(0.12)
Industry = Food and Drug Stores	0.25**	0.29***	-0.10	-0.10	-0.01	0.03
	(0.09)	(0.09)	(0.11)	(0.11)	(0.11)	(0.11)
Industry = General Merchandisers	-0.05	0.16	0.19*	0.19*	0.26**	0.25**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Type = link	-1.09***	-0.97***	-1.00***	-1.01***	-1.03***	-0.67***
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Type = photo	-0.28***	-0.05	-0.01	-0.02	0.04	0.32***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Type = video	-1.24***	-1.04**	-1.01**	-1.03**	-1.07**	-0.66
	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)
Log(Asset)	-0.05	-0.07**	0.07*	0.07	0.04	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Log(Word Count)		0.31***	0.29***	0.30***	0.26***	0.22***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ARI Score		-0.01**	-0.01*	-0.01*	-0.01**	-0.005
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(Page Popularity)			-0.16**	-0.15*	-0.13*	-0.10
			(0.06)	(0.06)	(0.06)	(0.06)
Log(Post-Level UGC)			-0.22***	-0.22***	-0.24***	-0.19***
			(0.01)	(0.01)	(0.01)	(0.02)
Log(Post-Level MGC)			0.08***	0.08***	0.08***	0.07***
			(0.02)	(0.02)	(0.02)	(0.02)
LexisNexis_1			0.0002	0.0001	-0.0002	0.002
			(0.00)	(0.00)	(0.00)	(0.00)
User Activeness				0.002*	0.002*	0.003**
				(0.00)	(0.00)	(0.00)
Positive Valence					-0.35***	
					(0.04)	
Negative Valence					0.05	
					(0.03)	
Positive Testimonial						-0.21***
						(0.04)
Quality Complaint						0.27***
						(0.04)
Money Complaint						0.13**
						(0.05)
Social Complaint						-0.21***
						(0.05)
Customer Question						0.36***
						(0.04)
Customer Suggestion						-0.05
						(0.05)
Irrelevant Message						-0.82***
						(0.08)
Deviance	34654.76	33996.5	33655.74	33651.78	33503.26	33121.1
ΔDeviance		658.26***	340.76***	3.96*	148.52***	530.68***
AIC	34678.75	34024.50	33691.75	33689.78	33545.25	33173.11
BIC	34766.02	34126.31	33822.65	33827.95	33679.97	33362.19

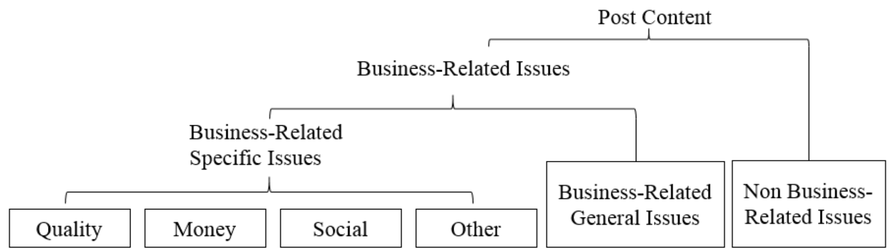
Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A13. Analyses of Engagement with an Alternative Content Coding Scheme

We repeated our main empirical analyses with an alternative coding scheme, under which the valence and content of user posts are treated as *orthogonal* dimensions. We considered 4 types of post valence as *positive*, *negative*, *neutral*, or *unclear*. Having an "unclear" valence means the valence of a post is ambiguous and cannot be determined (different from neutral valence). We considered 6 types of post content, based on whether the post is related to the focal business or not, and if so, whether the post is related to the *quality* of products and services, *money* issues, *social* issues, *other* specific business-related issues, or *general* business-related issues. The difference between the "*other*" content type and the "*general*" content type is that the former talks about specific aspects of the business that are not about quality, money, or social issues (e.g., "I want a job at Target"), whereas the latter talks about general aspects of the business without mentioning any specificity (e.g., "Macy's is a good place to shop"). Table A13.1 shows the alternative coding scheme. Two research assistants helped code the valence and content of the posts as two *orthogonal* dimensions, giving rise to 4 (valence) × 6 (content), or 24, possible valence/content categories. Because a post may occasionally contain multiple different valence/content expressions (e.g., a post may talk positively about quality and negatively about money), we allowed each post to be coded in more than 1 of the 24 valence/content categories, and only less than 6% of posts had multiple labels. In addition, the research assistants also coded whether each post contained any *question* or *suggestion* toward the business, *independently* of post valence and content. Inter-rater reliability between the two research assistants was reasonably high on all major categories (Cohen's kappa between 0.6 and 0.8).

Analyses of the new coding revealed similar distributions of valence and content categories as what we reported in Section 4.1. About 52% of the posts are negative, 21% are positive, and 19% are neutral. Second, posts coded as both negative and quality-related are most prevalent in Airlines (36%) and Commercial Banks (33%), and least prevalent in Consumer Products companies (9%). In comparison, posts coded as both negative and social-related are most prevalent in Consumer Products companies (42%) but least prevalent in Airlines (6%). Overall, descriptive patterns based on the new coding were consistent with earlier findings based on the content coding from the grounded-theory approach.

Table A13.1. Alternative Content Coding Scheme

<table>
<tr><th colspan="2">Orthogonal Dimensions</th><th>Coding Categories</th></tr>
<tr><td rowspan="2">Valence × Content Categories</td><td>Valence</td><td>Positive; Negative; Neutral; Unclear.</td></tr>
<tr><td>Content (actual categories are represented in boxes)</td><td>
</td></tr>
<tr><td colspan="2">Question</td><td>The post contains question toward the focal business: Yes or No</td></tr>
<tr><td colspan="2">Suggestion</td><td>The post contains suggestion toward the focal business: Yes or No</td></tr>
</table>

Next, we estimated a series of random effects negative binomial models to understand the impact of post valence and content, and the interaction of the two, on likes and comments respectively. The same set of control variables were included in these regressions. Tables A13.2 and A13.3 summarize the results. Note that we omitted coefficient estimates on all control variables for the sake of brevity.

Results in Tables A13.2 and A13.3 are qualitatively consistent with our main results.[1] According to Model 1 in both tables, compared to neutral posts, positive posts received more likes but fewer comments, and negative posts received both more likes and more comments. Furthermore, negative posts received both more likes and more comments than positive posts. Based on Model 2 and 3, under two different choices of comparison groups, posts about *social* issues received more likes but fewer comments than posts about *quality* or *money* issues. Moreover, as Model 4 indicated, negative posts about social issues (corresponding to *social complaints* in previous coding) received more likes but fewer comments than negative posts about quality and money issues (corresponding to *quality/money complaints* in previous coding). Finally, Model 5 showed that *questions* received fewer likes but more comments, whereas *suggestions* received more likes, than posts that did not contain questions and suggestions.

[1] Note that the estimated coefficients in Tables A13.2 and A13.3 are different from those in the main paper. This is because of the change in base comparison groups.

Table A13.2. Random Effects Negative Binomial Regression – Impact on the Number of Likes

	Model 1	Model 2	Model 3	Model 4	Model 5
Positive Valence	0.47*** (0.05)				
Negative Valence	0.64*** (0.05)				
Quality		−0.35*** (0.05)	−0.23*** (0.05)		
Money		−0.25*** (0.06)	−0.15*** (0.05)		
Social		0.70*** (0.06)	0.87*** (0.06)		
Other		−0.08 (0.07)			
Negative Quality				−0.32*** (0.05)	
Negative Money				−0.22*** (0.06)	
Negative Social				0.89*** (0.06)	
Negative Other				0.60*** (0.09)	
Question					−0.76*** (0.06)
Suggestion					0.26*** (0.04)
N	9,550	9,619	8,628	6,667	10,640
Sample Composition	Removed posts with unclear valence	Removed non business-related posts	Removed non business-related and general business-related posts	Removed non business-related and general business-related posts. Removed neutral and unclear posts	All posts
Base Comparison Group	Neutral posts	General business-related posts	*Other* business-specific posts	*Positive* posts related to *quality*, *money*, *social*, and *other* issues	Posts that do not contain *question* and *suggestion*

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Table A13.3. Random Effects Negative Binomial Regression – Impact on the Number of Comments

	Model 1	Model 2	Model 3	Model 4	Model 5
Positive Valence	−0.12***				
	(0.04)				
Negative Valence	0.24***				
	(0.04)				
Quality		0.21***	0.15***		
		(0.04)	(0.04)		
Money		0.20***	0.15***		
		(0.04)	(0.04)		
Social		−0.22***	−0.29***		
		(0.06)	(0.06)		
Other		−0.0002			
		(0.06)			
Negative Quality				0.35***	
				(0.04)	
Negative Money				0.28***	
				(0.04)	
Negative Social				−0.23***	
				(0.07)	
Negative Other				0.26***	
				(0.09)	
Question					0.45***
					(0.03)
Suggestion					−0.06
					(0.04)
N	9,550	9,619	8,628	6,667	10,640
Sample Composition	Removed posts with unclear valence	Removed non business-related posts	Removed non business-related and general business-related posts	Removed non business-related and general business-related posts. Removed neutral and unclear posts	All posts
Base Comparison Group	Neutral posts	General business-related posts	*Other* business-specific posts	*Positive* posts related to *quality*, *money*, *social*, and *other* issues	Posts that do not contain *question* and *suggestion*

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A14. Robustness Checks

We ran several robustness checks with alternative operationalizations of our variables. First, we tried an alternative measure of *user activeness*, by calculating the number of posts a user made on a business page within the 3 months before the focal post. Because we only had data for 2012 and this new user activeness measure was not available for posts posted in January through March, we included posts that were posted between April and December. The vast majority of our findings were qualitatively the same, except for the significance of *quality complaint* (Appendix A14.1). Second, we considered several alternative measures of *post context*. We repeated the analyses by measuring page popularity as the total number of user-generated and marketer-generated posts within the 3 months prior to the focal post. All of our main results were qualitatively the same (Appendix A14.2). We also repeated our analyses by measuring *post-level UGC* and *post-level MGC* as the number of user-generated and marketer-generated posts only 24 hours before a focal post. The rationale is that including the number of posts posted after a focal post may cause simultaneity bias, because earlier posts may affect subsequent number of posts. With the new measure, our results were qualitatively the same (Appendix A14.3). Finally, we also repeated our analyses by changing the time window for the *general interest* variable from 1 day (*LexisNexis_1*) to 1 week or 2 weeks (*LexisNexis_7* or *LexisNexis_14*). All main results remained qualitatively the same (Appendix A14.4).

To further check the robustness of our findings, we estimated an alternative model specification where the dependent variable is binary, showing whether a post had received *any* likes or comments. This helped us address the concern that, if Facebook were to artificially boost the visibility of certain posts that had already received some likes or comments, these posts might gain even more engagement simply due to increased visibility. Such concern can be alleviated if we only study whether a post received any likes or comments, instead of the number of likes and comments. We estimated random effects logistic regressions, and our main findings were qualitatively the same (Appendix A14.5). Finally, note that we included posts with videos in our main analyses, but our major findings stayed unchanged after dropping 37 posts with videos (see Appendix A14.6).

Appendix A14.1. Regression results using an alternative measure of *user activeness*, i.e., the number of posts from a user on a specific business page within the time window of 3 months before the focal post. Posts between January and March are dropped.

	Likes	Likes	Comments	Comments
Constant	1.6882***	1.6723***	0.2985	0.5467
	(0.4454)	(0.4511)	(0.5087)	(0.5100)
Industry = Airlines	-0.4421***	-0.2826*	0.0183	-0.0168
	(0.1113)	(0.1137)	(0.1043)	(0.1045)
Industry = Commercial Banks	-0.6525*	-0.8814**	-0.5076	-0.2738
	(0.2767)	(0.2842)	(0.2606)	(0.2597)
Industry = Consumer Products	-0.0588	-0.2311	-0.8605***	-0.7385***
	(0.1239)	(0.1267)	(0.1285)	(0.1288)
Industry = Food and Drug Stores	-0.7705***	-0.8290***	0.0233	0.0680
	(0.1258)	(0.1275)	(0.1176)	(0.1173)
Industry = General Merchandisers	-0.3051**	-0.3502**	0.2109*	0.2288*
	(0.1084)	(0.1095)	(0.1029)	(0.1029)
Type = link	-0.3116*	-0.4189***	-1.0900***	-0.7298***
	(0.1233)	(0.1230)	(0.1470)	(0.1471)
Type = photo	0.8164***	0.8273***	0.1036	0.3443***
	(0.0766)	(0.0782)	(0.0877)	(0.0884)
Type = video	0.1782	0.0399	-0.8043*	-0.4324
	(0.2921)	(0.2854)	(0.3768)	(0.3785)
Log(Asset)	-0.0728	-0.0191	-0.0003	-0.0538
	(0.0430)	(0.0442)	(0.0398)	(0.0399)
Log(Word Count)	0.1125***	0.1594***	0.2827***	0.2393***
	(0.0168)	(0.0168)	(0.0149)	(0.0159)
ARI Score	0.0096**	0.0070*	-0.0088**	-0.0047
	(0.0033)	(0.0033)	(0.0033)	(0.0032)
Log(Page Popularity)	-0.3348***	-0.3274***	-0.0524	-0.0520
	(0.0590)	(0.0603)	(0.0672)	(0.0666)
Log(Post-Level UGC)	0.1867***	0.1046***	-0.2571***	-0.2015***
	(0.0135)	(0.0140)	(0.0163)	(0.0171)
Log(Post-Level MGC)	-0.1362***	-0.0863*	0.1735***	0.1435***
	(0.0362)	(0.0359)	(0.0341)	(0.0341)
LexisNexis_1	0.0141***	0.0121***	-0.0026	-0.0007
	(0.0024)	(0.0024)	(0.0025)	(0.0025)
User Activeness	0.0106***	0.0072**	0.0045	0.0047
	(0.0024)	(0.0024)	(0.0033)	(0.0032)
Positive Valence	0.5153***		-0.3762***	
	(0.0556)		(0.0435)	
Negative Valence	0.7566***		0.0053	
	(0.0528)		(0.0387)	
Positive Testimonial		0.2144***		-0.1786***
		(0.0562)		(0.0493)
Quality Complaint		0.0735		0.2801***
		(0.0507)		(0.0418)
Money Complaint		0.0625		0.1724**
		(0.0752)		(0.0529)
Social Complaint		0.8967***		-0.2288***
		(0.0539)		(0.0581)
Customer Question		-0.5498***		0.3988***
		(0.0631)		(0.0411)
Customer Suggestion		0.3064***		-0.0338
		(0.0580)		(0.0632)
Irrelevant Message		-0.0526		-0.7969***
		(0.0851)		(0.0936)
Number of Observations	8221	8221	8221	8221

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A14.2. Regression results using an alternative measure of *page popularity*, i.e., the total number of user- and company-generated posts within the time window of 3 months prior to the focal post. Posts between January and March are dropped.

	Likes	Likes	Comments	Comments
Constant	-0.1431	-0.0427	0.0153	0.1911
	(0.3435)	(0.3461)	(0.3374)	(0.3402)
Industry = Airlines	-0.2860**	-0.1179	0.0406	0.0106
	(0.1075)	(0.1091)	(0.0981)	(0.0983)
Industry = Commercial Banks	0.4163	0.1498	-0.3854	-0.1096
	(0.2286)	(0.2307)	(0.1999)	(0.2018)
Industry = Consumer Products	0.3549**	0.1633	-0.8043***	-0.6637***
	(0.1095)	(0.1116)	(0.1048)	(0.1067)
Industry = Food and Drug Stores	-0.4917***	-0.5524***	0.0596	0.1147
	(0.1163)	(0.1167)	(0.1056)	(0.1058)
Industry = General Merchandisers	-0.3007**	-0.3299**	0.2071*	0.2223*
	(0.1094)	(0.1098)	(0.1022)	(0.1020)
Type = link	-0.3036*	-0.4076***	-1.0891***	-0.7260***
	(0.1232)	(0.1230)	(0.1470)	(0.1471)
Type = photo	0.8078***	0.8206***	0.1033	0.3437***
	(0.0760)	(0.0776)	(0.0872)	(0.0879)
Type = video	0.1287	0.0111	-0.8061*	-0.4376
	(0.2921)	(0.2850)	(0.3767)	(0.3784)
Log(Asset)	-0.2219***	-0.1626***	-0.0148	-0.0741*
	(0.0376)	(0.0380)	(0.0345)	(0.0349)
Log(Word Count)	0.1124***	0.1605***	0.2834***	0.2400***
	(0.0168)	(0.0169)	(0.0150)	(0.0159)
ARI Score	0.0094**	0.0067*	-0.0090**	-0.0049
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
Log(Page Popularity)	0.0077	-0.0063	-0.0114	0.0062
	(0.0370)	(0.0365)	(0.0408)	(0.0407)
Log(Post-Level UGC)	0.1641***	0.0853***	-0.2590***	-0.2069***
	(0.0140)	(0.0143)	(0.0175)	(0.0182)
Log(Post-Level MGC)	-0.1635***	-0.1130**	0.1716***	0.1412***
	(0.0359)	(0.0355)	(0.0340)	(0.0340)
LexisNexis_1	0.0131***	0.0113***	-0.0028	-0.0009
	(0.0024)	(0.0025)	(0.0025)	(0.0024)
User Activeness	0.0046***	0.0032**	0.0019	0.0023
	(0.0010)	(0.0010)	(0.0012)	(0.0012)
Positive Valence	0.5072***		-0.3772***	
	(0.0555)		(0.0435)	
Negative Valence	0.7682***		0.0065	
	(0.0527)		(0.0387)	
Positive Testimonial		0.1998***		-0.1796***
		(0.0560)		(0.0493)
Quality Complaint		0.0745		0.2806***
		(0.0504)		(0.0418)
Money Complaint		0.0644		0.1722**
		(0.0753)		(0.0530)
Social Complaint		0.9008***		-0.2263***
		(0.0536)		(0.0580)
Customer Question		-0.5516***		0.3988***
		(0.0630)		(0.0411)
Customer Suggestion		0.3105***		-0.0319
		(0.0578)		(0.0631)
Irrelevant Message		-0.0782		-0.8026***
		(0.0845)		(0.0935)
Number of Observations	8221	8221	8221	8221

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A14.3. Regression results using alternative measures for *post-level UGC* and *post-level MGC*, i.e., the number of user- and company-generated posts only 24 hours before a focal post, respectively.

	Likes	Likes	Comments	Comments
Constant	1.4828***	1.4965***	0.8385	0.8887
	(0.4042)	(0.4115)	(0.4678)	(0.4648)
Industry = Airlines	-0.4100***	-0.2603*	-0.0797	-0.1183
	(0.1012)	(0.1036)	(0.0926)	(0.0925)
Industry = Commercial Banks	-0.7714**	-0.9797***	-0.8007***	-0.5126*
	(0.2451)	(0.2519)	(0.2338)	(0.2317)
Industry = Consumer Products	-0.2474*	-0.4160***	-0.8966***	-0.7606***
	(0.1147)	(0.1176)	(0.1199)	(0.1194)
Industry = Food and Drug Stores	-0.7685***	-0.8148***	-0.0251	0.0271
	(0.1144)	(0.1161)	(0.1073)	(0.1067)
Industry = General Merchandisers	-0.3394***	-0.3881***	0.2649**	0.2633**
	(0.0996)	(0.1008)	(0.0925)	(0.0920)
Type = link	-0.3460**	-0.4665***	-1.0353***	-0.6694***
	(0.1172)	(0.1173)	(0.1318)	(0.1319)
Type = photo	0.9687***	0.9752***	0.0343	0.3250***
	(0.0670)	(0.0692)	(0.0784)	(0.0794)
Type = video	0.2109	0.1291	-1.0586**	-0.6356
	(0.2374)	(0.2349)	(0.3529)	(0.3544)
Log(Asset)	-0.0385	0.0064	0.0492	-0.0056
	(0.0372)	(0.0382)	(0.0348)	(0.0346)
Log(Word Count)	0.0987***	0.1462***	0.2655***	0.2269***
	(0.0152)	(0.0153)	(0.0129)	(0.0137)
ARI Score	0.0105***	0.0081**	-0.0082**	-0.0048
	(0.0030)	(0.0030)	(0.0029)	(0.0029)
Log(Page Popularity)	-0.3610***	-0.3480***	-0.1685**	-0.1414*
	(0.0522)	(0.0536)	(0.0609)	(0.0600)
Log(Post-Level UGC)	0.2237***	0.1420***	-0.2124***	-0.1605***
	(0.0124)	(0.0129)	(0.0143)	(0.0151)
Log(Post-Level MGC)	-0.0918***	-0.0742**	0.0644***	0.0530**
	(0.0229)	(0.0228)	(0.0179)	(0.0179)
LexisNexis_1	0.0125***	0.0108***	-0.0006	0.0013
	(0.0023)	(0.0023)	(0.0023)	(0.0022)
User Activeness	0.0040***	0.0025**	0.0026*	0.0033**
	(0.0009)	(0.0009)	(0.0011)	(0.0010)
Positive Valence	0.5498***		-0.3547***	
	(0.0490)		(0.0379)	
Negative Valence	0.7844***		0.0341	
	(0.0473)		(0.0337)	
Positive Testimonial		0.2489***		-0.2061***
		(0.0508)		(0.0430)
Quality Complaint		0.1000*		0.2714***
		(0.0469)		(0.0366)
Money Complaint		0.1304		0.1280**
		(0.0666)		(0.0468)
Social Complaint		0.9353***		-0.2500***
		(0.0499)		(0.0520)
Customer Question		-0.5461***		0.3673***
		(0.0571)		(0.0358)
Customer Suggestion		0.2884***		-0.0611
		(0.0538)		(0.0539)
Irrelevant Message		-0.0144		-0.8263***
		(0.0745)		(0.0795)
Number of Observations	10640	10640	10640	10640

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A14.4. Regression results using two alternative measures, *LexisNexis_7* or *LexisNexis_14,* for *LexisNexis_1*.

	Likes	Likes	Comments	Comments	Likes	Likes	Comments	Comments
Constant	1.7930*** (0.4265)	1.7108*** (0.4341)	0.2905 (0.4838)	0.3948 (0.4815)	1.5631*** (0.4392)	1.4595** (0.4465)	0.0186 (0.4935)	0.1211 (0.4911)
Industry = Airlines	-0.4160*** (0.1015)	-0.2688** (0.1038)	-0.0236 (0.0929)	-0.0691 (0.0930)	-0.4032*** (0.1017)	-0.2551* (0.1042)	-0.0056 (0.0931)	-0.0492 (0.0932)
Industry = Commercial Banks	-0.8071*** (0.2450)	-1.0078*** (0.2519)	-0.7097** (0.2327)	-0.4489 (0.2311)	-0.7854** (0.2457)	-0.9865*** (0.2528)	-0.6738** (0.2322)	-0.4136 (0.2307)
Industry = Consumer Products	-0.2527* (0.1149)	-0.4218*** (0.1177)	-0.8258*** (0.1191)	-0.7158*** (0.1188)	-0.2477* (0.1150)	-0.4175*** (0.1178)	-0.8054*** (0.1188)	-0.6953*** (0.1185)
Industry = Food and Drug Stores	-0.7143*** (0.1147)	-0.7811*** (0.1166)	-0.0268 (0.1068)	0.0182 (0.1063)	-0.7361*** (0.1152)	-0.8052*** (0.1171)	-0.0388 (0.1066)	0.0057 (0.1061)
Industry = General Merchandisers	-0.2988** (0.0996)	-0.3610*** (0.1009)	0.2344* (0.0922)	0.2363* (0.0919)	-0.3152** (0.0998)	-0.3782*** (0.1011)	0.2204* (0.0921)	0.2227* (0.0918)
Type = link	-0.3427** (0.1168)	-0.4626*** (0.1170)	-1.0305*** (0.1317)	-0.6697*** (0.1318)	-0.3412** (0.1169)	-0.4625*** (0.1171)	-1.0300*** (0.1317)	-0.6688*** (0.1318)
Type = photo	0.9761*** (0.0672)	0.9805*** (0.0693)	0.0348 (0.0782)	0.3197*** (0.0791)	0.9732*** (0.0672)	0.9792*** (0.0693)	0.0362 (0.0782)	0.3210*** (0.0792)
Type = video	0.2367 (0.2379)	0.1411 (0.2352)	-1.0713** (0.3527)	-0.6579 (0.3544)	0.2375 (0.2379)	0.1410 (0.2351)	-1.0715** (0.3527)	-0.6573 (0.3544)
Log(Asset)	-0.0586 (0.0378)	-0.0078 (0.0389)	0.0582 (0.0352)	0.0044 (0.0350)	-0.0442 (0.0383)	0.0080 (0.0394)	0.0685 (0.0354)	0.0150 (0.0353)
Log(Word Count)	0.0997*** (0.0152)	0.1467*** (0.0153)	0.2610*** (0.0129)	0.2245*** (0.0137)	0.0995*** (0.0152)	0.1468*** (0.0153)	0.2608*** (0.0129)	0.2244*** (0.0137)
ARI Score	0.0101*** (0.0030)	0.0078** (0.0030)	-0.0082** (0.0029)	-0.0050 (0.0029)	0.0102*** (0.0030)	0.0078** (0.0030)	-0.0081** (0.0029)	-0.0049 (0.0029)
Log(Page Popularity)	-0.3861*** (0.0531)	-0.3631*** (0.0545)	-0.0948 (0.0615)	-0.0768 (0.0607)	-0.3742*** (0.0534)	-0.3499*** (0.0549)	-0.0750 (0.0616)	-0.0571 (0.0608)
Log(Post-Level UGC)	0.2238*** (0.0126)	0.1404*** (0.0132)	-0.2423*** (0.0147)	-0.1916*** (0.0155)	0.2240*** (0.0127)	0.1397*** (0.0132)	-0.2425*** (0.0147)	-0.1919*** (0.0155)
Log(Post-Level MGC)	-0.1134*** (0.0228)	-0.0862*** (0.0224)	0.0811*** (0.0167)	0.0693*** (0.0168)	-0.1139*** (0.0228)	-0.0867*** (0.0225)	0.0809*** (0.0167)	0.0692*** (0.0168)
LexisNexis_7	0.0059*** (0.0011)	0.0046*** (0.0011)	-0.0024* (0.0010)	-0.0016 (0.0010)				
LexisNexis_14					0.0023*** (0.0007)	0.0016* (0.0007)	-0.0021** (0.0006)	-0.0017** (0.0006)
User Activeness	0.0042*** (0.0010)	0.0027** (0.0010)	0.0024* (0.0011)	0.0031** (0.0010)	0.0043*** (0.0009)	0.0027** (0.0010)	0.0024* (0.0011)	0.0031** (0.0010)
Positive Valence	0.5402*** (0.0490)		-0.3535*** (0.0379)		0.5411*** (0.0491)		-0.3536*** (0.0379)	
Negative Valence	0.7735*** (0.0474)		0.0528 (0.0337)		0.7731*** (0.0474)		0.0538 (0.0337)	
Positive Testimonial		0.2471*** (0.0509)		-0.2097*** (0.0429)		0.2475*** (0.0509)		-0.2095*** (0.0429)
Quality Complaint		0.1008* (0.0469)		0.2727*** (0.0365)		0.0978* (0.0469)		0.2731*** (0.0365)
Money Complaint		0.1318* (0.0667)		0.1311** (0.0468)		0.1298 (0.0667)		0.1323** (0.0468)
Social Complaint		0.9280*** (0.0502)		-0.2026*** (0.0518)		0.9345*** (0.0502)		-0.1997*** (0.0518)
Customer Question		-0.5436*** (0.0572)		0.3616*** (0.0357)		-0.5444*** (0.0572)		0.3620*** (0.0357)
Customer Suggestion		0.2889*** (0.0538)		-0.0547 (0.0538)		0.2857*** (0.0538)		-0.0544 (0.0538)
Irrelevant Message		-0.0146 (0.0747)		-0.8232*** (0.0793)		-0.0132 (0.0747)		-0.8233*** (0.0793)
Number of Observations	10640	10640	10640	10640	10640	10640	10640	10640

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A14.5. Regression results using random effects logistic regression model.

	Likes	Likes	Comments	Comments
Constant	2.1761*	2.3943**	-2.6147	-2.7000
	(0.9068)	(0.9159)	(1.5958)	(1.6444)
Industry = Airlines	-0.2703	-0.1796	-0.0060	-0.1672
	(0.2918)	(0.2947)	(0.5525)	(0.5680)
Industry = Commercial Banks	-1.0365	-1.1787*	0.5234	0.7698
	(0.5520)	(0.5575)	(1.0063)	(1.0360)
Industry = Consumer Products	-0.5117	-0.8009**	-0.4789	-0.2738
	(0.2984)	(0.3020)	(0.5491)	(0.5651)
Industry = Food and Drug Stores	-0.4913	-0.5474	0.2909	0.3115
	(0.3000)	(0.3030)	(0.5630)	(0.5789)
Industry = General Merchandisers	0.1038	0.0372	-0.1461	-0.1177
	(0.2627)	(0.2654)	(0.4815)	(0.4955)
Type = link	-0.5653***	-0.7132***	-1.6290***	-1.0273***
	(0.1548)	(0.1585)	(0.1691)	(0.1769)
Type = photo	1.7215***	1.7512***	0.0633	0.6372***
	(0.1384)	(0.1441)	(0.1331)	(0.1438)
Type = video	0.3357	0.2633	-1.4847***	-0.6829
	(0.3630)	(0.3633)	(0.4199)	(0.4400)
Log(Asset)	0.0168	0.0460	-0.0264	-0.0867
	(0.0902)	(0.0912)	(0.1675)	(0.1724)
Log(Word Count)	0.1212***	0.1797***	0.4875***	0.4145***
	(0.0225)	(0.0235)	(0.0246)	(0.0259)
ARI Score	0.0156***	0.0108*	-0.0132**	-0.0076
	(0.0047)	(0.0048)	(0.0050)	(0.0052)
Log(Page Popularity)	-0.5027***	-0.4814***	0.3693	0.3805
	(0.1158)	(0.1167)	(0.1986)	(0.2047)
Log(Post-Level UGC)	0.2929***	0.2030***	-0.4221***	-0.3334***
	(0.0228)	(0.0240)	(0.0244)	(0.0258)
Log(Post-Level MGC)	-0.1531***	-0.1212***	0.1536***	0.1274***
	(0.0330)	(0.0332)	(0.0351)	(0.0361)
LexisNexis_1	0.0149***	0.0134***	0.0045	0.0081*
	(0.0037)	(0.0037)	(0.0038)	(0.0040)
User Activeness	0.0040	0.0028	0.0003	0.0030
	(0.0023)	(0.0023)	(0.0023)	(0.0024)
Positive Valence	0.7526***		-0.4611***	
	(0.0653)		(0.0631)	
Negative Valence	1.0088***		-0.0280	
	(0.0632)		(0.0621)	
Positive Testimonial		0.3658***		-0.0920
		(0.0754)		(0.0788)
Quality Complaint		0.1981**		0.7200***
		(0.0717)		(0.0771)
Money Complaint		0.1538		0.1798
		(0.0944)		(0.1083)
Social Complaint		1.2497***		-0.4261***
		(0.0834)		(0.0863)
Customer Question		-0.6377***		1.0638***
		(0.0752)		(0.0791)
Customer Suggestion		0.3380***		0.0958
		(0.0892)		(0.0940)
Irrelevant Message		-0.2122		-1.1236***
		(0.1119)		(0.1186)
Number of Observations	10640	10640	10640	10640

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A14.6. Regression results after dropping 37 posts with videos

	Likes	Likes	Comments	Comments
Constant	2.3836***	2.3628***	2.0285***	2.0883***
	(0.2553)	(0.2548)	(0.2872)	(0.2873)
Industry = Airlines	-0.3924***	-0.2513*	-0.0549	-0.0986
	(0.1013)	(0.1036)	(0.0926)	(0.0926)
Industry = Commercial Banks	-0.7447**	-0.9584***	-0.7571**	-0.4839*
	(0.2449)	(0.2516)	(0.2333)	(0.2315)
Industry = Consumer Products	-0.2352*	-0.4086***	-0.8453***	-0.7291***
	(0.1149)	(0.1177)	(0.1197)	(0.1193)
Industry = Food and Drug Stores	-0.7391***	-0.7942***	-0.0046	0.0392
	(0.1143)	(0.1160)	(0.1071)	(0.1065)
Industry = General Merchandisers	-0.3164**	-0.3708***	0.2575**	0.2540**
	(0.0995)	(0.1007)	(0.0923)	(0.0919)
Type = link	-0.3414**	-0.4625***	-1.0328***	-0.6669***
	(0.1171)	(0.1172)	(0.1317)	(0.1318)
Type = photo	0.9636***	0.9701***	0.0321	0.3228***
	(0.0674)	(0.0696)	(0.0782)	(0.0792)
Log(Asset)	-0.0403	0.0043	0.0404	-0.0118
	(0.0372)	(0.0382)	(0.0348)	(0.0347)
Log(Word Count)	0.1003***	0.1466***	0.2625***	0.2255***
	(0.0152)	(0.0153)	(0.0129)	(0.0137)
ARI Score	0.0103***	0.0078**	-0.0085**	-0.0053
	(0.0030)	(0.0030)	(0.0029)	(0.0029)
Log(Page Popularity)	-0.3594***	-0.3425***	-0.1232*	-0.0994
	(0.0525)	(0.0538)	(0.0612)	(0.0603)
Log(Post-Level UGC)	0.2205***	0.1367***	-0.2425***	-0.1917***
	(0.0127)	(0.0133)	(0.0148)	(0.0155)
Log(Post-Level MGC)	-0.1134***	-0.0870***	0.0823***	0.0697***
	(0.0229)	(0.0225)	(0.0168)	(0.0168)
LexisNexis_1	0.0132***	0.0113***	-0.0002	0.0015
	(0.0023)	(0.0023)	(0.0023)	(0.0022)
User Activeness	0.0043***	0.0028**	0.0024*	0.0031**
	(0.0010)	(0.0010)	(0.0011)	(0.0010)
Positive Valence	0.5460***		-0.3538***	
	(0.0492)		(0.0379)	
Negative Valence	0.7782***		0.0499	
	(0.0476)		(0.0337)	
Positive Testimonial		0.2473***		-0.2118***
		(0.0509)		(0.0429)
Quality Complaint		0.1011*		0.2721***
		(0.0470)		(0.0365)
Money Complaint		0.1288		0.1287**
		(0.0667)		(0.0468)
Social Complaint		0.9308***		-0.2110***
		(0.0502)		(0.0519)
Customer Question		-0.5432***		0.3613***
		(0.0572)		(0.0358)
Customer Suggestion		0.2885***		-0.0526
		(0.0539)		(0.0537)
Irrelevant Message		-0.0140		-0.8409***
		(0.0752)		(0.0801)
Number of Observations	10603	10603	10603	10603

Note. * p<0.05; ** p<0.01; *** p<0.001. Bootstrap standard errors in parentheses.

Appendix A15. Exploratory online survey

Our objective in this paper is to examine what users post on Facebook business pages and the impact of post valence and content on engagement. Qualitative and quantitative analyses of archival data generated several insights and also raised some important questions. For example, who are the users who visit and post on Facebook business pages? What are their motivations for visiting the page, posting messages, and interacting with other users? What drives and explains the prevalence of negativity and the different antecedents of liking and commenting? We conducted an exploratory online survey in September 2017 to try to answer some of the questions and shed additional light on our key findings. We recruited participants from Amazon Mechanical Turk with two qualifications: (1) they must be in the U.S. and have Facebook accounts; and (2) they must have visited at least one business page on Facebook, and have read user posts on the page. We received a total of 123 valid responses. In the survey, we asked about (1) demographic information of users who have visited Facebook business pages including age, gender, and relationships with the businesses, and (2) motivations to visit business pages, read user posts, write posts, or like and comment on posts from other users using a five-point Likert scale. In designing the questions, we adapted established scales from relevant literature in online reviews and online communities (e.g., Hennig-Thurau and Walsh 2003; Hennig-Thurau et al. 2004; McAlexander et al. 2002), and created some new questions when we could not find established scales. A complete list of the survey questions is included in Table A15.1.

In addition, we report the top motivations reported by survey participants for five key behaviors, including visiting, reading, posting, liking and commenting on business pages of Fortune-500 companies. For each survey item, we calculated the average reported score (5-point Likert scale: 1 – strongly disagree, 5 – strongly agree) across participants who have visited the business pages of Fortune-500 companies (i.e., our research context). For each of the five key behaviors, we list the 5 items that received the highest average scores, indicating the top 5 most prevalent motivations, in Table A15.2.

Table A15.1. Complete List of Survey Questions.

Question	Response Type	Response Options	Source
We would like to ask about your experience with a specific company's Facebook page. Think of a company whose Facebook page you are most familiar with or have visited most frequently. Copy and paste the URL of the company's Facebook page below.	Text input	NA	NA
What is your relationship with this company?	Multiple choice	• I have purchased products or services from this company • I am interested in purchasing products or services from this company • I work for this company • Other. Please specify	NA
How frequently do you visit this company's Facebook page?	Multiple choice	• Daily • Weekly • Monthly • Quarterly • Yearly • Very Rarely	NA
Why do you VISIT this company's Facebook page? The following statements describe a list of possible reasons. Please indicate the degree to which you agree with each statement. 1. Because I enjoy learning about the company's products or services 2. Because it is fun to check out what happens with the company 3. Because browsing the company's Facebook page is pleasant 4. Because I enjoy learning about other users' experience with the company 5. Because it is fun to interact and exchange information about this company with other Facebook users 6. Because chatting with other Facebook users on the page is pleasant 7. Because visiting the company's page is useful to me 8. Because the company's page provides me with useful information 9. Because I visit the page to receive financial benefits from the company 10. Because I visit the page to communicate with the company about a particular issue 11. Because learning about other users' experience with the company is useful to me	5-point Likert scale	• Strongly disagree • Somewhat disagree • Neither agree nor disagree • Somewhat agree • Strongly agree	Adapted from McAlexander et al. (2002)

12. Because other users on the page provide me with useful information 13. Because I visit the page to ask other users to help me with a particular issue 14. Because I want to socialize with employees of the company 15. Because I want to interact with the social media staff of the company 16. Because I'm a loyal customer of the company 17. Because I feel emotionally connected with the company 18. Because I want to socialize with other users on the page 19. Because I want to interact with friends of mine on the page 20. Because I meet nice people on the page 21. Because I want to support the company 22. Because I like helping the company on its Facebook page 23. Because I want to help the company to be successful 24. Because I want to support the user community 25. Because I like helping other users on the company's Facebook page 26. Because I want to help other users to solve their problems			
How often do you engage in each of the following activities? 1. Reading posts written by other Facebook users on the page 2. Reading posts written by the company on the page 3. Posting on the page 4. Liking posts written by other Facebook users on the page 5. Liking posts written by the company on the page 6. Commenting on posts written by other Facebook users on the page 7. Commenting on posts written by the company on the page	Multiple choice	• Daily • Weekly • Monthly • Quarterly • Rarely • Never	NA
Why do you READ posts written by other Facebook users on the page? The following statements describe a list of possible reasons. Please indicate the degree to which you agree with each statement. 1. Because posts written by other users help me make the right decisions related to the company 2. Because I benefit from learning others' experiences before I buy a good or service 3. Because other users' posts give me fast information about the company 4. Because other users' posts give me credible information about the company 5. Because I can see if I am the only one who thinks of the company in a certain way 6. Because I like to compare my evaluation of the company with other users' 7. Because I feel much better when I read that I am not the only one who has a certain problem	5-point Likert scale	• Strongly disagree • Somewhat disagree • Neither agree nor disagree • Somewhat agree • Strongly agree	Adapted from Hennig-Thurau and Walsh (2003)

8. Because I like being part of the user community 9. Because I enjoy participating in this user community 10. Because I want to learn about what's happening in the user community 11. Because other users' posts provide me the right answers when I have questions or difficulties with a product or service 12. Because other users' posts provide me advice and solutions to my problems 13. Because the posts are written by other users that I frequent interact with 14. Because the posts are written by other customers of the company 15. Because the posts are written by members of the user community 16. Because other users' posts are fun to read 17. Because I enjoy reading other users' posts 18. Because reading other users' posts helps me kill time			
Why do you POST on the company's page? The following statements describe a list of possible reasons. Please indicate the degree to which you agree with each statement. 1. Because when I publicize the matter on Facebook, companies are more accommodating 2. Because It is more convenient to post on Facebook than writing to or calling the company 3. Because one has more power together with others on Facebook than writing a single letter of complaint 4. Because I want to get anger off my chest 5. Because I want to take vengeance upon the company 6. Because the company harmed me, and now I will harm the company 7. Because my posts help me shake off frustration about bad experiences 8. Because I want to help others by sharing my positive experiences 9. Because I want to help other users buy the right products or services 10. Because I want to warn other users about bad products or services 11. Because I want to save others from having the same negative experiences 12. Because I want to raise important corporate social responsibility issues among Facebook users 13. Because I can express my joy about a good experience 14. Because I can tell other users about a great experience 15. Because I feel good when I can tell others my buying success 16. Because my posts show others that I am a clever customer 17. Because a chat with like-minded people is a nice thing for me 18. Because it is fun to communicate with other users on the page	5-point Likert scale	• Strongly disagree • Somewhat disagree • Neither agree nor disagree • Somewhat agree • Strongly agree	Adapted from Hennig-Thurau et al. (2004); Nimako et al. (2012)

19. Because it is fun to communicate with employees of the company on the page 20. Because I want to share my feedback to a particular employee in the company 21. Because I meet and interact with nice people on the page 22. Because I receive incentives like coupons or discounts 23. Because I get rewards for posting 24. Because I post to support a good company 25. Because I am satisfied with the company and want to help it succeed 26. Because I want to make a suggestion to help the company with its products, services, social responsibility issues, etc. 27. Because I hope to receive advice from others to help solve my problems 28. Because I want to get tips or support from the company 29. Because I want to ask a question about the company' products, services, or other issues 30. Because I want to receive tips or support from other users 31. Because I want to seek corrective actions from the company about a bad experience 32. Because I want to seek explanations or apologies from the company about a bad experience 33. Because I want to seek remedy or compensation from the company about a bad experience			
Why do you LIKE posts written by other Facebook users on the page? The following statements describe a list of possible reasons. Please indicate the degree to which you agree with each statement. 1. Because I agree with what the users were saying 2. Because I agree with the content of the posts 3. Because I have had experiences similar to those of the users who posted the messages 4. Because I share the feelings of the users who posted the messages 5. Because I want to express my support to the users who posted the messages 6. Because I want other users to know that I support what they were saying 7. Because I want other users to know that I pay attention to their posts 8. Because I want to show that I care about what other users were saying 9. Because the users had liked my posts before 10. Because I want to return the favor of other users who had liked my posts before 11. Because I find the content of the posts interesting 12. Because liking others' posts on the page is a fun thing to do 13. Because I personally know the users who posted the messages	5-point Likert scale	• Strongly disagree • Somewhat disagree • Neither agree nor disagree • Somewhat agree • Strongly agree	Adapted from Scissors et al. (2016)

14. Because the users who posted the messages were my friends 15. Because liking is a nice way of interacting with other users on the page 16. Because I want to acknowledge other users' contribution to this community			
Why do you COMMENT on posts written by other Facebook users on the page? The following statements describe a list of possible reasons. Please indicate the degree to which you agree with each statement. 1. Because I agree with the posts 2. Because I want to express my support to the posts 3. Because I want to express my positive opinions and thoughts about what the users were saying 4. Because I disagree with the posts 5. Because I want to argue against the posts 6. Because I want to share my negative opinions and thoughts about what the users were saying 7. Because I want to add to the discussion by sharing my experience 8. Because I want to ask for clarifications 9. Because I want to follow up on what the users were saying 10. Because I want to raise awareness of the issues mentioned in the posts 11. Because I find the content of the posts interesting 12. Because commenting on others' posts is a fun thing to do on the page 13. Because commenting makes me feel less lonely 14. Because by commenting, I won't have to feel alone 15. Because commenting is a nice way of interacting with other users on the page 16. Because I want to interact with other users on the page 17. Because I personally know the users who posted the messages 18. Because the users who posted the messages were my friends 19. Because I want to answer other users' questions 20. Because I want to help other users with their problems by replying to their posts	5-point Likert scale	• Strongly disagree • Somewhat disagree • Neither agree nor disagree • Somewhat agree • Strongly agree	Adapted from Smock et al. (2011)
What is your gender?	Multiple choice	• Female • Male	NA
What is your age?	Multiple choice	• Under 25 years old • 25 - 34 years old • 35 - 44 years old • 45 - 54 years old • 55 years old and over • I prefer not to say	NA

Table A15.2. Top Motivations for Five Key Behaviors

Behavior	Top 5 Reported Motivations	Average Score
Visit business pages	• I enjoy learning about the company's products or services;	4.27
	• It is fun to check out what happens with the company;	3.59
	• Browsing the company's Facebook page is pleasant;	3.68
	• I enjoy learning about other users' experience with the company;	3.45
	• It is fun to interact and exchange information with other Facebook users.	3.22
Read user posts	• To benefit from others' experiences before I buy a good or use a service;	3.86
	• Because I like to compare my own evaluation of the company with that of others;	3.59
	• Because I really like being part of such a community of users;	3.45
	• Because I enjoy participating in this user community;	3.45
	• To find advice and solutions for my problems.	3.45
Post on business pages	• This way I can express my joy about a good experience;	3.95
	• I can tell others about a great experience;	3.79
	• I want to ask a question about the company' products, services, or other issues;	3.79
	• I want to give others the opportunity to buy the right products;	3.58
	• I want to make a suggestion to help the company about its products, services, social responsibility issues, etc.	3.53
Like user posts	• I agree with the content of the posts;	4.05
	• I agree with what the users were saying;	3.90
	• I find the content of the posts interesting;	3.80
	• I have had similar experiences as the users who posted the messages;	3.65
	• I share the feelings with the users who posted the messages.	3.50
Comment on user posts	• I agree with the content of the posts;	3.82
	• I find the content of the posts interesting;	3.76
	• I want to add to the discussion by sharing my experience;	3.65
	• I want to share my positive opinions and thoughts about what the users were saying;	3.47
	• I want to answer other users' questions.	3.47

Several things are worth noting from our survey responses. First, while the majority of visitors to Facebook business pages are customers with purchasing experiences, there are some visitors who have no purchasing experiences with the businesses. Second, users *visit* Facebook business pages and *read* user posts not only to get information about the companies' products and services and to learn about other users' experiences, but also for social reasons, e.g., being part of the user communities (agreed by 59% of participants). Third, the primary motivations for users to *post* on business pages include both sharing their experiences with other users, and requesting *customer service* from the businesses, by asking questions and making suggestions regarding the companies' products, services, or other issues (agreed by 55% of participants). Fourth, the motivations for liking versus commenting are indeed different. While users *like* posts mainly because they agree with the posts or they share similar experiences with the posters, users *comment* on posts also to join the discussions by sharing their own experiences and to answer other users' questions.

In summary, our survey responses confirmed our theoretical speculations that user-generated posts on Facebook business pages are conceptually different from online reviews. They are created by a combination of customers and users with no purchasing experiences. Their intended audience include both other users and the focal businesses. The motivations of creating and consuming user posts are not merely purchase-oriented and include a broad set such as requesting customer service and being part of the user community. As a relatively new platform for business-customer interactions, Facebook business pages seem to blend the elements of multiple phenomena, including but not limited to, electronic word-of-mouth among customers, online brand communities, and customer service interventions on social media.

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